

Do exports firms outperform non-export ones? An empirical study on different classification of manufacturing industries in China

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Using Chinese Industrial Enterprise Database between 2005 and 2009, this paper constructs indicators, from aspects of efficiency, size and financing condition to explore comprehensively the new entry exporters' performance advantage over non-exporters by the method of PSM. The manufacturing industries are then classified into four categories, namely high-technology, medium-high-technology, medium-low-technology and low-technology, for detailed study. The results show that neither self-selection effect nor learning-by-exporting effect exists in Chinese exporters on the whole. Firms with lower productivity show higher export preference. Export is helpful for employment expansion and income increase; however, it does not enhance productivity and return on asset improvement. Firms in medium-high-technology industry learn by exporting significantly with obviously better performance than those in other categories, while low-technology export firms' performance is the worst. The policy implications is as follows: first, foreign trade structure needs to be upgraded steadily; second, medium-high-technology industry is suggested to be the key area to cultivate competitive advantage for export; third, increasing support to high-technology industry should be considered.

Keywords: export performance, self-selection effect, learning effect, PSM

1. Introduction

The increase of data accessibility at the business level facilitates the research in the area of trade. Bernard, Jensen and Lawrence (1995) studies the business panel in manufacturing sector during 1976 and 1987. It turns out that exporting businesses always account for a minority among the same industry, and such businesses are the outstanding ones in most cases, occupying an obvious advantage over non-exporters in terms of scale, productivity level, income level, capital density, etc. Melitz (2003) innovatively demonstrates how productivity level exerts a key impact on businesses'

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selection of exporting, arguing that only those with high productivity could overcome the fixed cost of export and succeed in finding their ways into the international market, namely the “self-selection effect” of the productivity. Later on, researches regarding the heterogeneous business trade develop at an incredible speed, where the relation between export and productivity emerges as an important factor.

Most scholars have confirmed the existence of the “self-selection effect” based on their empirical study using micro business level data in different countries and during different times. Following the “self-selection effect” is the “learning effect” of export. Exporters can access the opportunities for study, exchange and improvement when they enter the international market. Businesses, in the meanwhile, are sitting among the intense competition in the global market due to export. That’s why they outperform non-exporters. Generally, there is still no agreed conclusion towards the existence of the “learning effect” whatsoever through any micro business’s study in any country (Bao, Ye and Shao, 2014).

Among the studies of China, whether the productivity of export enterprises is higher than that of non-export enterprises, and whether the “self-selection effect” and “learning effect” exist at the same time or exist separately, are delivering big gaps concerning related conclusions. Some studies agree that business export contributes to the productivity (Zhang, Li and Liu, 2009; Yang and Mallick, 2010; Yi and Fu, 2011; Hu, Lin and Tang, 2015); Others hold that export could merely play a limited role in boosting the productivity and even put a brake on it (Li, Lu and Zhu, 2008; Zhao and Zhao, 2011; Nie and Zhu, 2013; Bao *et al.*, 2014).

It should be pointed out that a majority of the existing papers are focusing on the “self-selection effect” and the “learning effect”, while turning a blind eye to the comprehensive study of businesses’ characteristics. Apart from productivity, the rest of these characteristics such as business scale, and financial indicators have their roots in the heterogeneity of businesses. Also, it is of paramount importance to gauge the export advantages depending on the existence of “self-selection effect” and “learning effect”.

However, so far, a few number of literature have included multiple indicators to conduct comprehensive study of export performance. Meanwhile, basically, industrial enterprises as a whole are the research subject among the existing studies. It is the fact, though, that a small number of scholars, from the perspective of heterogeneous enterprises, tried to distinguish different businesses from aspects of trade type (Lv, Shen and Jian, 2016), structure of ownership (Xing, Tao and Gao, 2013), export density (Fan and Feng, 2013) and capital density (Yang and Li, 2014), with many valuable conclusions reached.

However, the studies from the industrial point of view trying to distinguish between enterprises are relatively limited. It is even rare to see researches comparing different kinds of industries in terms of “self-selection effect” and “learning effect”.

In fact, the distinction of production complexity and technological features may lead to the differences in behaviors made by producers and managers, further resulting in the various performances of businesses following their entry into the international market. To study the “self-selection effect” and “learning effect” of exporters in each kind of industry is significant for scholars to discuss how to develop the competitive advantages of Chinese industrial businesses and, to drive forward the transformation and upgrading of industrial economy.

On the basis of what we have studied, this paper sets Chinese manufacturing enterprises as the target, builds indicator system from the angle of efficiency, scale and finance, and categorizes industries into high-tech, medium-to-high-tech, and low-to-medium-tech. Besides, this paper centers on the study of different kinds of new-entry exporters’ performance advantages over non-exporters in different industries, employing the PSM method. Specifically, (1) in this paper, the efficiency (total factor productivity, labor productivity, capital productivity), size (number of employees, industrial sales, total fixed assets), and finance (corporate profitability, total assets yield, return on net assets, per capita income) —three aspects regarding businesses are evaluated herein, which is favorable to take a comprehensive gauge of the performance advantages or disadvantages of exporters in an object manner. (2) In this paper, according to the different technical level, four categories are divided in terms of the whole industry — high-tech, medium-and-high-tech, low-and-medium-tech and low-tech. Then the “self-selection effect” and “learning effect” existing in different types of industries are studied and comparatively analyzed, which is beneficial to offer more targeted policy suggestions. (3) In this paper, PSM method is used to conduct two rounds of matching, which contributes to solving the problems of sample selectivity bias and confusion bias, as well as the endogeneity of variables.

To fathom out the extension of indicators, industrial classification and the improvement of research methods can be conducive to offering a more complete framework for analysis, so as to better understand export’s contribution to business performance. The structure of this paper goes as follows: the first part is proposing relevant issues; the second part offers the research framework involving the industrial classification, the selection of models, sample analysis and the construction of variables; the third part is PSM matching with the samples and the assessment of its stability; the fourth part is the analysis of exporters’ performance; the last part is the conclusion and policy implication.

2. Research framework

2.1. Industrial classification

In order to study the performance of manufacturing exporters in industries with

distinct technological characteristics, the priority is to classify the manufacturing industries. To this end, we refer to the way of classification of Organization for Economic Co-operation and Development (OECD)(2003). OECD categorizes manufacturing industries into four kinds: low-tech, low-to-medium-tech, medium-to-high-tech and high tech according to the technological density and research and development scale of manufacturing enterprises in the International Standard Industry Classification, ISIC (ISIC Rev. 3). In this paper, the International Standard Industry Classification, ISIC (ISIC Rev. 3) is in connection with the Industrial Classification for National Economic Activities (GBT4754-2002), and thus the industrial classification of manufacturing industry based on technological density is formed (see Table 1).¹ Under this framework of classification, the author of this paper aims to study the performance of exporters in different industries regarding the “self-selection effect” and “learning effect” and conduct comparative analysis.

Table 1

The classification of manufacturing based on technological density

Classification of Manufacturing Industries	Names and ISIC(Rev.3) codes	Classification of national economic industries (GBT4754-2002) names and codes
High-tech	aerospace vehicle (353); medicine (2423); office, accounting and computer equipment (30); radio, TV and telecommunication equipment (32); medical treatment, precision and optical equipment (33)	pharmaceutical manufacturing industry (27); telecommunication equipment, computer and other Electronic equipment manufacturing industry (40); instruments and meters, as well as culture-and-office-use machinery manufacturing industry (41)
Medium-to-high-tech	electronic machinery and other equipment (31); car, trailer and semi - trailer (34); chemical products excluding medicine (24 excludes 2423); locomotive and other vehicle equipment (352+359); other machinery equipment (29)	chemical material and chemical manufacturing industry (26); chemical fiber manufacturing industry (28); ordinary machinery (35); special equipment manufacturing (36); transportation Equipment Manufacturing (37); electric Equipment and Machinery (39)

¹ NBS (National Bureau of Statistics) of P.R. China referred to the classification method of high-tech industries and formulated and released the Classification Catalogue of High-tech Industry ([2002] 33) and the Classification Catalogue of High-tech Industry (Manufacturing) (2013). The reasons we chose OECD (2003) mainly rely on: (1) the classification of high-tech industries provided by NBS does not cover all manufacturing sectors. In comparison, NBS only covered two categories of “high-tech” and “medium-to-high-tech” listed in Table 1; the classification offered by OECD to analyze manufacturing is more complete and further distinguishes “high-tech” and “medium-to-high-tech” category; (2) although both NBS and OECD classify this industry according to the investment on R&D (research and development), NBS only employs one indicator (the proportion of R&D expenditure in the main business income). While, OECD takes into account two indicators (the ratio between R&D expenditure and output, the ratio between R&D expenditure and growth); (3) to adopt the classification used by OECD is conducive to the international comparison.

Classification of Manufacturing Industries	Names and ISIC(Rev.3) codes	Classification of national economic industries (GBT4754-2002) names and codes
Low-to-medium-tech	shipbuilding and maintenance (351); Rubber and plastic products (25); Coke, oil refining products and nuclear fuels (23); other Non-metallic mineral products (26); basic metal and metal manufacturing (27-28)	oil processing, coking and nuclear fuel processing (25) rubber product industry (29); plastic product industry (30); non-metal mineral product industry (31) ferrous metal smelting and rolling industry (32); non-ferrous metal metallurgy and rolling processing industry (33) metal product industry (34)
Low-tech	other manufacturing and recycled products (36-37); wood, pulp and paper products, printing and publishing (20-22); food, drinks and tobacco (15-16); fabrics, textile, feather and footwear product footwear product (17-19)	farm and sideline products processing industry (13); food manufacturing industry (14); beverage manufacturing (15); tobacco industries (16); textile industry (17); textile and garment, shoes, hat manufacturing (18); leather, fur, feather(velvet) and its product industry (19); timber processing and wood, bamboo, cane, palm fiber, and straw products (20); furniture manufacturing (21); papermaking and paper products (22); printing industry and the copy of recording medium (23); cultural educational and sports goods manufacturing (24)

Sources: OECD (2003), ISIC Rev.3, classification of national economic industries (GBT4754-2002), Li *et al.* (2008).

2.2. Model selection

An assessment model which can fully take the gauge of the business performance shall be selected so as to study the “self-selection effect” and the “learning effect” of exporters in the field of manufacturing sector. Up to now, in the empirical study about the relationship between export and productivity, the popular method is to conduct regression calculation of the “export premium” concerning cross section or panel data. However, the endogenous problem is what we cannot escape. Sample selective bias and mixed bias are also a major hurdle disturbing researchers. In order to solve the issues above, this paper adopts PSM model and examine the “self-selective effect” and “learning effect” of export, so as to avoid the separation of analysis of such two parts closely connected with the export performance.

In the RCM causal inference model proposed by Rubin (1974), a binary virtual variable $D_i \in \{0, 1\}$ is established, with figure “1” representing business i as the treatment business and figure “0” representing business i as the control business. In this paper, the business newly entering the export market is seen as the treatment business, and non-exporters as the control business.

It is defined that ATT , which means the average treatment effect, refers to the ratio between business i the exporter and the non-exporter. The extra profit is expressed

as: $ATT \equiv E(y_i^1 - y_i^0 | D_i = 1)$. Also, y_i^1 indicates business i the exporter, and y_i^0 indicates business i supposed to be the non-exporter. So, ATU the average treatment effect of the non-exporter can be expressed as: $ATU \equiv E(y_i^1 - y_i^0 | D_i = 0)$.

For any business i , whether or not it participates in export, y_i^1 and y_i^0 can be observed in only one case, while it is counterfactual in terms of the other case. If the observable data ($y_i^1 | D_i = 1$) and ($y_i^0 | D_i = 0$) are regarded as the approximate evaluation of the causal effect, the selective bias will be produced (Chen, 2014). Under the assumption of heterogeneous firms, the treatment effect is a random variable, so ATE (average treatment effect) of all businesses can be expressed as:

$$\begin{aligned}
 ATE &\equiv E(y_i^1 - y_i^0) = E(y_i^1 - y_i^0 | D_{i=1}) \cdot (1 - Q) + E(y_i^1 - y_i^0 | D_{i=0}) \cdot Q \\
 &= \underbrace{E(y_i^1 | D_{i=1}) - E(y_i^0 | D_{i=0})}_{NATE} - \underbrace{[E(y_i^0 | D_{i=1}) - E(y_i^0 | D_{i=0})]}_{First\ bias} \\
 &\quad - \underbrace{\{E(y_i^1 | D_{i=1}) - E(y_i^0 | D_{i=1})\}}_{ATT} - \underbrace{[E(y_i^1 | D_{i=0}) - E(y_i^0 | D_{i=0})]}_{ATU} \cdot Q \\
 &\quad \underbrace{\hspace{10em}}_{Second\ bias} \tag{1}
 \end{aligned}$$

Among them, Q stands for the proportion of control business in samples. Normally, the first kind of deviation is called “self-selection effect”, that is to say, the performance of exporter itself is superior to the non-exporter; the second kind of deviation has its roots in the inequality between ATT and ATU under the condition of non-random allocation of samples, namely, the “heterogeneous causal effect” existing in the treatment and control groups. (Bao *et al.*, 2014)

In order to remove such two kinds of deviations, Rosenbaum and Rubin (1983) put forward the idea of matching and estimation. A series of observable variable vectors X can be selected, and the impact of (y_i^1, y_i^0) on D_i can be ignored, that is the “conditional independence assumption”, denoted as $(y_i^1, y_i^0) \perp D_i | X_i$. It means that if X_i is given, the distribution of (y_i^1, y_i^0) in both treatment and control group is identical, namely: $F(y_i^1, y_i^0 | X_i, D_i = 1) = F(y_i^1, y_i^0 | X_i, D_i = 0)$. In more situations, a weaker mean independence is needed:

$$E(y_i^1, y_i^0 | X_i, D_i = 1) = E(y_i^1, y_i^0 | X_i, D_i = 0).$$

The counterfactual method can find out, from the businesses in the control group which are non-exporters, the performance variable of the sample matching with the features of businesses in the treatment group entering the export market. In doing so, it replaces export performance variables of those exporters, which do not have export behaviors assumed by counterfactual method, then calculates the ATT of exporters.

Assuming business i belongs to the treatment group, business j can be found which belongs to the control group, then values of observable vector X of business i and business j can be matched as far as possible. Based on the CIA assumption, the probability of the entry of business i and business j into the treatment group is close, and is equipped with comparability, then y_j^0 can be used as the estimation of y_i^0 , namely,

$\hat{y}_i^0 = y_j^0$. So, for business i , $ATT_i = y_i^1 - \hat{y}_i^0 = y_i^1 - y_j^0$.

Rosenbaum and Rubin (1983) put forward the PSM method. Given the condition of X_i , the observable vector, the Logit parameter estimation method is applied to calculate the conditional probability of business i when it enters the treatment group and the PS, export propensity score, of business i is acquired. When the matchings of figures of PS are undergone, information of multidimensional vector X is compressed, with PS figures sitting between $[0, 1]$, the dimensional “spell” problem can be solved. The form of typical PSM estimation is adopted as follows:

$$ATT = \frac{1}{N_i} \sum_{i \in |D_i=1|} \{ y_i^1 - \sum_{j \in |D_j=0|} w_{ij} \cdot y_j^0 \} \quad (2)$$

Among them, N_i is the number of businesses in the treatment group; weight $w_{ij} = 1/N_{is}^c$, N_{is}^c is number of businesses in the control group matching the business i , a new exporter, in the treatment group. In accordance with formula (2), the acquired performance advantage of businesses in the treatment group, when they enter the export market in the current period ($s = 0$) and after they enter the export market ($s = 1, 2, \dots, S$) in the following periods, can be calculated in comparison with that of businesses in the control group.

In the light of the philosophy of matching estimation, ATT calculated based on formula 2 is equivalent to the changes of different performance indicators, a comparison between exporters and assumed non-exporters by counterfactual method. If some indicator is significantly positive in ATT , it implies that export decision would encourage businesses to improve such indicators before export so as to fulfill the “self-selection effect”; it also signifies that businesses have acquired the “learning effect” after they level up the performance of these indicators through export behavior.

2.3. Sampling principles and variable construction

Chinese Industrial Enterprise Database (CIED) has been widely adopted for various economic and statistics analyses, yet there exist errors, a lack of key indicators, and even outliers in it, which, unless being corrected or eliminated, will lead to an inaccurate outcome (Nie, 2012).

To make out comprehensive samples and accurate data, this paper follows the practice of Brandt, Van Biesebroeck and Zhang (2012); Jefferson, Rawski and Zhang (2008), and trims the CIED 2005–2009 data by eliminating cases in which show a lack of key variables, a violation of accounting principles, and a workforce of less than 10 employees. Zhang and his co-authors (2009) point out that new export market entrants from the last accounting year (or 2009 in the paper) will probably lead to selection biases for their entailing operations are invisible, that intermittent exporters are forced into and out of the international market by irrational factors, and that it is

impossible to have a comparison of continuing exporters' performance before and after their first stepping into export market. Therefore, research objects are trimmed into two classifications, namely 3827 non-export enterprises which have been operating domestically and 67336 new entrants which turn themselves into exporters between the years 2006 and 2008, continuing their operation globally.

To conduct a comprehensive estimate on new entrants' performance, indicators are constructed from three dimensions, ie, efficiency, size, and financing, (related variables are shown in Table 2). Efficiency, or total factor productivity (TFP), labor productivity, and capital productivity, is closely related to the corporate production. Exporters' productivity is the major focus in academia and acts as a starting point for the trade study in heterogeneous enterprises, for researches in this dimension can better mirror the exporters' achievements in technological improvement and production structure transformation. Size, consisting of industrial sales, numbers of employees, and total fixed assets, shows these exporters' inputs and outcomes. Export means enterprises' global expansion and jobs created, thus reflecting their contribution to economic growth and employment improvement. Financing tells the enterprises' investment efficiency, which defines the driving force of going global, and financing constraints, which can better illuminate the export continuity, through return on sales (ROS), return on assets (ROA), return on equity (ROE), and personal wage. The indicators in this paper are for a comprehensively multilevel investigation into exporters' performance; efficiency and size for corporate competition, financing for ownership. To absorb influence from price factor, the paper, upon the basis of the bench year 2005, has deflated concerned indicators with Producer Price Index (PPI), Purchasing Price Indices of Raw Material (PPIRM), and Fixed Assets Investment Price Index, which are all from National Statistics Bureau of the People's Republic of China (NBS).

Table 2
Variable Construction

	Variables	Calculation methods	Study interval
Efficiency	<i>tfp</i> Total factor productivity	Follow Levinsohn and Petrin's practice(2003) ^a	2005–2007
	<i>lp</i> Labor productivity	Industrial sales/numbers of employees	2005–2009
	<i>cp</i> Capital productivity	Industrial sales/total fixed assets(Logarithm)	2005–2009
Size	<i>sales</i> Industrial sales	Industrial sales(Logarithm)	2005–2009
	<i>staff</i> Numbers of employees	Numbers of Employees(Logarithm)	2005–2009
	<i>tat</i> Total fixed assets	Total fixed assets(Logarithm)	2005–2009

	Variables	Calculation methods	Study interval
Financing	<i>prof</i>	Return of sales Ln (1+profit/Industrial sales)	2005–2009
	<i>roa</i>	Return on assets Ln (1+profit/total assets)	2005–2009
	<i>roe</i>	Return on equity Ln (1+profit/net assets)	2005–2009
	<i>pwage</i>	Personal wage (Salary+corporate benefits) /Numbers of Employees(Logarithm)	2005–2007
	<i>eio</i>	Enterprise input-output Ln(1+intermediate inputs/ industrial value added (IVA))	2005–2007
	<i>age</i>	Age Sampling Year-Corporations' Set-up Year	2005–2009
	<i>age</i> ²	Age ² Age2=age*age	2005–2009
Others	<i>fcp</i>	Foreign capital percentage Ln (1+Foreign Capital /Received Capital)	2005–2007
	<i>rd</i>	Research & Development Virtual variable. When Output of New Products >0, 1 is the number, or the number is 0.	2005–2007, 2009
	<i>owner</i>	Ownership Virtual variable. State-owned enterprise is 1 while the others 0.	2005–2009
	<i>area</i>	Located area Virtual variable.The Eastern China is 1 while the others 0.	2005–2009
	<i>Industry</i>	Industry Virtual variable from two-digit industry code.	2005–2009
	<i>year</i>	Year Virtual variable from sampled years	2005–2009

Notes: ^a, the relevance between productivity and inputs makes traditional OLS estimation and Fixed Effect unable to eliminate syn-chronic and sampling biases. Olley and Pakes (OP, 1996) develops a consistent semi-parametric estimator. By regarding the firms' current investment as non-measurable productivity-influenced proxy variable, the syn-chronic biases issue is tackled. But the success comes at a price of the impossibility to estimate the samples in which investment is zero. Later Levinsohn and Petrin (LP, 2003) takes OP method a step further by regarding the inputs in the middle of observation as non-measurable productivity-influenced proxy variable, thus data can be reached more easily. Therefore, this paper employs LP method to estimate AFP.

Source: Collected by Author.

3. Data and matching

3.1. Covariates selection

The method of PSM requires estimating the enterprise i 's probability of beginning to export or entering the treatment group, a number which indicates the export propensity score. According to Serti and Tomasi (2008), covariates matching is required to be independent of the firm's decision to step into the international market, for the decision could impact its maker's adjustment of corporate structure, thus leading to endogeneity biases. That is to say, the study should be on the basis of the covariates matching before the firm's entry. This paper follows the practice of existing researches (Serti and Tomasi, 2008; Zhang *et al.*, 2009; Yu, Lu and Liu, 2015), regards the observable variable X as a covariate vector, which is from the period before the

firm goes into the global market. Then comes the equation:

$$Pr(D_{i,s=0} = 1) = F(X_{i,s=-1}, \beta) = \Phi(X_{i,s=-1}'\beta) \quad (3)$$

$\Phi(\cdot)$ is a cumulative normal distribution function. $D_{i,s=0} = 1$ means the firm begins to export; $s = 0$ means the current export period, $s = -1$ the period before export and X covariate vector.

Productivity, size, and financing serve as the sources of firms' heterogeneity. Melitz's model (2003) claims that productivity decides the enterprises' export. Berman, Martin and Mayer (2012) see size as a determiner too. Generally size has a positive correlation with material assets, human resources and international competitiveness, thus enterprises of larger scale has greater potential to export. Chaney (2006) includes liquid constraints (LC) into Melitz's trade model (2003), proving that without available financing, enterprises are unable to export even they have a good profit. He also finds out that a positive financial performance is also one of the prerequisites of exportation. Domestically, Yi and Fu (2011) introduce productivity, which is divided into LP and TFP, and size, which is manifested by the number of employers, into their regression model at the same time. Yu *et al.* (2015) introduce LP, staff, personal wage, capital intensity, foreign capital parentage, ownership, and R&D among other virtual factors. Zhang, Zhou, Zheng and Lu (2011) bring in productivity, size, age and squared age, capital intensity, human resources, R&D, personal wage and market forces among other control variables, studying these factors' contribution to export intensity.

Above all, to analyze the performance advantages of new entering firms while taking into consideration the multicollinearity of all variables in Table 2, we finally choose TFP, LP, CP, EIO, size, staff, pwage, prof, lc, age, age², rd, R&D, ownership, area and industry to form the covariate vector X . Before PSM matching on the basis of every sampled year, we examined the relevance of all these variables according to the same sampled year, finding the relevance value are quite low except TFP and LP which are between 0.5 and 0.6 separately.

3.2. PSM matching estimation

Using the equation (3), we get each firm's export propensity score (or PS index), and set the samples' 1/4 PS index standard deviation (or $0.25 \sigma_p$) through nearest-neighbor matching within caliper as bench data. Consequently, we have an 1-to-3 Matching and engine the first round of non-repetitive matching of the treatment group and the control group based on the covariates from the sampled years 2005, 2006, and 2007 respectively. The result is as follows.

Table 3

Logit estimation of new export entrants between the years 2006 and 2008

	Variables	2006	2007	2008
<i>tfp</i>	Total factor productivity	-9.865*** (1.118)	-7.592*** (1.456)	-10.66*** (1.607)
<i>lp</i>	Labor productivity	8.016*** (0.947)	5.847*** (1.228)	9.433*** (1.368)
<i>cp</i>	Capital productivity	1.446*** (0.172)	1.042*** (0.222)	1.442*** (0.246)
<i>eio</i>	Enterprise input and output	-9.673*** (1.124)	-7.380*** (1.468)	-10.41*** (1.615)
<i>sales</i>	Industrial sales	0.0768 (0.249)	0.373 (0.361)	-0.532 (0.343)
<i>staff</i>	Number of employees	7.128*** (0.777)	5.453*** (1.010)	8.487*** (1.123)
<i>pwage</i>	Personal wage	0.565*** (0.0506)	0.605*** (0.0646)	0.395*** (0.0693)
<i>prof</i>	Profit	-0.0225 (0.240)	0.0580 (0.389)	0.792* (0.462)
<i>lc</i>	Liquid constraints	0.118 (0.266)	0.339 (0.316)	0.424 (0.270)
<i>age</i>	Age	-0.0330*** (0.00601)	-0.0389*** (0.0103)	-0.0298** (0.0121)
<i>age2</i>	Age square	0.000282** (0.000112)	0.000145 (0.000240)	-9.92e-05 (0.000296)
<i>fcp</i>	Foreigncapital percentage	2.230*** (0.0942)	2.264*** (0.131)	2.517*** (0.139)
<i>rd</i>	R&D	0.563*** (0.0916)	0.722*** (0.101)	0.749*** (0.105)
<i>owner</i>	Ownership	-0.873*** (0.317)	-0.502 (0.356)	-0.646 (0.400)
<i>area</i>	Area	0.647*** (0.0710)	0.830*** (0.0924)	0.849*** (0.0961)
<i>industry</i>	Industry	Yes	Yes	Yes
<i>Constant</i>	Constant	-9.794*** (1.033)	-6.868*** (0.411)	-10.50*** (1.077)
<i>Observations</i>	Number of objects observed	65,982	58,626	57,110

Notes: Observations means the total of samples from the control group and the treatment group; Industry is a virtual variable; the number in brackets are standard deviations; *** means $p < 0.01$; ** means $p < 0.05$; * means $p < 0.1$.

Source: Reorganized with Stata13 by Author.

We can see that in the previous period before export (or when $s = -1$), LP, CP, staff, pwage, FCP, R&D, and area (the Eastern part of China) deliver positive impacts on export, while AFP, EIO, age, ownership(state-owned and collectively owned enterprises) negative impact. Also, when $s = -1$, export enterprises and non-export ones bear obvious differences in every variable, which leads to the various probability of being exporters. Without this consideration, it would be quite blurry pertaining to the debate whether the differences are shared or are caused by export selection only, resulting in misleading analysis. Therefore, it is necessary to absorb these differences by PSM Matching, or by locating non-export enterprises which share matching variables with export enterprises when $s = -1$. Subsequently by observing the dynamic performance changes between domestic operation and global business, we can tell if the enterprise wins performance advantages because of export solely.

After the first round, we synthesize the matching data, set new time variable s , assign the values of the year when the firm turn international to be 0($s = 0$), and then make the years of domestic operation be $s = -1$, $s = -2$...and the years of global

dealings be $s = 1, s = 2, \dots$. Then we treat the new export entrants between the years 2006 and 2008 as a new control group, engine our second matching with the same 1-to-3 Matching.

3.3. Matching estimation

The paper examines matching results by balancing estimation. Rosenbaum and Rusin(1985) conclude that standard deviation should always be less than 20 per cent. The result shows that the the absolute value of most unmatched variables is far smaller than this number, but even after the first round of estimation the new export market entrants matched during 2006–2008 bear the number of less than 10 percent, not to tell the noteworthy number of less than 5 percent in the second round when we assume $s = -1$. So we are confident that the matched samples do work well, for if not, the result would be a disappointing one.

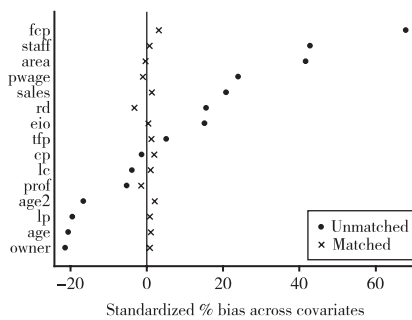


Figure 1a. PSM balancing mapping of new exporters in 2006

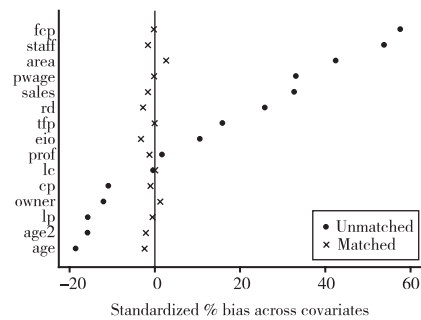


Figure 1b. PSM balancing mapping of new exporters in 2007

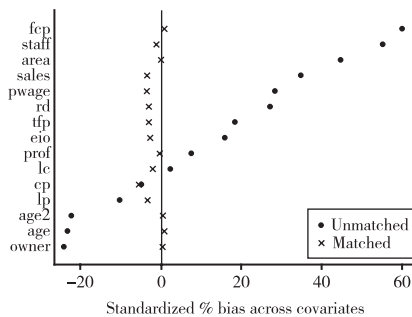


Figure 1c. PSM balancing mapping of new exporters in 2008

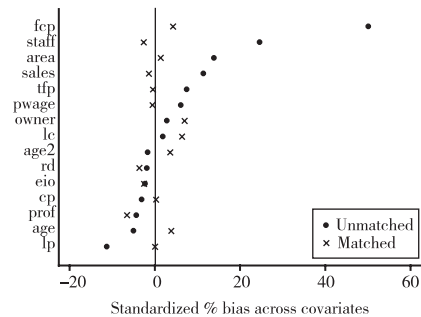


Figure 1d. PSM balancing mapping of new exporters in 2006–2008

Figure 1. PSM Matching Balancing Estimation

Source: the Author delivers with Stata13.

3.4. Post-matching samples estimation

Table 4 shows a year-based matching result and the technology intensity-based new export entrants' landscape between the years 2006 and 2008.

Table 4
Post-matching samples estimation

		Treated group(3777 firms totally)						Control group(9869 firms totally)					
		Year=2006		Year=2007		Year=2008		Year=2006		Year=2007		Year=2008	
		Num- ber	Share (%)	Num- ber	Share (%)	Num- ber	Share (%)	Num- ber	Share (%)	Num- ber	Share (%)	Num- ber	Share (%)
		1798	47.60	1036	27.43	943	24.97	4586	46.47	2747	27.83	2536	25.70
Technology intensity	Low- technology	689	38.32	338	32.63	275	29.16	1674	36.50	872	31.74	732	28.86
	Medium- low- technology	380	21.13	215	20.75	199	21.10	1024	22.33	584	21.26	547	21.57
	Medium- high- technology	537	29.87	383	36.97	367	38.92	1404	30.61	1060	38.59	1019	40.18
	High- technology	119	6.62	76	7.34	74	7.85	297	6.48	167	6.08	174	6.86
	Others	73	4.06	24	2.32	28	2.97	187	4.08	64	2.33	64	2.52

Notes: In the second round of PSM matching, “common” option in Stata13 deletes some firms with bad records from the original 3827 firms in control group; Technology Intensity is classified based on OECD (2003) data.

Source: collected by the author with Stata13.

4. Performance analysis

4.1. Exporters' efficiency performance analysis

The analysis is carried out in terms of TFP, LP, and CP (Table 5). (1) As far as AFP is concerned, the whole sample *ATT* value is negative before the firms' going global, most notably shown when $s = -3$ and -2 , thus is not in favor of the “self-selection hypothesis” concerning export productivity. In the current export period ($s = 0$) and after that ($s = 1$), *ATT* turns positive, even though it is not so notable as expected. Concerning technology, low-tech firms' *ATT* value remains negative, especially during the periods of $s = -1$ and $s = -2$. Medium-high firms' *ATT* been positive since $s = -1$, and is quite impressive when $s = 0$ and $s = 1$. The productivity of high-tech exporters is obviously lower than that of non-exporters, yet the number turns positive in the current period despite the fact that the value is still lower than that of medium-high ones. This tells the truth that there is no self-selection effect and learning effect in TFT among

low-tech exporters while the medium-high technology firms do get learning effect through export even if there is no self-selection effect. (2) As far as LP is concerned, the whole sample analysis tells a negative *ATT* value, which is quite noteworthy in several periods. But after going international the absolute value of *ATT* is lower than that of before, showing a sign of progress. Considering the analysis on staff expansion, the reason why the improvement, after entering the global market, is not notable as expected may be the expansion of employees. Observing from the industry classifications, we can see a widening gap between the LP of low-tech exporters and that of non-exporters, a fact which is manifested in the shift from the negative *ATT* value when $s = -1$ to positive thereafter, and also an increasing absolute value of *ATT*. Medium-high-tech firms' *ATT* value has been positive even when $s = -1$, differentiating themselves from others. (3) As far as CP is concerned, *ATT* value remains negative except when $s = -1$. The value of low-tech firms is higher than that of non-exporters, especially when $s = -1$, $s = 0$, and $s = 3$. When $s = 1$, $s = 3$, the value of medium-high firms is continuously lower than that of non-exporters. Evaluating the data from the equations which constructs LP and CP, we can conclude that in investing to boost production, low-tech firms in China pay more attention to labor expansion while medium-high-tech firms to capital inflow.

Table 5
ATT result of exporters efficiency estimation

Variable	Classifications	$s = -3$	$s = -2$	$s = -1$	$s = 0$	$s = 1$	$s = 2$	$s = 3$
Total factor productivity (TFP)	Whole sample	-0.107**	-0.102***	-0.00150	0.0160	0.0145		
	Low-tech	-0.0754	-0.145**	-0.113**	-0.0810*	-0.118**		
	Medium-low-tech	-0.0467	-0.0975	-0.0642	-0.0542	-0.00968		
	Medium-high tech	-0.0615	-0.0714	0.0727	0.110**	0.206***		
	High-tech	-0.366*	-0.304**	0.0203	0.0129	0.0240		
Labor productivity (LP)	Whole sample	-0.0884**	-0.0621**	-0.000147	-0.0112	-0.0391*	-0.0390	-0.0489
	Low-tech	-0.109	-0.0642	-0.0894**	-0.0740**	-0.109***	-0.125***	-0.126***
	Medium-low-tech	-0.00988	-0.0455	-0.0527	-0.0454	-0.0584	-0.0613	0.000571
	Medium-high-tech	-0.0615	-0.0864*	0.0622*	0.0282	0.0157	0.0368	0.0249
	High-tech	-0.287*	-0.224*	0.0242	-0.0231	-0.0649	-0.0154	-0.165
Capital Productivity (CP)	Whole sample	-0.0565	-0.0289	0.000474	-0.0136	-0.0393	-0.0188	-0.00807
	Low-tech	0.137	-0.0259	0.0946**	0.101**	0.0694	0.115**	0.0948
	Medium-low-tech	-0.0893	-0.0406	0.00291	-0.0214	0.00128	-0.0336	0.0702
	Medium-high-tech	-0.0715	-0.0573	-0.0432	-0.0609	-0.0828*	-0.130**	-0.155*
	High-tech	-0.423	-0.0740	-0.0785	-0.0710	-0.138	-0.0358	-0.0387

Notes: Standard deviation is a result of Bootstrapping; the number of samples and standard deviation value is deleted., but if it is needed, the author is in an email away; the blank means the data can not be calculated on account of the lack of related data in China Industry Business Performance Data; *** means $p < 0.01$, ** means $p < 0.05$, * means $p < 0.1$; the same goes to the next table.

Source: collected by author with Stata 13.

4.2. Exporters' scale performance analysis

We will approach the analysis through industrial sales, staff, and aggregate fixed assets (Table 6). (1) Through industrial sales, we find that the whole sample *ATT* value is negative before export and turns positive in the current period thereafter, bespeaking the export increase's contribution to sales. Of various industries medium-high-tech exporters enjoy the most notable increase in their sales, *ATT* value going up since $s = -1$; yet the sales of low-tech exporters remain lower than that of non-exporters. (2) Through the staff factor, we find that the whole sample *ATT* value shows the sign of a notable increase after export, denoting the fact that going international spurs the social employment. Specifically, among medium-high-tech exporters shows the most noteworthy increase while the low-tech ones do not create jobs as expected. (3) Through aggregate fixed assets we find the *ATT* value turns notably positive in the current period (or when $s = 0$), telling the truth that export help assets expansion. The expansion is outstanding in medium-high-tech exporters while in non-exporters the assets increase does not show itself.

Table 6
ATT result of exporters scales estimation

Variable	Single period	$s = -3$	$s = -2$	$s = -1$	$s = 0$	$s = 1$	$s = 2$	$s = 3$
Industrial sales	Whole sample	-0.0824	-0.0758*	-0.00465	0.0640**	0.0925***	0.107***	0.167***
	Low-tech	-0.126	-0.113*	-0.165***	-0.102**	-0.0955*	-0.0878	-0.0351
	Medium-low-tech	-0.0185	-0.0960	-0.0799	0.0225	0.0783	0.104	0.180*
	Medium-high tech	-0.00446	-0.0261	0.0980*	0.151***	0.197***	0.264***	0.423***
	High tech	-0.303	-0.232	-0.0210	0.0207	0.0679	0.152	0.211
	Whole sample	0.0123	-0.0158	-0.00679	0.0750***	0.135***	0.156***	0.222***
Staff	Low-tech	-0.0245	-0.0582	-0.0758**	-0.0267	0.0169	0.0426	0.0937*
	Medium-low-tech	0.00150	-0.0494	-0.0282	0.0697	0.141***	0.177***	0.180**
	Medium-high tech	0.0652	0.0630	0.0346	0.122***	0.186***	0.241***	0.409***
	High-tech	-0.00784	-0.00808	-0.0482	0.0566	0.135	0.171	0.412**
	Whole sample	-0.0196	-0.0490	-0.00741	0.0776**	0.135***	0.136***	0.181***
Aggregate fixed assets	Low-tech	-0.270*	-0.0965	-0.260***	-0.202***	-0.162**	-0.197***	-0.127
	Medium-low tech	0.0810	-0.0543	-0.0838	0.0466	0.0819	0.151	0.115
	Medium-high-tech	0.0753	0.0338	0.140**	0.212***	0.285***	0.407***	0.589***
	High-tech	0.128	-0.158	0.0545	0.104	0.208	0.191	0.285

4.3. Exporters' financing performance analysis

The analyses are based on sales profit, return on total assets, return on equity (ROE),

and personal wage. (1) The whole sample *ATT* value of profit is negative except when $s = -3$ and $s = 3$, mirroring the truth that, in part, fixed investment in export lowers the firms' sales profit. Medium-high-tech exporters boost a bigger profit margin than their non-exporter counterparts when $s = 1$ and thereafter, the number reaching a notable level when $s = 3$; yet other exporters do not enjoy such a progress. (2) The *ATT* value of return on total assets is negative straight to the end, and various classifications show no persuasive figure. (3) The *ATT* value of ROE is similar to that of return on total assets. (4) Through the indicator of personal wage, the whole sample *ATT* is positive except when $s = -1$, standing by the hypothesis in new trade theory that export divisions budget more in their wage expenditure. Personal wage in medium-high-tech exporters are higher than that in non-exporters, especially when $s = -3$, $s = 0$, and $s = 1$. Low-tech and medium-low-tech exporters also budget more in their salary expenditure than their counterparts. Nevertheless, the number in high-tech exporters is lower than that in their non-export counterparts.

Table 7

ATT result of exporters financing estimation

Variable	Single period	$s = -3$	$s = -2$	$s = -1$	$s = 0$	$s = 1$	$s = 2$	$s = 3$
Sales profit	Whole Sample	0.00102	-0.000689	-0.00147	-0.000392	-0.00175	-0.00173	0.00358
	Low-tech	-0.00172	0.000108	-0.00422	-0.00190	-0.00900**	-0.00400	-0.00524
	Medium-low-Tech	-0.00681	0.00551	-0.000905	-0.000734	-8.61e-05	-0.00925*	0.00278
	Medium-high -tech	0.000831	-0.00845	-0.00101	-0.00269	0.00569	0.00387	0.0108*
	High-tech	0.0240	0.00730	-0.00662	0.00384	-0.0182*	-0.0153	-0.00978
Return on total assets	Whole sample	-0.0153**	-0.0146***	-0.0142***	-0.0189***	-0.0240***	-0.0252***	-0.0152***
	Low-Tech	-0.0184	-0.0207**	-0.0198***	-0.0237***	-0.0307***	-0.0398***	-0.0324***
	Medium-low-tech	-0.0133	-0.00760	-0.00933	-0.0126*	-0.0196**	-0.0239***	-0.00527
	Medium-high-tech	-0.0157	-0.0144**	-0.0146***	-0.0180***	-0.0185***	-0.0163**	-0.00750
	High-tech	-0.000786	-0.0272	-0.0147	-0.00512	-0.0257**	-0.0369**	-0.0135
Return on equity	Whole sample	-0.0343**	-0.0161	-0.0197**	-0.0291***	-0.0445***	-0.0363***	-0.00666
	Low-tech	-0.0297	-0.0366*	-0.0440***	-0.0293**	-0.0424**	-0.0444**	-0.0174
	Medium-low-tech	-0.0751*	-0.00179	-0.00328	-0.0125	-0.0531***	-0.0621***	0.0147
	Medium-high-tech	-0.0453*	-0.0138	-0.0112	-0.0293**	-0.0359**	-0.0524***	-0.0149
	High-tech	0.0304	-0.0316	-0.0112	0.0178	-0.0539*	-0.00748	0.0107
Personal wage	Single Period	0.0595**	0.0445***	-0.000958	0.0675***	0.0714***		
	Whole sample	0.0566	0.0373	-0.0150	0.0423*	0.0406		
	Low-tech	0.0556	0.0534	-0.0150	0.0747**	0.0954**		
	Medium-low-tech	0.103**	0.0251	0.00479	0.0721***	0.109***		
	Medium-high -tech	-0.0131	-0.0708	-0.0796*	-0.0259	-0.00628		

5. Conclusion and policy implications

5.1. Conclusion

On the basis of Chinese Industrial Enterprise Database, this paper constructs

indicators from aspects of efficiency, size and financing condition, in a bid to explore comprehensively the new exporters' performance advantages over non-exporters by the method of PSM. The manufacturing industries are then classified into four categories, namely high-technology, medium-high-technology, medium-low-technology and low-technology, for detailed study. The results show as below.

(1) According to the whole sample analysis, there exists no self-selection effect in export but a size performance advantage for exporters. And more cost are consumed in wage expenditure. New export market entrants sport no competitiveness in TFP, LP, and CP, and firms with lower productivity show higher export propensity. There also exists no obvious productivity improvement through learning-by-exporting effect among new export market entrants. Besides, export does not help improve exporters' financing conditions. The size performance advantage lies in the obvious employment expansion and personal income increase.

(2) "Learning-by-exporting effect (or learning effect)" exists in medium-high-tech exporters. After export these firms have experienced notable increases in TFP, LP, and size expansion. The authors deem there stands two reasons behind medium-high-tech exporters' performance advantages over others. First, for their industrial basis and R&D foundation, Chinese exporters are endowed with good "learning ability". A country's upgrading and transforming its industrial structure does not come out of nothing, but of a solid industrial foundation and R&D basis. The learning ability in medium-high-tech exporters enables these firms to bring in a more obvious "learning-by-exporting effect". Second, Chinese medium-high-tech exporters are mostly funded domestically, thus enjoying a relatively complete industry chain and making themselves more than processing plants for multinationals. Most of the medium-high-tech exporters in the industry of Chemical Materials and Products, Chemical Fibers, General Equipment, Special Equipment, Transportation Equipment Manufacturing, and Electric Apparatus, which are desperate of technological improvement, are funded domestically. And most exporters in Computers, Telecommunication, and other Electronic Products, by contrast are foreign funded enterprises which serve basically as processing plants for their parent office. The multinationals' global business planning and operation strategy inhibit the technological progress of these firms, thus not showing obviously the learning effect.

(3) Low-technology exporters' performance is the worst of all. TFP and LP in low-tech exporters, far from an increase, are obviously lower than that of their counterparts, even showing a widening gap between the two. After stepping on the international market, low-tech exporters experience staff expansion at the expense of shrinking industrial sales, aggregate fixed assets, industrial added value, and of course less profit.

5.2. Policy Implications

The paper gives policy implications as follows.

(1) Foreign trade structure needs to be upgraded steadily. China's export trade expansion following its access to the WTO plays a pivotal role in its economic growth, employment expansion, and personal wage increase. Whereas many new export market entrants fail to experience the expected "learning-by-export effect" which is supposed to spur technological progress and lift productivity in these firms but delivers otherwise instead, especially in low-tech exporters. We can assume, in the next phase, these low-tech entrants will be confronted with mounting operating pressure, for which some will even fall out of the international business stage for sheer competition and shrinking profit margin. Therefore, the government needs to provide guidance that more emphasis should be placed on brand building through trade and industry policies. To improve value-added rate and profit margin, these firms are required to improve products quality and upgrade these products technologically, be they for export or labor intensive. Meanwhile, the government and firms should also equip the low-tech workers with new skills, in a bid to avoid structural unemployment from industrial transformation.

(2) Medium-high-technology industry is suggested to be the key area to cultivate competitive advantage for export. The brilliant performance of these exporters enables their size expansion and efficiency improvement, putting themselves to the pattern of endogenous economic development. Or it is safe to say, with the aid of China's growing industrial foundation and infrastructure and also from its workforce's better education backgrounds, the medium-high-tech field has the potential to be counted as one of the country's most globally competitive industries. To cultivate their competitiveness, the government should channel more resources to promote their technological upgrading and R&D. To create an export-friendly climate domestically, the government should also provide better services, thus more favorable trade conditions being shaped in global market.

(3) Increasing support to indigenous innovation in high-technology industry should be considered. While developing electronics and other high-tech fields in the past, China, who had a weak foundation and a lack of technical reserve, was forced to be the foundry and the destination of western countries' industrial transfer so that it could build up its industrial structure and bring in size expansion in a short time. Now, consequently, squeezed by the growing market share of foreign-owned enterprises and their patent strategy, domestically funded firms' operating space is extremely limited. According to related statistics, the domestic electronic information industry counts only 1/3 of the total market share. As processing plants of multinationals, foreign-funded enterprises, based on China's low labor force cost, lacks the motivation of technological upgrading. Facing the international market though, they show no sign

of “learning-by-exporting” effect, resulting in the slow speed of the entire industrial transformation. To reverse the trend, the government should develop policies favorable to the change from the low-end to the high-end, and the development of national brands. The high-tech enterprises should change the mindset of benefiting from “overflow effect” into the new model of being self-dependent, as an effort to boost innovation and surmount critical technical difficulties. The government should also, guided by the “Schumpeter Innovation” theory, perfect the development model of an effective combination of production and research and better the market mechanism, while these enterprises aim at the needs in socioeconomic development, and pinpoint the most promising fields as breakthrough points, thus leading the technological progress and industrial upgrading.

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