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Firm R&D, Absorptive Capacity and Learning by Exporting: Firm-level Evidence from China

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1. INTRODUCTION

EXPORTERS are generally found to be more productive than non-exporters in firm-level trade literature. Their higher productivity can be attributed to either 'selection into export' (i.e. more productive firms choose to export) or 'learning by exporting' (i.e. exporting raises firm productivity). Empirical studies on various countries since Bernard and Jensen (1999) find mixed evidence for the learning-by-exporting hypothesis.[1] The inconclusiveness of research results suggests the importance of not only econometric techniques but also factors affecting the productivity effect of exporting. Cross-country differences in the stock of factors affecting the productivity effect of exporting could explain why exporting raises firm productivity in some countries but not in others. However, although there are many studies estimating the productivity effect of exporting, there are relatively few studies focusing on the determinants of such effect.[2]

In this study, we argue that a firm's absorptive capacity, developed through its investment in pre-export R&D, is crucial in learning by exporting. Intentional and persistent R&D investment before export helps build a firm's ability to value, assimilate and exploit external knowledge, thereby increasing its efficiency of learning when exposed to foreign advanced technologies and managerial experience.

Econometrically, we estimate the instantaneous and long-run productivity effects of exporting using data from China Annual Survey of Manufacturing Firms (2001–07). Our matching estimators suggest large differences in productivity effect for firms with different pre-export R&D status. First, for firms with pre-export R&D investment, starting to export raises firm productivity by 16 per cent instantaneously and 20 per cent three years after starting to export. However, for firms with no pre-export R&D investment, starting to export basically has no significant effect in raising productivity. Second, the productivity effect of exporting generally increases with the number of years of pre-export R&D investment. Firms with just a year of pre-export R&D investment have an instantaneous productivity gain of around 8 per

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[1] See Clerides et al. (1998) for Colombia, Mexico and Morocco; De Loecker (2007) for Slovenia; Greenaway and Yu (2004) and Greenaway and Kneller (2008) for The UK and Greenaway et al. (2005) for Sweden. See Martins and Yang (2009) for a review.

[2] Few studies have made attempts to find variables affecting the productivity effect of exporting, such as industry competition (Greenaway and Kneller, 2007) and development level of export destinations (De Loecker, 2007).

cent, whereas firms with three years of pre-export R&D investment have an instantaneous productivity gain of 32 per cent. These results suggest that firms with intentional and persistent investment in pre-export R&D are better equipped with absorptive capacity than firms with accidental R&D involvement and therefore benefit from higher productivity gains after exporting.

The importance of R&D for building absorptive capacity has been discussed intensively in the industrial organisation literature.[3] However, its effect on learning by exporting is not well documented. For two reasons, we expect firms with better absorptive capacity to have higher productivity gains from exporting. First, they can effectively identify valuable and important technological developments in foreign markets. When potential catch-up opportunities emerge, firms with no absorptive capacity may not become aware of them (Cohen and Levinthal, 1990). Second, firms with better absorptive capacity are more efficient learners of foreign advanced technologies. Because of the accumulative nature of knowledge, firms equipped with more knowledge stock in a given field find it easier to catch-up with recent technological developments in such field and in related fields and are more efficient in learning.

This study is related to two strands of literature. First, it is related to the literature testing the learning-by-exporting hypothesis. Research on the export–productivity relationship using firm-level micro data from China has only recently begun (Park et al., 2010; Feenstra et al., 2011; Ma et al., 2011; Yu, 2011). Some results are suggestive of the learning-by-exporting hypothesis. Park et al. (2010) find that firms whose export destinations experience large currency depreciations have slow growth in exports and that exports growth increases productivity. Yang and Mallick (2010) find supportive evidence of learning by exporting using a small sample of Chinese firms operating in 2000–02. Our study contributes to this line of research in two aspects. First, this is the first study that directly investigates the productivity effect of exporting using an annual firm survey data set from the National Bureau of Statistics of China, which has wider coverage and better representativeness than other data sources. Second, we find that pre-export R&D matters much for learning by exporting, a finding not mentioned in previous studies.

This study is also related to studies on the interaction between firm productivity, exporting behaviour and technological investment activities like R&D. Bustos (2011) finds that Argentinian firms in industries facing higher reductions in Brazil's tariff increase their investment in technology faster. Lileeva and Trefler (2010) assert that there are labour productivity gains from exporting for low-productivity Canadian manufacturing plants that are induced to export because of the Canada–US Free Trade Agreement and that firms gain by investing in technology. These studies ascertain that technological investment activities like R&D have a direct effect on raising productivity, that is, the innovative effect mentioned by Cohen and Levinthal (1989). However, the effect of increasing absorptive capacity is not mentioned. This study focuses on the absorptive capacity-building function of R&D and assesses its effect on learning by exporting.

The rest of the study is organised as follows. Section 2 describes the data and conducts some preliminary analysis. Section 3 estimates the productivity effects of exporting using

[3] For example, Kinoshita (2001) finds that the effect of R&D in increasing a firm's absorptive capacity is more important than the innovative effect for Czech manufacturing firms in 1995–98; Griffith et al. (2004) find R&D to be statistically and economically important in both technological catch-up and innovation using a panel of industries across 12 OECD countries and Hu et al.(2005) find that in-house R&D significantly complements technology transfer for a panel of Chinese manufacturing firms.

propensity score matching techniques. Section 4 evaluates the role of pre-export R&D on the productivity effect of exporting. Section 5 checks for robustness and makes further discussion. The last section concludes the study.

2. DATA DESCRIPTION

Data used in the present study come from a rich firm-level panel data set collected and maintained by the National Bureau of Statistics from annual surveys of manufacturing firms. The data set covers all state-owned enterprises (SOEs) and non-SOEs that are 'above scale', that is, with annual sales above RMB5 million (or equivalently, $800,000 approximately), from 2001 to 2007. On average, more than 200,000 firms are included each year, covering 33 industries and 31 provinces. To clean the data, we drop observations: (i) that report missing or negative values on overall revenue, total employment, fixed capital, total sales, intermediate inputs or export value; (ii) that have employment less than 8; (iii) that have values of total sales smaller than corresponding export values; and (iv) that have missing R&D data. Due to data availability, firm-level studies on China's R&D and innovations are sometimes restricted to include only a short period of time. The data set used in this study reports R&D investment in all seven years except in 2004, which is a census year. To enable analysis, we interpolate R&D investment in 2004 by averaging the R&D investment of firms in 2003 and 2005. After interpolation, we still have 433,444 observations with missing R&D data, and these observations are excluded. The final sample for analysis includes 1,592,246 observations for 490,302 firms.

Table 1 provides summary statistics for the main variables: employment, total sales, capital, total factor productivity (TFP), exporter dummy and R&D dummy. TFP in this study is calculated using the method proposed by Olley and Pakes (1996), which uses firm investment and capital stock as proxies for unobservable productivity.[4,5] Table 1 shows that about 27 per cent of firms export annually and about 12 per cent of firms conduct R&D activities. We further divide the exporting status of firms into three detailed categories: new exporter, existing exporter and never exporters. New exporters are firms that start to export at least one year after they are included in the sample, existing exporters are firms that already export when they are first entered into the sample,[6] and never exporters are firms that do not export during the whole sample period. New exporters constitute about 9 per cent of all firms, never exporters constitute another 63 per cent, and the rest are existing exporters (see Table 1).[7] We are mainly interested in productivity gains when and after a firm starts to export, so we compare the postexport productivity of new exporters and never exporters in our subsequent analysis.

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[4] The detailed estimation procedure is available online in the working paper version of this study circulated as 'Pre-Export R&D, Exporting and Productivity Gains: Evidence from Chinese Firms'.
[5] In later sections, we also calculate TFP using the Levinsohn and Petrin (2003) method.
[6] We do not know whether firms have exported prior to the observation period, so we assume that all firms already exporting at the beginning of the observation period have already begun exporting even before such period.
[7] Note that all new exporters and existing exporters combined account for 37 per cent of all firms, which is higher than the share of exporters in Table 1 (27.1 per cent). The reason is that the exporter share in Table 1 is calculated by averaging the share of exporters in each year, while the status of new exporters and existing exporters does not depend on year. For example, if a firm first appears in the sample in 2001, starts exporting in 2003 and stops exporting in 2005, it is not included in the calculation of exporter share in 2006 and 2007, but it is still included as a 'new exporter'. In other words, the share of new exporters and existing exporters added together equals the share of firms that have exported during the sample period.

TABLE 1
Summary Statistics

Variable	*Mean*	*Standard Deviation*	*Min*	*Max*
Log employment	4.74	1.09	2.20	12.15
Log sales	9.96	1.51	0	19.05
Log capital	8.34	1.86	0	18.87
TFP(OP)	4.21	1.15	−8.41	10.59
TFP (LP)	3.43	1.89	−7.38	14.65
FIE dummy	0.21	0.40	0	1
Exporter dummy	0.27	0.45	0	1
R&D dummy	0.12	0.32	0	1
New exporter	0.09	0.26	0	1
Existing exporter	0.28	0.42	0	1
Never exporter	0.64	0.46	0	1

TABLE 2
Firm Characteristics by Exporting Status

	By Exporting Status		*By Detailed Exporting Status*		
	Exporter	*Non-exporter*	*New Exporter*	*Existing Exporter*	*Never Exporter*
Panel A: basic firm characteristics					
Log employment	5.25	4.55	4.99	5.24	4.50
Log sales	10.44	9.78	10.35	10.39	9.72
Log capital	8.68	8.21	8.67	8.63	8.16
TFP_OP	4.26	4.21	4.30	4.25	4.20
TFP_LP	3.69	3.34	3.58	3.67	3.31
Panel B: R&D measures					
Log R&D	0.92	0.48	0.91	0.87	0.44
R&D dummy	0.16	0.10	0.17	0.15	0.09
R&D/Sales	0.002	0.008	0.003	0.002	0.01
Number of years investing in R&D			3.23	3.22	2.41

Table 2 summarises firm characteristics by different exporting status. Panel A reports basic firm characteristics, and Panel B reports various R&D measures: log value of R&D, R&D dummy, R&D intensity (defined by R&D investment divided by total sales) and number of years of R&D investment. Consistent with the literature, exporters are found to be larger, more productive and more capital intensive than non-exporters. Panel B reveals that exporters also invest more in R&D; the value of R&D investment for exporters is almost twice as large as that for non-exporters. Exporters also have higher propensity to invest in R&D (16 per cent) than non-exporters (10 per cent).[8] The last three columns further classify all firms down

[8] The fact that non-exporters have higher R&D intensity than exporters looks surprising at first. However, it makes sense if one realises that the relationship between R&D intensity and firm size is inverse-U shaped, and exporters usually stay on the right side of the firm size distribution. Very large exporters have low R&D intensity, making the average R&D intensity of exporters lower than that of non-exporters.

into new exporters, existing exporters and never exporters. Again, new exporters and existing exporters have superior performance over never exporters in almost every aspect of firm performance. Panel B includes the total number of years of R&D investment during the sample period; the number of years is assessed based on reports of positive R&D investment in at least one year. Note that this measure cannot be obtained when we divide firms into exporters and non-exporters because the exporter dummy is based on firm year. The last row of Panel B suggests that new exporters and existing exporters on average have more years of R&D investment (3.23 years) than never exporters (2.41 years).

3. ESTIMATING THE POST-ENTRY PRODUCTIVITY EFFECT

We now turn to econometrics to examine rigorously the post-entry productivity effect of exporting. The basic idea is to take exporting as a ‘treatment’, so its effects can be evaluated by the standard methods of average treatment effect on the treated (ATT). We rescale the year that a firm starts to export as period 0 and use $s \geq 0$ to denote the number of years after a firm starts to export. The average treatment effect of starting to export on starters can be written as

$$E(\omega_{is}^1 - \omega_{is}^0 | Start_i = 1) = E(\omega_{is}^1 | Start_i = 1) - E(\omega_{is}^0 | Start_i = 1). \tag{1}$$

The outcome of interest, TFP in our case, is denoted by ω^1 if a firm starts to export and ω^0 if it does not. $\text{Start}_i = 1$ represents a starter (a firm that starts to export). The practical difficulty is that ω^0 is not observable for starters. To get unbiased estimates of the ATT, we need to construct a control group consisting of firms that are conceptually identical to starters had they not started to export. Following the recent literature (De Loecker, 2007; Greenaway and Kneller, 2008), we adopt the propensity score matching method to construct such control groups. We use information prior to the year of exporting to estimate the propensity score:

$$P(Start_i = 1) = \Phi(h(Xi, -1)), \tag{2}$$

where X_i, -1 includes a series of firm characteristics one year prior to the period that a firm starts to export. As suggested by the literature, the most important characteristic is productivity. Other variables include firm size as measured by total employment, fixed capital (all in logs) and a set of region, ownership and two-digit industry classification dummies. To get an unbiased estimation of the propensity score, we allow for a flexible functional form of $h(.)$ by including higher-order and interaction terms. Probit model is used to estimate the propensity score, so $\Phi(.)$ represents the cumulative density function (CDF) of a normal distribution. The propensity score is estimated on a year-by-year basis. We conduct the propensity score matching following the algorithm by De Loecker (2007) and Greenaway and Kneller (2008).[9] To avoid the risk of comparing firms that are affected by different macroeconomic and

[9] The exact procedure of matching follows four steps. First, divide the propensity score into k equally spaced intervals so that the average propensity scores of the treated and control groups do not differ. Second, within each interval, test whether the first moment of the covariates differs between the treatment and control groups, that is, test the balancing condition. Third, if the balancing condition is rejected, alter the functional form of the propensity score by further adding higher-order and interaction terms and repeat the first two steps. Finally, after the balancing condition is satisfied, match the sample based on nearest neighbours.

industry conditions, the matching is conducted on a year-by-year and industry-by-industry basis. After identifying matching pairs, we pool all the years and industries together and calculate the average difference in outcomes between the treated and control group. The matching estimator can be written as follows:

$$ATT_s = \frac{1}{N_s} \sum_i (\omega_{is}^1 - \sum_{j \in C(i)} w_{ij} \omega_{js}^c) \quad s = 0, 1, 2, \ldots, \tag{3}$$

where ω^1 is the productivity of the treated firm, ω^c is the productivity of matched firms in the control group, $C(i)$ is the set of firms that are matched to the treated firm i, w_{ij} is the weight assigned to firm j that is matched to firm i and N_s is the total number of matches.[10] The matching estimator calculates the average outcome difference between treatment firms and firms in the control group matched to the treated firms.

Before turning to the results, it is useful to discuss matching quality. Two conditions are important for the consistency of the matching estimator: (i) the propensity score should be consistently estimated; and (ii) and the propensity score should have considerable overlap, so a large proportion of the treated group can be matched. We now turn to check these two conditions. Table A1 in the Appendix provides estimates of the propensity scores by year and their counterparts in the data. Our propensity score estimates are very close to the real data, and the differences are less than 1 per cent for all years, suggesting that our propensity scores provide reasonable estimates of the data. Table A2 provides the number of new exporters and matched exporters by year, as well as the proportion of firms that are matched. There are two reasons why a new exporter may not be matched. First, investment data are missing for some firms so that TFP (Olley-Pakes) cannot be calculated. Second, the propensity score of the treated observation lies outside the common support of the treated and control groups. However, Table 2 shows that our matching exercise has successfully matched over 80 per cent of new exporters in most years. There are lower matching rates for 2003 and 2006 compared with the other years, but we are still able to match around half of the new exporters.[11]

Table 3 reports the matching results. Results show that, on average, the sampled Chinese manufacturing firms experience only weak productivity gains from exporting over the years 2001–07; the effect is marginally significant only in the first year they start to export (instantaneous effect). After three years, the productivity gains from exporting (long-term effect) disappear. This result is consistent with the general pattern found in other previous studies that productivity gains are highest in the first year that firms start exporting (Greenaway and

[10] The standard error of the estimator is calculated by the square root of the formula

$$\frac{1}{N_T} Var(\omega^1) + \frac{\sum_{i \in I_C} w_i^2}{N_C^2} Var(\omega^c),$$

where N_T and N_C are the numbers of treated and control units, respectively; ω^1 and ω^c are the outcomes of treated and control units, respectively, and w_i is the weight assigned to each control unit in the matching. I_C is the set of control units. We report the one-to-one matching results. The results are qualitatively similar if nearest neighbours matching is used.

[11] In addition, it should be noted that for the long-run effects of exporting, we only estimate the s year effect for firms that still continue to export s years after starting to export. Therefore, the long-run effects do not apply to those firms that exit the export market afterwards. Because it is not unusual for firms to exit the export market after their first year of entry (Eaton et al., 2008), we expect the number of treated units to shrink by a large extent when estimating the long-run effects.

TABLE 3
Instantaneous and Long-run Productivity Effects of Exporting (Full Sample)

S	*0*	*1*	*2*	*3*
Average treatment effect on the treated	0.0210	0.0111	0.0230	0.0341
(SE)	(0.0122)*	(0.0223)	(0.0302)	(0.0398)
Number of treated units	17,357	8,371	4,291	2,306

Notes:
(i) This table reports the estimated average gains from exporting using the matching approach. s indicates the number of years after the firm starts to export for the first time.
(ii) * indicates significance at the 10% level.

Kneller, 2008; Martins and Yang, 2009). Decreasing productivity gains are subject to several interpretations. First, firms may learn most in their initial period of globalisation when they are exposed to advanced foreign technologies and faced with foreign competition for the first time. As their exporting experience grows, they learn less from foreign markets. Second, the increase in productivity in the first year of exporting may simply reflect greater utilisation of the productive capacity of firms after suddenly getting access to foreign demand.

4. PRE-EXPORT R&D AND THE PRODUCTIVITY EFFECT OF EXPORTING

In this section, we argue that pre-export R&D is important in generating the productivity effect of exporting. As described in the introduction, R&D not only directly affects productivity by improving the production process or innovation of high-quality goods but also enriches the knowledge stock of firms, increases their ability to identify and absorb advanced technologies and thus equips them to exploit future productivity enhancement opportunities. Following this logic, when exposed to foreign technologies after exporting, firms with higher absorptive capacity developed through pre-export R&D learn more from exporting and therefore experience higher productivity gains. We test this hypothesis in the following subsections.

a. Productivity Effects of Exporting for Firms With/Without Pre-export R&D

We first divide all firms into two subgroups: firms with pre-export R&D and firms without. Specifically, for a new exporter, pre-export R&D is positive if it has positive R&D expenditure in at least one year before it starts to export. Table 4 reports the number of new exporters with and without pre-export R&D and their proportions. Around 20 to 30 per cent of exporters invest in R&D before exporting, depending on the year involved. It is impossible to find the pre-export R&D status of never exporters. However, our matching is conducted on a year-by-year basis, so we include firms with (without) positive R&D expenditure before year t as the control group for new exporters in year t with (without) pre-export R&D. Propensity score matching is then conducted on each subsample.

Results from the two subsamples are shown in Table 5. ATTs for the subsample with pre-export R&D are shown in Panel (A), whereas ATTs for the subsample without pre-export R&D are shown in Panel (B). There exist huge differences in the productivity effects of exporting between subsamples with different pre-export R&D status. In Panel (A), all ATTs from the first year of export to three years after starting to export are positively significant, and the magnitude is around 14 to 20 per cent, which is much higher than the 2 per cent

TABLE 4
Number and Proportion of New Exporters with Pre-export R&D

Year	*With Pre-export R&D*	*Without Pre-export R&D*	*Proportion With Pre-export R&D(%)*
2002	330	1,449	22.8
2003	566	2,003	28.3
2004	1,060	3,919	27.0
2005	1,129	5,330	21.2
2006	587	3,012	19.5
2007	612	2,916	21.0

TABLE 5
Instantaneous and Long-run Productivity Effects of Exporting by Pre-Export R&D Status

S	*0*	*1*	*2*	*3*
Panel (A): Results for firms with pre-export R&D				
ATTs (SE)	0.1644	0.1377	0.2163	0.1956
	(0.0295)***	(0.0417)***	(0.0570)***	(0.0757)***
Number of Treated Units	3,421	1,715	958	548
Panel (B): Results for firms without pre-export R&D				
ATTs (SE)	−0.0147	−0.0216	−0.0325	−0.0161
	(0.0134)	(0.0193)	(0.0275)	(0.0366)
Number of Treated Units	13,936	6,656	3,333	1,758

Notes:
(i) This table reports the estimated average gains from exporting using the matching approach. *S* indicates the number of years after the firm starts to export for the first time. Panel (A) shows the result using only the subsample of firms with pre-export R&D. Panel (B) shows the results using only the subsample of firms without pre-export R&D.
(ii) ATT, average treatment effect on the treated.
(iii) *** indicates significance at the 1% level.

marginally significant effect we obtain using the full sample in Section 3. In Panel (B), however, none of the ATTs are positively significant. These results are strongly supportive of the hypothesis that pre-export R&D helps generate additional productivity gains from exporting. Although the productivity effect of exporting is weak and transient for all firms on average, it is large and lasting for firms with pre-export R&D. The effect is large because firms with more absorptive capacity can better recognise the most effective productivity-enhancing technologies and learn them more efficiently. The effect is lasting because firms with more absorptive capacity can better continuously discover new learning opportunities in the export process. For firms without pre-export R&D, however, productivity gains do not exist even instantaneously.

b. Productivity Effects for Firms with Different Years of Pre-export R&D Experience

The previous zero–one classification of R&D status cannot allow us to distinguish firms with intentional and persistent R&D investment from firms that are only accidentally involved in R&D. However, we expect the productivity effect to be different for these two types of firms. As pointed out by Cohen and Levinthal (1989), absorptive capacity is built by

TABLE 6
Productivity Effects of Exporting for Subsamples with Different Years of Pre-export R&D

N	*0*	*1*	*2*	*3*	*4*	*5*	*6*
Panel (A): Instantaneous effect							
ATTs (SE)	−0.0147	0.0754	0.2336	0.3188	0.2222	0.3644	0.3572
	(0.0134)	(0.0466)*	(0.0729)***	(0.1025)***	(0.1518)*	(0.2743)	(0.4262)
Number of Treated Units	13,936	1,809	842	480	205	61	24
Panel (B): Two-year effect							
ATTs (SE)	−0.0325	0.1997	0.2447	0.3350	0.1204	n.a.	n.a.
	(0.0275)	(0.0733)***	(0.1210)***	(0.1480)***	(0.2911)	(n.a.)	(n.a.)
Number of Treated Units	3,333	615	202	114	27	n.a.	n.a.

Notes:
N indicates the number of years a firm conducts pre-export R&D investment. Panel (A) shows the instantaneous effect, using the matching approach in section 3; Panel (B) shows the two-year effect.
(ii) ATT, average treatment effect on the treated.
(iii) * and *** indicate significance at 10% and 1% levels, respectively.

intentional and *persistent* R&D investment. Therefore, firms that persistently invest in R&D before exporting are likely to have more absorptive capacity – and thus experience larger productivity gains from exporting – than firms that are only accidentally involved in R&D.

One natural proxy for the extent of pre-export R&D is the number of years a firm has invested in pre-export R&D.[12] We therefore divide all firms into several subsamples by the number of years of their pre-export R&D investment and conduct the matching exercises as before for each subsample. Again, we cannot determine the number of years never exporters have invested in pre-export R&D. Hence, when we conduct matching on year t, we take never exporters that have N years of R&D investment before year t as the control group for new exporters that have N years of pre-export R&D. Results presented in Table 6 generally show that the productivity effect of exporting increases with the number of years of pre-export R&D. For firms with one year of pre-export R&D, the instantaneous effect and the two-year effect are 8 and 20 per cent, respectively, which are smaller than the 16 and 22 per cent effects found in subsection 4.a for all firms with pre-export R&D. The effects are much higher for firms with three years of pre-export R&D; the instantaneous effect is 32 per cent, and the two-year effect is 34 per cent.[13] These results are supportive of our hypothesis that firms with intentional and persistent pre-export R&D have better absorptive capacity and benefit from greater productivity gains from exporting.

5. ROBUSTNESS CHECKS AND FURTHER DISCUSSION

a. Alternative Measures of Productivity

To check whether our main results are sensitive to the estimation method of productivity, we also estimate TFP using the method suggested by Levinsohn and Petrin (2003), which uses

[12] This proxy is suggested in an influential study by Zahra and George (2002).
[13] Instantaneous effects for firms with five or six years of pre-export R&D are even larger, but they are not statistically significant. This may be due to too few matched observations in these categories.

intermediate inputs to proxy for unobservable productivity.[14] The matching exercise is first repeated on the subsamples with and without pre-export R&D, as in subsection 4.a, but we now use TFP calculated by LP instead of OP. Qualitatively, the results are very similar. Compared with firms without pre-export R&D, firms with pre-export R&D experience larger and more lasting productivity gains from exporting. All ATTs for the subsample with pre-export R&D are positively significant, with the instantaneous effect being 20 per cent and the three-year effect being 26 per cent. For the subsample with no pre-export R&D, the productivity effects are all positive, but the instantaneous and three-year effects are insignificant. The one-year and two-year effects, although significant, are much smaller than the corresponding effects found in the subsample with pre-export R&D. The matching exercises are also repeated for subsamples with different number of years of pre-export R&D, as in subsection 4.b. The results again show that the productivity gains of firms from exporting increase with the number of years of pre-export R&D investment. The instantaneous effects (two-year effects) are 15 per cent (20 per cent) and 29 per cent (47 per cent) for firms with one year of pre-export R&D and for firms with three years of pre-export R&D, respectively. In addition, the instantaneous effect for firms with four years of pre-export R&D now becomes significant because of the increased number of matched observations.[15]

b. Controlling for Confounding Variables

One might worry about possibilities that the huge heterogeneity in productivity effect is actually picking up the effect of other variables that are correlated with pre-export R&D, not the effect of pre-export R&D itself. We therefore investigate four possible confounding variables: firm size, ownership, productivity and post-export R&D.

First, we consider firm size as a possible confounding variable. If large firms systematically gain more from exporting compared with small firms, the result in the previous section is likely to emerge even if R&D does not matter.[16] In column (1) of Table 7, we report the matching results on subsamples of small and large firms, where small and large firms are defined according to the median firm size of an industry-year pair. We would like to compare productivity gains between firms with and without pre-export R&D *within* each firm size category. First, column (1) of Table 7 shows that within small firms, exporters with pre-export R&D have an instantaneous productivity gain (Panel A1) of 9 per cent and a two-year gain of 5 per cent (Panel B1). However, for firms without R&D, neither the instantaneous nor two-year effect is positive (Panel A2 and Panel B2).[17] Second, for large firms, the instantaneous and two-year effects are 18 and 22 per cent for firms with pre-export R&D. For firms without pre-export R&D, neither effect is positively significant. Therefore, our main result in Section 4 still holds irrespective of firm size.

[14] Compared with Olley and Pakes (1996), the method of Levinsohn and Petrin (2003) has the advantage of requiring only data on intermediate inputs to proxy for productivity, instead of requiring investment data which in many cases are reported to be zero or missing.

[15] The tables of results using TFP (LP) are not given here due to space constraints. These tables may be provided to interested readers upon request.

[16] We find in our data that R&D investment is highly concentrated in large firms. The value of R&D investment made by large firms is three times that made by small firms. Furthermore, large firms have a higher propensity (16 per cent) to conduct R&D activities than small firms (7 per cent).

[17] Although the two-year effect for small firms with pre-export R&D is insignificant due to too few matched firms, the point estimate is still much larger than the point estimate for firms without pre-export R&D.

TABLE 7
Productivity Effects of Exporting, Controlling for Other Confounding Firm Characteristics

	(1) Firm Size		*(2) Ownership*		*(3) Productivity*	
	Small	*Large*	*FIE*	*Non-FIE*	*Low*	*High*
Panel (A1): Instantaneous effects, for firms with pre-export R&D						
ATTs (SE)	0.0905	0.1847	0.2797	0.1578	0.0610	0.0607
	(0.0538)*	(0.0345)***	(0.0706)***	(0.0324)***	(0.0342)*	(0.0301)***
Number of Treated Units	844	2,655	629	2,765	2,136	1,245
Panel (A2): Instantaneous effects, for firms without pre-export R&D						
ATTs (SE)	−0.0056	−0.0004	−0.0469	0.0029	0.0183	−0.0248
	(0.0191)	(0.0188)	(0.0285)	(0.0152)	(0.0157)	(0.0137)*
Number of Treated Units	5,939	7,855	3,454	10,379	6,204	7,580
Panel (B1): Two-year effects, for firms with pre-export R&D						
ATTs (SE)	0.0540	0.2188	0.2203	0.2197	0.1886	0.1437
	(0.1374)	(0.0628)***	(0.1250)*	(0.0641)***	(0.0867)***	(0.0703)***
Number of Treated Units	159	794	214	732	319	561
Panel (B2): Two-year effects, for firms without pre-export R&D						
ATTs (SE)	−0.0590	−0.0007	−0.0692	−0.016	0.0831	−0.0406
	(0.0409)	(0.0363)	(0.0495)	(0.0328)	(0.0373)***	(0.0378)
Number of Treated Units	1,304	1,995	1,109	2,204	1,461	1,606

Notes:
(i) This table reports the estimated average gains from exporting using the matching approach. Columns 1–3 report productivity gains for firms with different sizes (big and small), ownership types (FIE and Non-FIE) and productivity (high and low), respectively. Panel (A1)/(A2) reports instantaneous effects for firms with/without pre-export R&D; Panel (B1)/(B2) reports two-year effects for firms with/without pre-export R&D.
(ii) ATT, average treatment effect on the treated.
(iii) * and *** indicate significance at 10% and 1% levels, respectively.

Second, we deal with firm ownership. Firms with foreign background may be more efficient in absorbing external knowledge and more responsive to foreign advanced technology than domestic firms. The result in the previous section may have just picked up the effect of foreign ownership if R&D investment is higher in foreign firms than in domestic firms. To rule out this possibility, in column (2) of Table 7, we report matching results on foreign-owned firms and domestic firms. Again, our main result is not sensitive to firm ownership. Within foreign-owned firms, the instantaneous and two-year effects for firms with pre-export R&D are 28 and 22 per cent, respectively. For firms without pre-export R&D, neither effect is positively significant. A similar pattern holds for domestic firms.

Third, we assess the possible effect of productivity on our findings. Firm productivity itself might help learning by exporting; high-productivity firms are likely to be more efficient learners and to learn more from exporting than low-productivity firms. To show that pre-export R&D matters irrespective of productivity levels, we divide firms into high-productivity and low-productivity firms and repeat the matching exercise on each subsample. The results are shown in column (3) of Table 7. It is clear that firms with pre-export R&D experience positive and large productivity gains (ranging from 6 to 18 per cent) irrespective of their productivity levels. For firms without pre-export R&D, however, the effects are generally smaller

TABLE 8
Productivity Gains from Exporting for Firms with Post-export R&D

	Instantaneous Effect	*Two-year Effect*
Panel A Pre-export R&D = 1 & Post-export R&D = 1		
ATTs (SE)	0.2164	0.2285
	(0.0368)***	(0.0622)***
Number of Treated Units	2,318	810
Panel A Pre-export R&D = 0 & Post-export R&D = 1		
ATTs (SE)	0.1545	0.1490
	(0.0601)**	(0.0759)**
Number of Treated Units	764	513

Notes:
(i) This table reports the estimated average gains from exporting using the matching approach. Panel (A) shows the result using only the subsample of firms with both pre-export R&D and post-export R&D. Panel (B) shows the results using the subsample of firms without pre-export R&D but with post-export R&D.
(ii) ATT, average treatment effect on the treated.
(iii) ** and *** indicate significance at 5% and 1% levels, respectively.

and less significant, and none of the effects are significant for high-productivity firms. As such, our previous results are not affected by productivity levels.

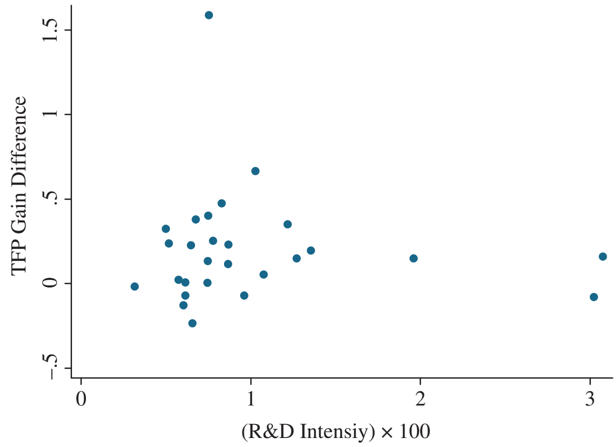
Finally, we evaluate the effect of post-export R&D investment on our results. Considering the persistence of R&D investment (Aw et al., 2011), firms with pre-export R&D are very likely to make R&D investment after exporting, and such post-export R&D may explain the productivity effect of exporting. To check for this possibility, we restrict the new exporters to the firms with positive post-export R&D and conduct our matching exercise on firms with different pre-export R&D status. Panel A of Table 8 shows that for firms with pre-export R&D and post-export R&D, the instantaneous and two-year effects are 22 and 23 per cent, respectively. Meanwhile, for firms without pre-export R&D but with post-export R&D, the instantaneous and two-year effects are both 15 per cent (Panel B).

Some may argue that the positive productivity effect of exporting is observed in firms without pre-export R&D but with post-export R&D, so pre-export R&D is not important. We challenge this argument from two aspects. First, although we see positive effects for firms without pre-export R&D, the magnitude is still 8 per cent smaller than that for firms with pre-export R&D. This 8 per cent difference, which is not small, should be attributed to pre-export R&D. Second, pre-export R&D may indirectly increase the productivity effect by inducing increased post-export R&D investment. Whether a firm invests in R&D after exporting depends on the benefits and costs of R&D. From the benefit side, the absorptive capacity developed from the pre-export R&D of firms may enhance the learning efficiency of firms and increase the effectiveness of their post-export R&D. From the cost side, pre-export R&D reduces the cost of post-export R&D because of the 'standing on the shoulders of giants' effect or the sunk cost of R&D activities (Aw et al., 2011). Both aspects induce firms with pre-export R&D to enhance their postexport R&D investment. In this regard, pre-export R&D still matters in the productivity effects of exporting.

c. Pre-export R&D and Productivity Effect of Exporting: Industry Heterogeneity

We have seen in Section 4 that pre-export R&D has a significant impact on productivity gains from exporting. However, does this impact differ across industries? Intuition tells us that

FIGURE 1
Average Treatment Effect on the Treated difference and Industry R&D Intensity



R&D investment should matter more for learning in R&D-intensive industries than in other industries, so we expect the impact of pre-export R&D to be larger in industries that are more R&D intensive. To test this expectation, we calculate differences in instantaneous productivity gains between firms with pre-export R&D and firms without pre-export R&D within each two-digit industry classification. In Figure 1, we plot the differences against each industry's R&D intensity. The pattern in Figure 1 turns out to be weakly supportive of larger impact in more R&D-intensive sectors. A clear positive relationship is detected in the lower left part of the graph. However, there exist some outlier industries. For example, the two outlier industries on the right, 'Manufacture of Communication Equipment, Computers, and Other Electronic Equipment' and 'Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work', have very high R&D intensity but show low impact of pre-export R&D on the productivity effect of exporting. One possible explanation for this counter-intuitive result lies in the nature of processing trade (Yu, 2011). Both of these industries have a large share of processing trade. It is possible that R&D and absorptive capacity do not matter very much for processing firms because they mostly do low-end assembly jobs. We leave this possibility for future research.

6. CONCLUDING REMARKS

While it is well established in recent firm-level trade literature that exporters are more productive than non-exporters, the evidence on learning by exporting is mixed. Unveiling the variables that affect the productivity effect of exporting is an important step towards understanding and unifying the mixed evidence. In this article, we argue that absorptive capacity developed through pre-export R&D investment is crucial for learning to occur. We estimate the instantaneous and long-run productivity effects of starting to export on the universe of Chinese manufacturing firms over the years 2001–07 using propensity score matching techniques. The baseline results show that while the productivity effect of exporting is weak and transient for all firms on average, it is large and lasting for firms with pre-export R&D. For firms without pre-export R&D, exporting has no significant productivity effect even instantaneously. In addition, the productivity effect of exporting increases with the number of years of pre-export R&D investment, suggesting that firms involved in intentional and persistent R&D activities enjoy greater learning effects compared with firms only accidentally involved in R&D activities. Our qualitative results are robust to alternative TFP measures and even after controlling for possible confounding variables.

The major findings of this article have important policy implications. Many developing countries have resorted to trade openness as a way to boost economic growth. Although it is quite established that trade liberalisation increases industry productivity at the aggregate level, more often than not, industry productivity growth is attributed to cross-firm resource reallocation rather than to within-firm productivity growth. Our results suggest that the lack of within-firm productivity growth may be due to the lack of absorptive capacity caused by inadequate R&D investment by firms. Therefore, policies that encourage firm R&D and other absorptive capacity-building activities should be combined with trade liberalisation to reap the full growth benefits of openness.

APPENDIX: MATCHING QUALITY

TABLE A1
Propensity Score Estimates and Counterparts in the Data

Year	*Estimate*	*Data*
2002	0.072	0.063
	(0.096)	(0.244)
2003	0.049	0.042
	(0.063)	(0.2)
2004	0.093	0.081
	(0.102)	(0.272)
2005	0.069	0.061
	(0.144)	(0.239)
2006	0.027	0.023
	(0.031)	(0.149)
2007	0.029	0.025
	(0.031)	(0.157)

TABLE A2
Number and Proportion of Matched Firms

Year	*Number of New Exporters*	*Number of Firms Matched*	*Proportion of Firms Matched (%)*
2002	1,779	1,551	87.00
2003	2,569	1,169	46.00
2004	4,979	4,124	83.00
2005	6,459	5,370	83.00
2006	3,599	2,024	56.00
2007	3,528	3,119	88.00

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