China Economic Review 45 (2017) 89–102

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Do bigger and older firms learn more from exporting? — Evidence from China☆

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ARTICLE INFO

Keywords:
Learning-by-exporting
Firm experience
Firm age
Firm size
China study

ABSTRACT

The literature has extensively discussed whether firms benefit from exporting (referred to as the learning-by-exporting (LBE) effect), but the empirical evidence is inconclusive. This paper draws on firm experience (age) to explain this question by using Chinese firm-level data for the period 1998–2007 to examine whether younger firms learn more from exporting than older firms. Employing propensity score matching and the difference-in-difference approach, we show significant LBE effects for older firms, especially those engaging in R & D activities, having large-scale production, and under private ownership. However, the yearly or cumulative LBE effects are either insignificant or rather limited for younger firms regardless of their R & D status and firm size.

1. Introduction

Like the learning-by-doing hypothesis (Arrow, 1962), participating in export activities also involves a learning process that may affect firm performance. Exporting exposes firms to an international environment that acts as a source of new knowledge, thus enabling exporters to engage in various forms of learning. For example, it allows firms to learn advanced technologies and best practices from foreign buyers and competitors that may not be available to non-exporters whose operations are confined to domestic markets. Exporting also allows firms to have access to international markets and industry networks, as well as to amass market information regarding the preference of foreign consumers. As a result, exporters may become more productive than non-exporters - an outcome referred to as the learning-by-exporting (denoted as LBE hereafter) effect. Despite the potential learning benefits that may stem from exporting, the empirical evidence on LBE has been inconclusive. Some show no significant LBE, e.g., studies on the United States (Bernard & Jensen, 1999), Slovenia (Damijan & Kostevc, 2005), Germany (Arnold & Hussinger, 2005), and India (Haidar, 2012); others find that LBE holds under limited circumstances (Silva, Afonso, & Africano, 2013; Yang & Mallick, 2010); while still others obtain unambiguously positive LBE for the cases of China (Hu, Lin, & Wang, 2016; Kraay, 1999; Lin, 2015), India (Mallick & Yang, 2013), and Egypt (Atkin, Khandelwal, & Osman, 2014).

Several reasons are provided to explain the mixed results. Silva et al. (2013) attribute it to the lack of a coherent theoretical framework to present guidance for empirical studies on LBE. Aw, Roberts, and Winston (2005) argue that LBE takes some time to occur, and that the data may not be long enough to detect its effects. Direct tests on LBE effects cannot be performed, as relevant data on advances, innovations, and adaptations are not available (Crespi, Criscuolo, & Haskel, 2008). The characteristics of firms or industries also play some roles. Past studies show that LBE holds only for new entrants and younger firms (Greenaway & Yu, 2004; Harris & Li, 2008), for firms with low and medium productivity levels (Cassiman and Golovko, 2007), for those with export intensity

☆ An earlier version of the paper was presented at the conference of 'The Pattern of China's Economic Development VII', Academia Sinica, Taipei, Taiwan, December 2014. The author thanks the conference participants and two anonymous referees of this journal for their very helpful comments and suggestions.

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http://dx.doi.org/10.1016/j.chieco.2017.06.005
Received 16 November 2016; Received in revised form 21 April 2017; Accepted 19 June 2017
Available online 20 June 2017
1043-951X/

exceeding a certain threshold (Castellani, 2002; Isgut & Fernandes, 2007), and for firms from laggard industries (Yasar, Garcia, Nelson, & Rejesus, 2007). In the case where LBE does exist, the extent of the learning effect may vary across different types of firms. Hu et al. (2016), for example, find that firms exporting to high-income regions and engaging in more processing trade or more varieties of exports generate a greater learning effect than other types of exporters. Mallick and Marques (2016) compare the export-pricing behaviors of China and India and find that the pricing strategies differ, depending on the quality of their products. This may in turn affect the extent of export learning, as exporting firms producing high-quality goods may concentrate their sales in high-income markets, thus providing greater incentives for them to upgrade their production technologies.

Country factors matter, too. Martins and Yang (2009), Yang and Mallick (2010), and Mallick and Yang (2013) show that the scope to learn from exporting may be relatively large for exporters from large emerging economies (e.g., China and India), because of their significant technological gap, limited experience in export businesses, and trade reform, which makes cheaper and high-quality imported inputs available; on the contrary, LBE is likely to be limited for exporters from developed countries selling to markets of similar development levels, as their export markets are equally competitive. Using meta-analysis, Yang and Mallick (2014) further show that countries with higher competitiveness and bigger external demand tend to experience higher export performance.

Different methods are proposed to solve for the problems in estimating productivities and may therefore affect the size of LBE. Some conduct the traditional OLS regression without taking into account the endogeneity problem between firm performance and export decisions; others implement the instrumental variable method to address the endogeneity problem (e.g., Hu et al., 2016; Lin, 2015) or adopt propensity score matching to allow a like-for-like comparison between exporters and non-exporters in the estimation (e.g., De Loecker, 2007; Yang & Mallick, 2010; Yang & Mallick, 2013). Atkin et al. (2014), on the other hand, use a randomized control trial through carefully designed surveys to identify the causal impact of exporting on firm performance. Using a meta-analysis approach on > 30 papers that study the relationships between exporting and firm productivity, Martins and Yang (2009) show that the OLS estimates of the export performance effect are systematically upward biased versus those having taken the endogeneity problem into consideration. Correcting for unobserved prices also leads to substantially lower productivity gains stemming from trade liberalization (De Loecker, 2011). Hu et al. (2016), however, show the opposite result: the OLS estimates indeed severely under-report the economic benefits from exporting in the case study of China.

The above studies suggest that being in the export market is not sufficient enough to generate LBE, and some other conditions need to be met in order to improve firms' post-entry productivities. In this paper we draw on firm heterogeneity to explain this inconclusiveness and in particular study how firm experience (age) affects LBE.[1] Most studies on the relationship between firm experience and learning effects are based on learning-by-doing models, but so far no consistent conclusions have been reached.[2]

Earlier studies argue that older firms tend to have greater work experience, established contacts with customers, and easier access to resources (e.g., Arrow, 1962; Chang, Gomes, & Schorfheide, 2002), which help them to identify, filter, and exploit business opportunities more accurately and therefore lead to a higher performance. This is in contrast to younger firms that face a liability of newness (Coad, Daunfeld, & Halvarsson, 2014) and may lack experience and foresight to achieve better performance or higher growth. However, more recent empirical works show that the relationship tends to be the opposite, i.e., older firms in general grow slower than younger firms. The liability of obsolescence (i.e., not being able to fit in well to the changing business environment) and the liability of senescence (i.e., becoming ossified by accumulated rules, routines, and organizational structures) often help explain why firms become less productive as they get older (Coad, Segarra, & Teruel, 2013). Younger firms, on the other hand, are said to be more likely to face new stimulus situations and can adapt to changing business conditions (Coad et al., 2014). They also need to grow faster in order to achieve economies of scale and overcome their "liability of newness" (Coad et al., 2014). Younger firms therefore tend to grow faster than older firms, but mainly for those that have been set up 5 years or less (Coad et al., 2014; Haltiwanger, Jarmin, & Miranda, 2013).

Only a few studies have looked at the relationship between firm experience and the learning effect from the perspective of learning-by-exporting, and the results all support the hypothesis that younger firms learn more from exporting than older firms. Delgado, Farinas, and Ruano (2002), for example, show LBE to be limited to younger exporters in a study of Spanish manufacturing firms. Baldwin and Gu (2003) find strong evidence of higher productivity growth for younger manufacturing plants. Fernandes and Isgut (2005) argue that younger manufacturing plants are much more likely to face new and organizational challenges and therefore benefit from larger LBE effects than their older counterparts.

In this paper we use Chinese manufacturing firm-level data for the period 1998–2007 to study the LBE effects with a special focus on their relationship with firm experience. We divide firms into two groups (older firms vs. younger firms), using the median age of the sample firms (i.e., 6 years) as the cut-off point, where younger firms refer to firms set up < 6 years and older firms are the rest. We show significant LBE effects for the sample as a whole, but reject the hypothesis that younger firms perform better and grow faster through LBE than older firms. Specifically, we show that the significant LBE effects mainly come from older firms, especially from those investing in research and development (R & D) activities, having large-scale production, and with ownership other than stated-owned or foreign-invested firms. The yearly and cumulative LBE effect is insignificant or relatively limited for the younger firms, regardless of their R & D status, firm size, and ownership. Moreover, for both younger and older firms, exporters' productivity growth rate is not significantly different from that of non-exporters. The above results are in contrast to the findings by Delgado et al. (2002), Baldwin and Gu (2003), and Fernandes and Isgut (2005) that younger firms learn more or grow faster from exporting than older firms.

[1] This paper looks at the export gains from firms' perspective. There are numerous papers discussing export gains at the macro level. See, for example, Lin & Sim (2013).

[2] The empirical studies on firm experience (firm age) and learning-by-doing are quite rare due to the lack of firm age data (Coad, Daunfeld, & Halvarsson, 2014).

One reason why older firms perform better than younger firms in LBE may be because the extent of exporters' productivity exceeding that of non-exporters is much larger for older firms than for younger firms, allowing older exporters to learn more from exporting than younger exporters. The other reason may have something to do with different learning capabilities (Dai & Yu, 2013) and different types of firms having a comparative advantage in different forms of learning (Liu, Wright, & Filatotchev, 2013). While older firms tend to have a comparative advantage in experiential learning due to their past production and business experiences, younger firms may be better positioned to capture benefits through vicarious learning (through learning by observing or knowledge spillovers) in order to overcome their "newness". To engage in vicarious learning from exporting, it is important for younger exporters to have better absorptive capability. Compared with younger non-exporters, younger exporters are more likely to engage in R & D activities, but their R & D intensities are smaller (not significant), suggesting that they may have inferior absorptive capability versus non-exporters. Although younger exporters are more productive than non-exporters, the productivity gap is rather limited and may not be large enough to offset the smaller learning effects due to relatively poor absorptive capability when compared with non-exporters. Such evidence helps explain why younger exporters do not receive a significant export premium. The story is quite different for older firms. Older exporters not only have a comparative advantage in experiential learning based on their past production and business experiences, but are also much more productive and capable of undertaking vicarious learning due to their much larger R & D intensity than non-exporters. These reasons allow older exporters to learn more from exporting and thus receive a significant export premium.

Section 2 defines different types of firms according to firm experience and exporting status and provides some preliminary analysis on their characteristics. Section 3 follows Levinsohn and Petrin (2003) to estimate total factor productivity and then uses the propensity score matching approach to identify the appropriate control groups of firms (non-exporters) so as to compare their productivity with exporters. Section 4 then uses the difference-in-difference approach to estimate LBE effects, discusses the relationship between LBE and firm experience, and presents the role of investing in R & D activities and firm size on LBE. The final section concludes.

2. Data and descriptive analysis

The data are drawn from the annual survey on Industrial Enterprise Statistics, compiled by China's National Bureau of Statistics for the period 1998–2007. The survey provides detailed information on firm-level statistics, including variables related to inputs (capital, labor, materials), output, and exports, which can be used to derive total factor productivity (denoted as TFP hereafter). The data make up an unbalanced panel, and firms with < 10 employees and duplicated observations are excluded. The number of observations is 1,470,106 for the whole sample period, with the number being 119,845 in 1998 and then increasing to 290,762 in 2007.

Firms are classified into older firms and younger firms based on firm experience measured by firm age, where the age of older firms is greater or equal to the medium age of the whole sample (i.e., 6) and that of younger firms is smaller than 6. Firms are also divided into 5 types according to their exporting status: *Starter*, *Quitter*, *Always*, *Never*, and *Switcher*. Firms that started exporting in a certain year and have stayed as exporters since then are defined as *Starter*. Exporting firms that decided to exit export markets for good during the sample period are defined as *Quitter*. Firms engaging in only exporting or domestic sales throughout the whole period of time are classified as *Always* or *Never*, respectively. Firms that joined and dropped out of export markets more than once are denoted as *Switcher*.

Table 1 shows the distribution of firms by firm experience and exporting status, presenting that the proportion of older firms is slightly more than that of younger firms (56% vs. 44%). Firms never engaging in exporting (*Never*) make up the largest group of firms, accounting for about 2/3 of the sample. Continuing exporters (*Always*) are the second largest group (about 23%). *Starter*, *Quitter*, and *Switcher* occupy only a small portion of the sample at 1.96%, 1.93%, and 4.93%, respectively.

Older firms are significantly different from younger firms in many aspects (Table 1). Compared to younger firms, older firms are more likely to export, tend to be larger in firm scale (measured by the number of employees), and adopt more capital-intensive technology. On the other hand, younger firms are more productive (measured by sales, value added, or TFP per worker) and pay on average higher wages than older firms. These facts are consistent with the argument in the literature that as late comers, younger firms tend to adopt the best-practice technology, but they are less likely to undertake R & D activity regardless of their exporting status, and their average R & D intensity is also smaller when compared to older firms.

According to the literature, there are some stylized facts about exporters. For example, exporters tend to be larger, more capital intensive, and perform better versus non-exporters. To see whether these stylized facts hold for manufacturing firms in China, we run the following panel regression with fixed effects:

$$y_{ijt} = \alpha_0 + \alpha_1 DEX + \alpha_2 l_{ijt} + \sum_j \alpha_j Ind_j + \sum_t \alpha_t Time_t + \in_{it},$$

where y_{ijt} refers to the features of firm i (e.g., firm size, capital-labor intensity, and performance) in industry j at year t; DEX is a dummy variable equal to 1 if firm i is an exporter and equal to 0 otherwise; l_{ijt} is the number of employees of firm i; and Ind_j and $Time_t$ are industry dummy and year dummy, respectively. All variables (except dummy variables) are in logarithm.

Table 2 reports the regression results, showing that compared to non-exporters, exporters are larger in scale (in terms of the number of employees), tend to be more capital intensive, pay a higher average wage, and perform better as measured by sales per worker, value added per worker, and TFP per worker.[3] Exporters are also more likely to engage in R & D activities, but are indifferent in R & D intensity as compared to non-exporters. These findings hold regardless of whether firms are older or younger. The above

[3] For the derivation of TFP, please see Section 3.

Table 1
Descriptive statistics for older firms and younger firms.

	Whole sample	Older firms	Younger firms
Observations, %	100	56.26	43.74
Starter, %	1.96	2.65	1.08
Never, %	68.38	65.53	72.05
Always, %	22.79	22.01	23.80
Quitter, %	1.93	2.83	0.78
Switcher, %	4.93	6.99	2.28
Characteristics			
Proportion of exporters, %	27.02	28.04***	25.69
Employment	271	336***	187
Capital per worker, log	3.50	3.52***	3.48
Average wage, log	2.21	2.18	2.24***
Sales per worker, log	5.12	4.98	5.29***
Value added per worker, log	3.86	3.72	4.03***
TFP per worker, log	2.37	2.21	2.56***
% of firms engaging in RD[a]	12.22	14.26***	9.75
Starter	28.39	29.36***	23.05
Never	9.92	11.19***	8.58
Always	15.79	18.53***	12.46
Quitter	18.90	19.11***	17.51
Switcher	21.44	21.67***	19.91
RD intensity,* %	0.27	0.36*	0.16
Starter	0.32	0.35***	0.20
Never	0.27	0.39	0.15
Always	0.24	0.29***	0.18
Quitter	0.20	0.21	0.17
Switcher	0.29	0.31	0.18

*** Denotes significance larger than the other group of firms at the 1% level.
* Denotes significance larger than the other group of firms at the 10% level.
[a] For the years 2001–2007, with 2004 being excluded.

Table 2
Characteristics of exporters and non-exporters.

	Whole sample	Older firms	Younger firms
Employment	0.44 (0.002)***	0.40 (0.002)***	0.47 (0.003)***
Sales per worker	0.17 (0.002)***	0.21 (0.003)***	0.13 (0.003)***
Capital per worker	0.07 (0.003)***	0.10 (0.003)***	0.03 (0.004)***
Average wage	0.21 (0.001)***	0.21 (0.002)***	0.21 (0.002)***
Value added per worker	0.12 (0.002)***	0.17 (0.003)***	0.06 (0.003)***
TFP per worker	0.10 (0.002)***	0.15 (0.003)***	0.05 (0.003)***
Engaging in R & D	0.022 (0.001)***	0.024 (0.001)***	0.017 (0.001)***
R & D intensity	− 0.01 (0.05)	− 0.02 (0.06)	− 0.005 (0.01)

*** Indicates significance at the 1% level.

results are largely in line with the findings of past studies for developing countries (e.g., De Loecker (2007) for Slovenia) and developed countries (such as Bernard & Jensen (1995) and Bernard and Wanger (1997) for the U.S. and Germany, respectively).

Table 2 also shows that exporters are on average 12% (or 10%) more productive than non-exporters when using value added (or TFP) per worker as a measure of productivity. These results may not imply the existence of the learning-by-exporting effect for three reasons. The first is that exporters tending to be more productive may simply reflect the self-selection effect (i.e., more productive firms are more likely to engage in exporting activity), but not the LBE effect. The second is that there are in fact 4 types of exporters: *Always*, *Switcher*, *Starter*, and *Quitter*. To detect the LBE effect, we need to know the year when firms started exporting. The problem with the group of *Always* is that the data about the starting year of exports are not available. The problem with *Switcher* is that it is a type of firm that has entered into export markets more than once. Moreover, without controlling for firm characteristics, the productivity differential between exporters and non-exporters may come from their difference in characteristics rather than the learning-from-exporting effect. This suggests that a control group (non-exporters) having similar characteristics as exporters is needed in order to more accurately estimate LBE effects. We will discuss how to construct the control group in the following sections.

One interesting observation from Table 2 is that the productivity differential between exporters and non-exporters is on average much larger for older firms than for younger firms, 17% vs. 6% (or 15% vs. 5%) in terms of value added (or TFP) per worker. Whether this implies a larger LBE for older firms than for younger firms will become clearer in a later discussion.

3. Productivity dynamics and identification of the control group

In this section we first use the approach developed by Levinsohn and Petrin (2003) to estimate TFP and discuss the productivity dynamics for different types of firms. We then follow De Loecker (2007) and employ a propensity score matching approach to construct the control group in order to better estimate the LBE effect, i.e., the productivity gap between exporters (the treated group) and non-exporters (the control group).

3.1. Productivity dynamics

We assume the production technology to have a Cobb-Douglas form:

$$v_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it}, \tag{1}$$

where v is firm i's value added; l and k are the inputs of labor and capital; and ω is firm i's productivity. All variables are in logarithmic form, and v and k are deflated by the 2-digit industry output price and input price, respectively.[4]

A simultaneity problem may arise between state variables k and ω, making the OLS estimators of Eq. (1) be inconsistent. This is because a positive (negative) shock that affects productivity (ω) may also induce a profit-maximizing firm to respond to it by expanding (shrinking) output, thereby changing its input usage (k). Levinsohn & Petrin (2003) propose to use intermediate inputs (m) as a proxy for the productivity shocks and show that estimators so derived are consistent.[5]

We follow the procedure proposed by Levinsohn & Petrin (2003) and estimate the production function for each 2-digit industry j separately. We then use consistent estimators $\widehat{\beta_0}$, $\widehat{\beta_l}$, and $\widehat{\beta_k}$ to calculate firm i's productivity ω in industry j:

$$\omega_{ijt} = v_{ijt} - \widehat{\beta_{0j}} - \widehat{\beta_{lj}} l_{ijt} - \widehat{\beta_{kj}} k_{ijt}. \tag{2}$$

We can now compare the productivity for the five groups of firms (i.e., *Always*, *Starter*, *Never*, *Quitter*, and *Switcher*) graphically. We redefine the time scale (denoted as s) for all groups of firms. For *Starter* and *Quitter*, the time scale is rescaled as zero for the year when the firms enter or exit the export market; and $s = -n$ or $s = n$ indicates n years before or after the entry or exit year. For firms that never export or always export throughout the sample periods, $s = 0$ is the median of the sample period for the firm.[6] Similarly, for the group of *Switcher*, $s = 0$ is also the median of the sample period for the firm.

We can observe whether more productive firms self-select themselves into becoming exporting firms (i.e., the self-selection hypothesis) by comparing the average productivity of *Starter* with *Never* prior to exports (i.e., before the year of $s = 0$). If the average productivity of *Starter* is greater than that of *Never* before the year of $s = 0$, then the self-section hypothesis holds. For the learning-by-exporting hypothesis to hold, the average productivity will increase after exports (i.e., after the year of $s = 0$).

Fig. 1 plots the productivities for the five groups of firms before, during, and after the year of entry into export markets, where the vertical axis is the average productivity and the horizontal axis is the time scale (s) rescaled to zero when a firm starts exporting. It shows that the productivity of *Starter* is greater than that of *Never* before entry into export markets (i.e., for $s < 0$), suggesting that more productive firms tend to self-select into exporting. The self-selection hypothesis also holds for both older firms and younger firms, but the productivity gap between *Starter* and *Never* before entering into export markets seems to be much smaller for younger firms than for older firms, a result supporting the finding from Table 2.

Fig. 1 also shows that the productivity gap between *Starter* and *Never* (or *Quitter*) widens after entering into export markets (i.e., $s > 0$). This provides some evidence for the existence of the LBE effects. Moreover, the productivity gap between *Starter* and *Never* (or *Quitter*) when $s > 0$ is much smaller for younger firms than for older firms, suggesting that LBE may be rather small for younger firms.

3.2. Identification of the control group

To estimate the LBE effect, a more accurate approach is to compare the productivity of a firm if it starts to export (denoted as $\omega_{is}{}^1$) with the productivity if it decides not to export (denoted as $\omega_{is}{}^0$):

$$E\{\omega_{is}^1 - \omega_{is}^0 \mid Starter_i = 1\} = E\{\omega_{is}^1 \mid Starter_i = 1\} - E\{\omega_{is}^0 \mid Starter_i = 1\}. \tag{3}$$

The crucial problem here is that once a firm decides to export, we cannot observe $\omega_{is}{}^0$. As the counterfactual productivity cannot be observed, we have to construct the control group in some way in order to derive a proxy for $\omega_{is}{}^0$. Following Becker & Ichino (2002) and De Loecker (2007), we use the propensity score matching method to identify the appropriate control group. The control group is selected such that the treated firms and the control firms have similar characteristics and their probability to start exporting is as close

[4] Since the firm-level price data are not available, we follow the standard solution in the literature and deflate the firm-level value added by the 2-digit industry output price index. According to De Loecker (2011), this may cause the productivity estimates to be biased if inputs are correlated with prices. The productivity measures so derived may also contain price and demand variations.

[5] Olley & Pakes (1996) employ investment as a proxy for productivity shocks. According to Levinsohn and Petrin (2003), the use of intermediate input rather than investment offers several benefits: the data of intermediate input are easier to get and intermediate input also responds more fully to productivity shocks as compared to investment. They also show that under the assumption on the demand for intermediate input (i.e., $m_{it} = m_{it}(k_{it}, \omega_{it})$, the parameters of the value-added equation can be estimated consistently.

[6] Here, we employ the median of the sample period for each firm.

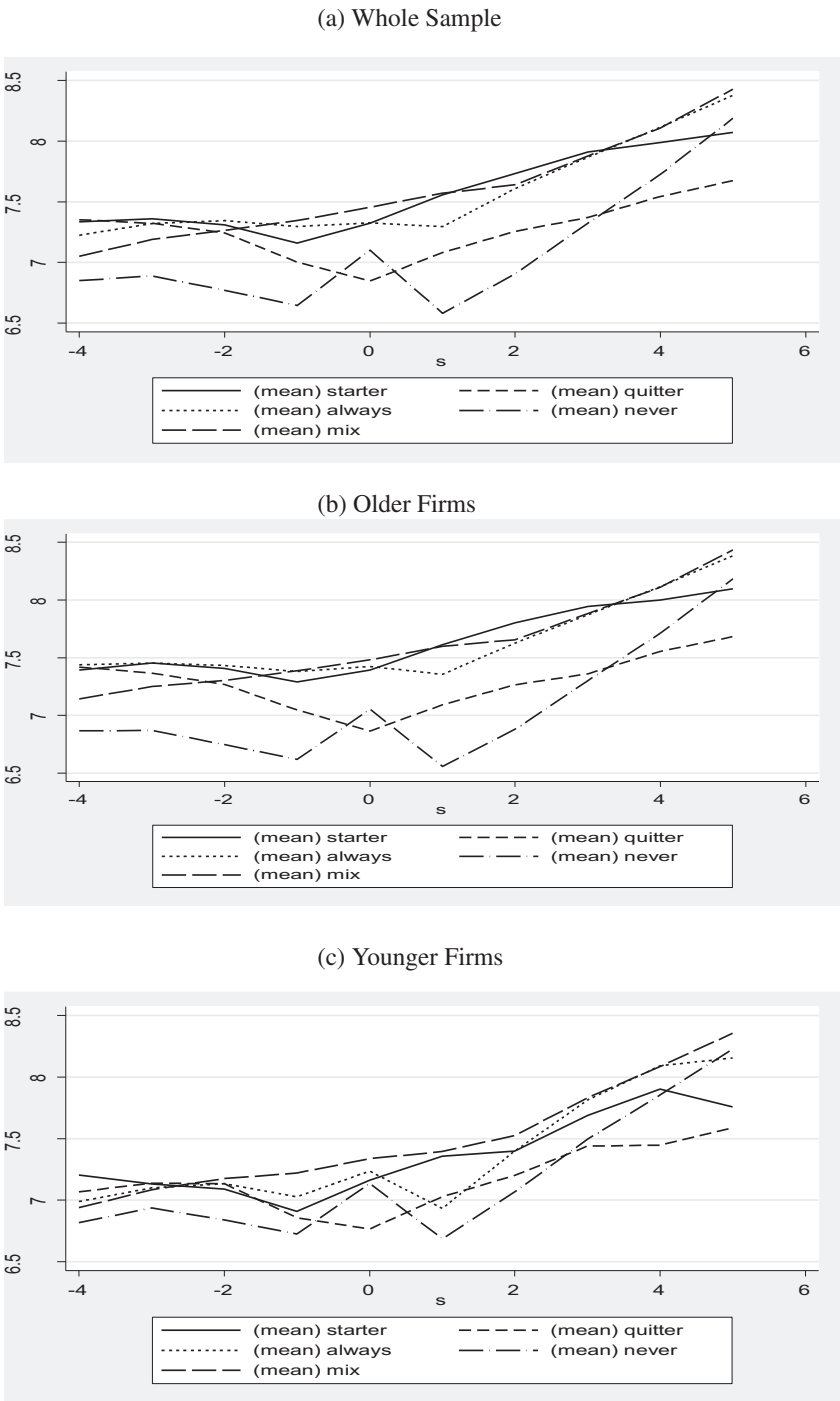

Fig. 1. Productivity trajectory for different types of firms.

as possible to that of the exporting firms.

To estimate the probability of a firm to start exporting (i.e., s = 0), we run the following equation with a probit model for each 2-digit industry:

$$Starter_{i0} = \gamma_0 + \gamma_1 \omega_{i,-1} + \gamma_2 k_{i,-1} + \gamma_3 Ownership_{i,-1} + \gamma_4 Ind3 + \gamma_5 Year, \tag{4}$$

where *Starter* is a dummy variable, which is 1 when the firm starts exporting and zero otherwise. We use lagged productivity, capital, and ownership as the explanatory variables. The ownership variables include *SOE* (state-owned enterprises), *FIE* (foreign-invested

enterprises), and *Private* (firms other than *SOE* and *FIE*); to avoid the multicolinearity problem, only two of them are included in the regression. To allow for industry and year effects, we also add a set of 3-digit industry dummies and year dummies.

The propensity score matching is performed for each 2-digit industry with *Always* and *Switcher* being excluded for reasons mentioned in Section 2. All regressions satisfy the balancing hypothesis.[7] We select non-exporting firms with a propensity score closest to that of the export entrant based on the method of 3 nearest neighbors. The group so selected is then used as the control group.

4. Estimation of learning-by-exporting

With the treated group and the control group in hand, we are ready to estimate the LBE effects. Assume that at each period s, there are N_s firms that start exporting (i.e., the treated group); and for each exporting firm i, there are N_i^c non-exporting firms with the propensity score being matched with firm i. The weighted average of the productivity of the control group (denoted as $C(i)$) is then used to compare with the productivity of exporters, with the weight being the inverse of N_i^c. Using a difference-in-difference approach, we estimate the LBE effects as the mean difference between the productivity of the treated firms and the weighted-average productivity of its corresponding control group at each period s (De Loecker, 2007):

$$LBE_s = \frac{1}{N_s}\sum\nolimits_i (\omega_{is}^1 - \sum\nolimits_{j\in C(i)} w_{ij}\omega_{ijs}^0).$$

A positive *LBE* indicates the existence of a productivity premium for firms starting to enter into export markets. The larger LBE_s is, the larger the LBE effect is at time s.

Table 3 reports *LBE* for all periods (i.e., s = {0, 1, …, 8}). Here, we impose the common condition by dropping treatment observations whose propensity score (denoted as pscore) is higher than the maximum or less than the minimum pscore of the controls. Table A2 in the Appendix reports the *t*-test results for the comparability of the treated and control groups after the Three-Nearest-Neighbors matching.[8] The covariates between the treated and control groups for the subsample of young firms are shown to be similar for s = 0 to s = 4, but they are not for the full sample and old firms after s > 2. This is not surprising as the pscore used for the matching is derived based on s = 0 (see Eq. (4)); if there is significant learning from exporting, then the treated and control groups will not look like each other several years after entry into export markets. This point will become clearer later on.

The findings show that significant LBE effects exist, beginning in the first year of exporting, lasting for another five years, and becoming insignificant after six years (i.e., s = 6). Exporting firms become 40% more productive once they start exporting (i.e., s = 0). As Pisu (2008) argues, the first-year productivity premium may not be the "true" LBE as the learning effects may take some time before they are detected.[9] It is more likely that the initial productivity gain comes from the scale effect induced by access to larger international markets (Damijan & Kostevc, 2005) or from differences in product mix between exporters and non-exporters (Alvarez & Lopez, 2005). Here, the continued increases in the productivity premium suggest that LBE does exist. In fact, LBE is a concave function of export experience (indicated by s), i.e., it increases with s and reaches a peak at 62.4% three years after the first time to export (i.e., s = 3), but then decreases to 62.1% at s = 5 and becomes insignificant at s = 6. This is consistent with the arguments by Fernandes & Isgut (2005), whereby entering into export markets puts pressure on firms to improve their production and marketing capability to meet any new challenges, but once firms succeed in meeting these challenges, the scope for further learning diminishes.

Compared to other studies where the productivity premium is around 10% (De Loecker, 2007 for Slovenia; Bryla, 2010 for Denmark; Yang & Mallick, 2014 for meta-analysis) and about 23% for China during 2000 to 2002 (Yang & Mallick, 2010, Table 2), the productivity premium for Chinese manufacturing firms herein is relatively large. The duration of a significant LBE also lasts longer, six years, compared to four years for Slovenian (De Loecker, 2007) and five years for Danish firms (Bryla, 2010). Here, starters are defined in a stricter sense, i.e., once firms start exporting they will continue to export throughout the sample periods. We are looking at the export premium of successful exporters, which, according to Manova & Zhang (2012), tend to use higher quality inputs to produce higher quality goods and may therefore generate greater learning effects than other types of exporters. This may help explain why a much larger productivity premium arises versus other country studies. China's transformation from a command economy toward a market economy may also make LBE much larger than those firms operating in market economies (Mallick & Yang, 2013), because so much can be learned from market economies.

Table 3 also reports the LBE effects for older firms and younger firms. While older firms obtain a significant export premium, there is no LBE for younger firms. The Welch's *t*-test also confirms that the LBE effects are significantly larger for older firms than for younger firms. If we gather the productivity gains over time,[10] younger firms do benefit from the average cumulative productivity gain, but only

[7] The balancing hypothesis refers to the condition that the first movements of the co-variates are not different for the treated and the control groups. Following De Loecker (2007), we consider higher polynominal-order terms of independent variables in Eq. (4), which includes the square terms of lag productivity and lag capital when the balancing hypothesis is rejected; in some cases, we only drop some of the industry or year dummies. With the above adjustment, all regressions satisfy the balancing condition for each 2-digit industry. For detailed discussions about the algorithm performed to test the balancing hypothesis, please see De Loecker (2007). The balancing test results are available upon request.

[8] Here, the results are reported for s = 0 to s = 4, but not for s ≥ 5 due to insufficient observations.

[9] This is because managerial improvements, innovations, and adoption of new technologies stemming from exporting cannot cause immediate lasting effects in productivity.

[10] The average cumulative gain gathered over a period S after the decision to start exporting is calculated as follows: $LBE_s = \frac{1}{N_s}\sum_i (\sum_{s=0}^{S}\omega_{is}^1 - \sum_{s=0}^{S}\sum_{j\in C(i)} w_{ij}\omega_{ijs}^0)$. See De Loecker (2007).

Table 3
Learning by exporting effects - older firms vs. younger firms.

	Whole sample		Older firms		Younger firms		Welch's *t*-test Old vs. young
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)	
s = 0	0.400	(0.224)*	0.441	(0.255)*	0.238	(0.230)	24.12***
s = 1	0.525	(0.191)***	0.585	(0.261)**	0.356	(0.270)	20.85***
s = 2	0.589	(0.244)**	0.638	(0.298)**	0.459	(0.317)	12.62***
s = 3	0.624	(0.242)***	0.656	(0.290)**	0.556	(0.366)	5.90***
s = 4	0.600	(0.248)**	0.645	(0.283)**	0.589	(0.447)	2.59***
s = 5	0.621	(0.345)*	0.633	(0.403)	0.538	(0.386)	3.97***
s = 6	0.520	(0.395)	0.480	(0.564)	0.321	(0.557)	4.16***
s = 7	0.475	(0.359)	0.483	(0.498)	0.321	(0.596)	3.69***
s = 8	0.565	(0.614)	0.620	(0.733)	0.308	(0.946)	3.49***
Cumulative productivity							
s = 0	0.400	(0.224)*	0.441	(0.255)*	0.238	(0.230)	24.12***
s = 0 ~ s = 1	0.948	(0.395)**	1.056	(0.474)**	0.610	(0.460)	23.38***
s = 0 ~ s = 2	1.548	(0.621)**	1.712	(0.745)**	1.059	(0.719)	19.69***
s = 0 ~ s = 3	2.181	(0.846)***	2.386	(0.997)**	1.589	(0.949)*	16.70***
s = 0 ~ s = 4	2.784	(1.056)***	3.042	(1.211)**	2.159	(1.321)	12.62***
s = 0 ~ s = 5	3.387	(1.193)***	3.674	(1.353)***	2.671	(1.616)*	10.83***
s = 0 ~ s = 6	3.901	(1.455)***	4.163	(1.601)***	2.903	(1.834)	10.62***
s = 0 ~ s = 7	4.374	(1.676)***	4.649	(1.865)**	3.216	(2.308)	8.54***
s = 0 ~ s = 8	4.936	(2.001)**	5.270	(2.442)**	3.515	(2.769)	6.38***

Note: "s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.
*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

marginally at s = 4 and s = 6 (see the lower panel of Table 3). Nevertheless, the average cumulative productivities of older firms are statistically significant and are higher than those of young firms throughout the whole sample years following their entry into export markets. This is in contrast to Fernandes & Isgut (2005) for Colombia, where LBE is shown to be more important for younger plants than for older plants,[11] perhaps because the productivity gap between exporters and non-exporters is much larger for older firms than for younger firms as illustrated in Table 2, allowing older exporters to learn more from exporting and to therefore benefit more from LBE as compared to younger exporters.

The other reason why older firms learn more from exporting than younger firms may have something to do with their different learning capabilities and comparative advantage in different forms of learning. According to the literature (Liu, Wright, & Filatotchev, 2013), there are two forms of learning: experiential learning (based on past experience of conducting business activities) and vicarious learning (through learning by observing or knowledge spillovers). While older firms tend to have a comparative advantage in experiential learning due to their past experience, younger firms may be better positioned to capture benefits through vicarious learning in order to overcome their lack of resources and experience. However, the extent for firms to engage in vicarious learning so as to capture the benefits from learning-by-exporting depends crucially on their absorptive capabilities. The lower the absorptive capabilities are, the smaller the learning effects will be.

Following the literature, we use R & D as a measure of absorptive capabilities (Dai & Yu, 2013). As Table 1 shows, younger firms are much less likely to undertake R & D activities and have smaller R & D intensity than older firms regardless of their exporting status. Although younger exporters are more likely to undertake R & D, their R & D intensity, on average, is smaller (but insignificant) than younger non-exporters (Table 2). This suggests that younger exporters may not be more capable of capturing the benefits from vicarious learning than older firms; younger exporters also do not improve productivity relative to non-exporters even though they are exposed to a new source of knowledge that may not be available to non-exporters.

The above argument can be seen by estimating the LBE effects for firms with or without R & D. Table 4 shows that only older exporters with R & D receive a significant export premium, while younger exporters have no LBE at all regardless of whether they undertake R & D or not. This supports the argument by Dai & Yu (2013) that R & D matters in determining the LBE effect, but we further show that it matters only for older firms and not for younger firms. In fact, R & D is a good indicator of product quality. Higher R & D propensity and intensity on the part of older firms suggest that older firms tend to produce higher-quality goods exported to higher income markets, thereby generating larger learning effects as they strive for upgrading their product quality via gaining access to foreign markets (Mallick & Marques, 2016).

Since large-sized firms tend to accumulate production experience faster than small- and medium-sized firms, their experiential learning effect may be more significant. For the Chinese manufacturing firms we study, large-sized firms are also more likely to engage in R & D and have larger R & D intensity than small- and medium-sized firms, suggesting that large-sized exporters may be

[11] Fernandes & Isgut (2005) attribute the results to the fact that younger plants are much more likely to face new stimulus situations, which require managers and workers to find solutions to new technical and organizational problems.

Table 4
Learning by exporting effects for firms with and without R & D.

	Whole sample		Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
With R & D						
s = 0	0.399	(0.259)	0.428	(0.299)	0.258	(0.277)
s = 1	0.529	(0.245)**	0.595	(0.286)**	0.365	(0.313)
s = 2	0.595	(0.291)**	0.672	(0.303)**	0.410	(0.346)
s = 3	0.640	(0.287)**	0.687	(0.314)**	0.512	(0.432)
s = 4	0.605	(0.317)**	0.650	(0.352)**	0.493	(0.528)
s = 5	0.640	(0.409)	0.622	(0.407)	0.493	(0.414)
s = 6	0.528	(0.415)	0.478	(0.478)	0.370	(0.616)
s = 7	0.475	(0.355)	0.481	(0.490)	0.331	(0.589)
s = 8	0.570	(0.608)	0.636	(0.728)	0.307	(0.948)
Without R & D						
s = 0	0.348	(0.317)	0.409	(0.326)	0.142	(0.627)
s = 1	0.428	(0.315)	0.489	(0.389)	0.263	(0.566)
s = 2	0.539	(0.356)	0.542	(0.432)	0.505	(0.675)
s = 3	0.631	(0.385)	0.578	(0.467)	0.658	(0.613)
s = 4	0.656	(0.486)	0.649	(0.385)	0.667	(0.767)
s = 5	0.681	(0.406)	0.656	(0.497)	0.381	(0.790)
s = 6	0.568	(0.782)	0.593	(1.084)	0.557	(0.757)
s = 7	–		–		–	
s = 8	–		–		–	

Note: "s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.
** Indicates statistical significance at the 5% level.

more capable of engaging in vicarious learning. We therefore expect large-sized firms to have a significant export premium while small- and medium-sized firms do not.

To examine what role firm size plays in determining the export premium, we divide firms into eight groups according to firm experience (older vs. younger), whether or not engaging in R & D, and firm size, where firm size includes small- and medium-sized firms (with employees below 250) and large-sized firms (employees equal to or above 250). Table 5 shows that for younger firms, there is no significant LBE regardless of R & D status and firm size; and for older firms, only large-sized firms with R & D investment

Table 5
Learning by exporting effects - by R & D and firm size.

	Large-sized firms				Small- and medium-sized firms			
	Older firms		Younger firms		Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
With R & D								
s = 0	0.578	(0.350)*	0.432	(0.467)	0.278	(0.336)	0.115	(0.263)
s = 1	0.649	(0.359)*	0.401	(0.480)	0.453	(0.409)	0.252	(0.335)
s = 2	0.753	(0.457)*	0.367	(0.469)	0.531	(0.462)	0.381	(0.325)
s = 3	0.844	(0.496)*	0.523	(0.496)	0.562	(0.408)	0.424	(0.370)
s = 4	0.801	(0.473)*	0.527	(0.618)	0.387	(0.491)	0.360	(0.511)
s = 5	0.766	(0.480)	0.481	(0.651)	0.417	(0.656)	0.467	(0.497)
s = 6	0.761	(0.475)	0.404	(0.819)	0.259	(0.919)	0.473	(0.574)
s = 7	0.637	(0.574)	0.543	(0.917)	0.342	(0.675)	0.325	(0.664)
s = 8	0.686	(0.762)	0.616	(1.074)	0.406	(0.757)	0.030	(1.025)
Without R & D								
s = 0	0.459	(0.366)	0.353	(0.412)	0.318	(0.361)	− 0.01	(0.722)
s = 1	0.488	(0.396)	0.511	(0.638)	0.397	(0.409)	0.064	(0.685)
s = 2	0.608	(0.486)	0.939	(0.561)	0.406	(0.553)	0.061	(0.834)
s = 3	0.620	(0.588)	0.841	(0.564)	0.412	(0.859)	0.528	(0.909)
s = 4	0.495	(0.589)	0.938	(0.727)	0.602	(0.817)	0.379	(0.794)
s = 5	0.591	(0.744)	0.680	(0.588)	0.487	(0.521)	0.293	(0.926)
s = 6	0.632	(1.080)	0.765	(0.550)	0.481	(0.519)	0.298	(0.879)
s = 7	–		–		–		–	
s = 8	–		–		–		–	

Note: large-sized firms and small- and medium-sized firms refer to firms with employees L ≥ 250 and L < 250, respectively.
"s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.
* Indicates statistical significance at the 10% level.

Table 6
Learning by exporting effects for firms engaging in R & D - by firm size and ownership.

	Large-sized firms				Small- and medium-sized firms			
	Older firms		Younger firms		Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
SOE								
s = 0	0.571	(0.898)	0.132	(0.856)	0.257	(1.288)	0.809	(1.125)
s = 1	0.583	(1.099)	0.231	(1.407)	0.307	(1.094)	− 0.116	(1.393)
s = 2	0.587	(0.719)	0.229	(0.792)	0.587	(1.342)	1.330	(1.701)
s = 3	0.796	(0.684)	0.466	(0.782)	0.021	(1.643)	1.659	(1.457)
s = 4	0.745	(0.752)	0.249	(1.098)	0.339	(1.156)	1.143	(2.367)
s = 5	0.965	(0.724)	0.408	(1.418)	0.455	(1.115)	0.116	(0.990)
s = 6	0.739	(0.953)	0.537	(1.141)	− 0.702	(1.917)	0.098	(0.975)
s = 7	0.407	(1.035)	0.180	(0.734)	1.037	(0.171)	− 0.786	(0.050)
s = 8	1.057	(1.161)	− 0.116	–	1.145	–	− 0.663	(0.733)
FIE								
s = 0	0.067	(0.764)	− 0.099	(0.743)	0.162	(0.538)	0.009	(0.597)
s = 1	0.162	(1.257)	− 0.119	(1.037)	0.314	(0.564)	0.110	(0.906)
s = 2	0.002	(0.939)	− 0.088	(0.945)	0.090	(0.599)	0.231	(0.744)
s = 3	0.069	(0.945)	0.010	(0.978)	0.351	(0.508)	0.195	(0.596)
s = 4	0.040	(1.040)	0.160	(0.761)	0.170	(0.698)	0.177	(0.675)
s = 5	0.286	(1.063)	− 0.136	(0.714)	− 0.154	(0.714)	0.095	(0.846)
s = 6	0.337	(1.016)	− 0.172	(0.811)	0.078	(0.497)	− 0.219	(1.149)
s = 7	0.423	(1.479)	0.131	(1.027)	0.366	(0.604)	− 0.026	(1.027)
s = 8	0.941	(1.408)	0.165	(1.225)	0.809	(1.429)	− 0.349	(1.102)
Other								
s = 0	0.465	(0.319)	0.378	(0.368)	0.193	(0.279)	0.097	(0.286)
s = 1	0.529	(0.259)**	0.484	(0.388)	0.292	(0.290)	0.221	(0.289)
s = 2	0.623	(0.325)*	0.562	(0.535)	0.374	(0.438)	0.297	(0.276)
s = 3	0.659	(0.401)	0.619	(0.530)	0.379	(0.412)	0.383	(0.368)
s = 4	0.646	(0.376)*	0.617	(0.626)	0.434	(0.499)	0.385	(0.400)
s = 5	0.663	(0.466)	0.534	(0.677)	0.447	(0.505)	0.359	(0.574)
s = 6	0.629	(0.405)	0.279	(0.899)	0.299	(0.739)	0.369	(0.452)
s = 7	0.618	(0.548)	0.446	(0.897)	0.351	(0.805)	0.511	(0.553)
s = 8	0.623	(0.716)	0.617	(0.690)	0.336	(0.713)	0.127	(1.127)

Note: "s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

significantly learn from exporting. This suggests that for LBE to occur, firms have to be older, larger, and invest in R & D in order to facilitate experiential and vicarious learning. For a younger firm or a small- and medium-sized firm, the accumulation of production and business experience is not large enough for it to be able to engage in experiential learning from exporting; neither is it capable of benefitting from vicarious learning, because of its rather limited absorptive capability.

Firm performance in China varies significantly across ownerships. To see whether this is the case for LBE, we further divide firms with R & D by their size and ownership. Again, Table 6 shows that the productivity premium is not significant for younger firms regardless of their size and ownership types. However, for older firms with large-scale production, the productivity gain is significant only for *Private*. The result is not surprising, as some studies have shown that, on average, *SOE* performs worse than other groups of firms and may not have the capability to learn from exports. Foreign-invested firms (*FIE*), on the other hand, have already accumulated much international business experience before they invested in China; exporting therefore may not help improve their productivity as not much more can be learned.

To see whether the productivity growth of exporters also exceeds that of non-exporters, we use the productivity growth rate as the measure of LBE. Table 7 shows that the productivity growth rates do not differ significantly between exporters and non-exporters regardless of whether firms are older or younger and regardless of firm size and whether or not it invests in R & D.[12] This differs from Baldwin & Gu (2003), who find strong evidence of higher productivity growth for younger plants.

For a robustness check, we follow Fernandes & Isgut (2005) and classify firms according to whether a firm is established before a specific year. Alternatively, we can use the average age of the whole sample of firms (i.e., 12) as the cutoff point. The findings exhibit that using the average age or the year 1998 as the cutoff point for older and younger firms offers qualitatively the same results as those found here.[13] Moreover, if we classify firms into 4 groups according to their age quantile (i.e., Age $<$ P25, P25 $\leq$ Age $<$ P50, P50 $\leq$ Age $<$ P75, and Age $\geq$ P75, where P denotes percentile), we can show that the LBE effect increases with the age quantile in terms of either the size of LBE or the statistical significance in most cases (see Table 8). This provides more evidence for the

[12] The results for the cases of whether or not a firm invests in R & D and for different firm sizes are not shown in Table 6, but are available upon request.
[13] The results are available upon request.

Table 7
Growth rate of productivity.

Time scale	Whole sample		Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)
s = 0	0.109	(0.117)	0.082	(0.153)	0.124	(0.176)
s = 1	0.052	(0.093)	0.030	(0.099)	0.092	(0.171)
s = 2	0.078	(0.090)	0.093	(0.126)	0.100	(0.201)
s = 3	0.084	(0.095)	0.042	(0.116)	0.147	(0.232)
s = 4	0.041	(0.130)	0.036	(0.143)	0.089	(0.293)
s = 5	0.045	(0.142)	0.031	(0.168)	0.060	(0.201)
s = 6	− 0.014	(0.205)	− 0.052	(0.275)	− 0.042	(0.308)
s = 7	− 0.003	(0.193)	0.043	(0.242)	− 0.004	(0.316)
s = 8	− 0.057	(0.263)	0.025	(0.310)	− 0.114	(0.270)

Note: "s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.

Table 8
Learning-by-exporting effects - by age quantile.

	Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)
	Quantile 1: Age ≥ P75		Quantile 3: P25 ≤ Age < P50	
s = 0	0.523	(0.235)**	0.252	(0.311)
s = 1	0.620	(0.223)***	0.395	(0.309)
s = 2	0.692	(0.260)***	0.473	(0.370)
s = 3	0.619	(0.264)**	0.647	(0.391)*
s = 4	0.577	(0.367)	0.644	(0.525)
s = 5	0.671	(0.416)	0.612	(0.417)#
s = 6	0.616	(0.518)	0.483	(0.579)
s = 7	0.364	(0.631)	0.447	(0.689)
s = 8	0.385	(1.072)	0.464	(1.049)

	Older firms		Younger firms	
	Coeff.	(s.e.)	Coeff.	(s.e.)
	Quantile 2: P50 ≤ Age < P75		Quantile 4: Age < P25	
s = 0	0.329	(0.305)	0.27	(0.406)
s = 1	0.495	(0.384)#	0.295	(0.664)
s = 2	0.501	(0.387)#	0.326	(0.688)
s = 3	0.584	(0.393)#	0.254	(0.655)
s = 4	0.587	(0.473)	0.127	(0.509)
s = 5	0.639	(0.697)	0.264	(0.735)
s = 6	0.426	(0.575)	− 0.022	(0.967)
s = 7	0.669	(0.812)	0.162	(0.840)
s = 8	0.490	(0.946)	0.023	(1.447)

Welch's *t*-statistics	Quantile 1 vs. Quantile 2	Quantile 2 vs. Quantile 3	Quantile 3 vs. Quantile 4
s = 0	18.69***	5.52***	− 0.74
s = 1	8.98***	5.84***	2.14**
s = 2	11.43***	1.34#	2.71***
s = 3	1.87*	− 2.68***	6.98***
s = 4	− 0.36	− 1.70*	9.92***
s = 5	0.75	0.64	4.55***
s = 6	3.89***	− 1.18	4.65***
s = 7	− 3.94***	2.96***	2.61***
s = 8	− 0.70	0.20	1.86*

Note: "s" is the time scale for exporting; s = o indicates the year when firms start exporting; s = n refers to n years after exporting.
*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.
# Indicates statistical significance at the 20% level.

conclusion that firm age does matter in capturing the learning effects from exporting. The more experience a firm has in production and business, the higher the learning effect is from exporting at least for the first 3 years of exporting. The main conclusions that the LBE effect is larger (either in yearly or cumulative terms) for older firms than for young firms also hold when using the alternative productivity measures derived from the approach of Olley & Pakes (1996). See Table A3 in the Appendix for the results.

5. Concluding remarks

While the notion that learning-by-exporting is intuitively appealing, the empirical evidence as to whether such learning effects exist has been mixed. Using Chinese manufacturing firms for the period 1998–2007, this paper finds significant LBE effects, especially for older firms engaging in R & D, having large-scale production, and under private ownership. While younger firms tend to be more productive than older firms, the yearly and cumulative LBE effects are either insignificant or relatively small regardless of their R & D status, firm size, and ownership. The above findings suggest that older firms learn more from exporting than younger firms - a result opposite to most studies on LBE.

The reason behind these findings may have something to do with the fact that the productivity gap and absorptive capabilities between exporters and non-exporters are quite different for older firms and younger firms, which in turn affect their engagement in experiential learning and vicarious learning. Although younger exporters have relatively larger productivity and are more likely to undertake R & D than non-exporters, the rather small productivity gap and limited vicarious learning do not allow them to produce a significant export premium. On the contrary, being older and larger (especially for private firms) allows firms to engage in more experiential learning, and investing in more R & D makes older exporters more capable of undertaking vicarious learning from exporting due to their superior absorptive capabilities compared with non-exporters. The above findings suggest the importance of firm experience, scale economies, and investment in R & D in capturing and enhancing the learning-by-exporting effects.

Appendix A

Table A1
Industry classification.

Industry	Description	Industry	Description
Ind13	Processed food	Ind29	Rubber
Ind14	Food	Ind30	Plastics
Ind15	Beverages	Ind31	Non-metallic mineral
Ind17	Textile	Ind32	Ferrous metals
Ind18	Apparel	Ind33	Non-ferrous metals
Ind19	Leather	Ind34	Metal products
Ind20	Plywood	Ind35	General purpose machinery
Ind21	Furniture	Ind36	Special purpose machinery
Ind22	Paper	Ind37	Transport equipment
Ind23	Printing	Ind39	Electrical machinery and equipment
Ind24	Toys & sports equipment	Ind40	Electronics
Ind26	Chemical products	Ind41	Precision instrument
Ind27	Medicines	Ind42	Others
Ind28	Chemical materials		

Table A2
Covariate imbalance testing from propensity score matching.

Sample	Mean		*t*-Test	
	Treated	Control	t	P > |t|
Full sample				
s = 0	7.8643	7.3286	0.96	0.349
s = 1	8.2099	7.4559	1.19	0.247
s = 2	8.5338	7.5734	1.09	0.293
s = 3	9.2607	7.6842	1.88	0.084
s = 4	9.9844	8.0735	3.65	0.007
Older firms				
s = 0	8.2439	7.6739	0.66	0.521
s = 1	8.9878	7.3055	1.69	0.130
s = 2	9.2575	7.3214	1.57	0.168
s = 3	9.8137	6.9979	2.02	0.090

s = 4	10.029	7.5992	2.13	0.100
Younger firms				
s = 0	7.3799	6.7692	0.89	0.397
s = 1	7.4296	7.1073	0.46	0.655
s = 2	7.3323	7.3084	0.02	0.982
s = 3	8.1248	7.1834	0.47	0.688
s = 4	–	–	–	–

Table A3
Robustness check using the productivity measures from the approach of Olley & Pakes (1996).

	Whole sample		Older firms		Younger firms		Welch's *t*-test Old vs. young
	Coeff.	(s.e.)	Coeff.	(s.e.)	Coeff.	(s.e.)	
s = 0	0.446	(0.222)**	0.498	(0.255)*	0.364	(0.222)*	15.139***
s = 1	0.617	(0.206)***	0.726	(0.309)**	0.460	(0.260)*	21.704***
s = 2	0.683	(0.190)***	0.757	(0.299)**	0.551	(0.288)**	14.261***
s = 3	0.696	(0.203)***	0.752	(0.297)***	0.679	(0.299)**	4.536***
s = 4	0.733	(0.214)***	0.781	(0.212)***	0.730	(0.338)**	2.887***
s = 5	0.573	(0.253)**	0.611	(0.403)	0.654	(0.469)	− 1.428
s = 6	0.501	(0.342)	0.546	(0.497)	0.566	(0.468)	− 0.528
s = 7	0.431	(0.377)	0.522	(0.608)	0.386	(0.480)	2.627***
s = 8	0.444	(0.733)	0.610	(0.955)	0.367	(0.784)	2.128**
Cumulative productivity							
s = 0	0.446	(0.222)**	0.498	(0.255)*	0.364	(0.222)	15.139***
s = 0 ∼ s = 1	1.069	(0.423)**	1.242	(0.557)**	0.796	(0.389)**	22.378***
s = 0 ∼ s = 2	1.752	(0.593)**	2.005	(0.826)**	1.323	(0.627)**	19.613***
s = 0 ∼ s = 3	2.449	(0.762)***	2.763	(1.079)**	1.985	(0.840)**	15.413***
s = 0 ∼ s = 4	3.178	(0.877)***	3.550	(1.223)**	2.695	(1.082)**	12.391***
s = 0 ∼ s = 5	3.747	(1.015)***	4.176	(1.495)***	3.317	(1.383)**	8.774***
s = 0 ∼ s = 6	4.240	(1.192)***	4.739	(1.831)***	3.831	(1.667)**	6.611***
s = 0 ∼ s = 7	4.664	(1.376)***	5.376	(2.149)**	4.206	(1.996)**	6.004***
s = 0 ∼ s = 8	5.105	(1.838)***	5.932	(2.787)**	4.739	(2.342)**	3.552***

*** Indicates statistical significance at the 1% level.
** Indicate statistical significance at the 5% level.
* Indicate statistical significance at the 10% level.

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