Product Differentiation, Export Participation and Productivity Growth: Evidence from Chinese Manufacturing Firms1

Hu, Cui and Tan, Yong

school of International Trade and Economics, Central University of Finance and Economics, Department of International Economics Trade, Nanjing University

27 January 2015

Product Differentiation, Export Participation and Productivity Growth: Evidence from Chinese Manufacturing Firms[1]

Cui Hu[a]

a: School of International Trade and Economics, Central University of Finance and Economics, 39 South College Road, Haidian District, Beijing, P.R.China, 100081.contact information:pkucuihu@gmail.com

Yong Tan[b]

b: Department of International Economics & Trade, Nanjing University, 22 Hankou Road, Nanjing, P.R. China, 200093.contact information: yong.tan@nju.edu.cn

Abstract: In this paper, we investigate how the degree of export participation and product differentiation affect firms' productivity growth through learning-by-exporting. We extend the model of Melitz and Ottaviano (2008) to endogenize the effort firms allocate to learning. This choice depends on both the degree to which firms enter export markets and the extent to which products are differentiated across producers. Using a firm-level dataset from China's manufacturing industries, we implement propensity score matching methods to test the model's predictions. Our results indicate that the degree of export participation is positively correlated with TFP improvements. Simultaneously, we empirically verify that firms exporting less differentiated products experience faster TFP growth than those exporting more differentiated products.

Keywords: Export participation, Product differentiation, TFP, Learning-by-exporting.

JEL Classification: L1, F1, D24

---

[1]Contact information: pkucuihu@gmail.com(C. Hu), and yong.tan@nju.edu.cn (Y.Tan). Yong Tan is the corresponding author.

Product Differentiation, Export Participation and Productivity Growth: Evidence from Chinese Manufacturing Firms

Abstract: In this paper, we investigate how the degree of export participation and product differentiation affect firms' productivity growth through learning-by-exporting. We extend the model of Melitz and Ottaviano (2008) to endogenize the effort firms allocate to learning. This choice depends on both the degree to which firms enter export markets and the extent to which products are differentiated across producers. Using a firm-level dataset from China's manufacturing industries, we implement propensity score matching methods to test the model's predictions. Our results indicate that the degree of export participation is positively correlated with TFP improvements. Simultaneously, we empirically verify that firms exporting less differentiated products experience faster TFP growth than those exporting more differentiated products.

Keywords: Export participation, Product differentiation, TFP, Learning-by-exporting.

JEL Classification: L1, F1, D24

1. Introduction

Exporting is treated as a driving force behind economic growth, and is also believed to be a source of productivity growth. Not surprisingly, a large number of export promotion programs have been implemented to stimulate export growth, especially in developing countries. However, whether exporting leads to firm-level productivity gains is controversial. While some papers find a significant exporting impact on firm-level productivity growth (e.g. De Loecker, 2007; Biesebroeck, 2005;Girma, Greenaway and Kneller,2004; and Dai and Yu, 2013), others provide little supporting evidence for the learning-by-exporting hypotheses. (e.g. Clerides, Lach and Tybout, 1998; Bernard and Jensen, 1999;Aw,Chung and Roberts,2000;Kim, Gopinath and Kim, 2009; Haidar, 2012; and McGregor, Isaksson and Kaulich, 2014). The diverse evidence could be attributed to the analysis design. In particular, the impact of exporting on productivity growth might be different across firms. Lileeva and Trefler (2010) state that among firms which endogenously enter export markets, those which are initially smaller experience faster growth. Understanding this difference is important, in order to encourage export programs to work more effectively despite limited resources. Therefore, it is crucial to identify which firms stand to gain more from trade in terms of productivity growth.

In this paper, we theoretically and empirically investigate how the impact of trade on firms' productivity varies with firm-specific export intensity and product –specific differences in product differentiation. In the theory, we extend the model of Melitz and Ottaviano (2008) to endogenize the effort exporting firms allocate to learning. This choice depends on the degree of their product differentiation in their industry and firm-specific export sales. Empirically, we test the model's predictions by using Chinese firm-level data. China provides an ideal setting to analyze the impact of exporting on firm-level productivity growth. In China, export flows demonstrate substantial variation across firms and product classes. For instance, in electronic heater industry, the largest exporters export more than 20,000 times of the smallest exporters in 2006. In the same year, China exports more than 7,000 types of products, which vary widely in their degree of product differentiation.

The model predicts first that firms exporting less differentiated products acquire faster productivity growth than those exporting more differentiated products; Second, firms with high export sales experience larger productivity improvements than those with low export sales. In particular, we use export sales to measure the degree to which firms enter export markets, and classify products into homogeneous and heterogeneous categories according to Rauch (1999) to proxy for product differentiation. Using propensity score matching methods, we find that exporting increases new exporters' productivity by 4%--8%. Furthermore, firms exporting homogeneous products gain 5%--11% faster productivity growth than those exporting heterogeneous products. Meanwhile, large exporters have, on average, 17.2% faster productivity growth than that of small exporters.

Our work is closely related to the work of Du, Lu, Tao, Yu (2012), who investigate the different impact exporting has on domestic firms and foreign affiliates located in China. Relative to their work, this paper attempts to clarify the mechanisms through which the impact of exporting varies across firms. Intuitively speaking, firms are differentiated in their learning efficiency and productivity gains, which determine their optimal learning effort choice. As such, they obtain different productivity growth. Differing from Lileeva and Trefler (2010), we point out that the pre-exporting productivity is not the only factor that is affecting firm level productivity growth that arises from firm level learning gains.

Some recent studies document that product differentiation and export sales can potentially influence firm learning efficiency. Das, Roberts and Tybout (2007) point out that the small exporting firms are reluctant to invest in R&D since the profit gains cannot cover their fixed investment cost. Aw, Roberts, and Xu (2011) claim that the return of R&D is higher for exporting firms with higher initial productivity and larger exporting volume. This is because the additional profits of these firms cover the fixed investment cost in R&D. However, firms with larger export sales have a more sophisticated structure in terms of organizational capability which reduces the learning cost (eg. Castellani, 2002.).[2] Aghion, Bechtold, Cassar and Herz (2014) find that increased competition leads to an increase in R&D investments among "neck and neck" firms. Meanwhile, Aghion, Bloom, Blundell, Griffith and Howitt (2005) document that, in a "neck and neck" industry[3], firms have a relatively larger incentive for innovation. In our framework, the escape-competition effect results in different learning incentives across firms exporting homogeneous products and those exporting heterogeneous products. Similar evidence has been documented in Yu (2014), where he finds that the tariff absorption elasticity is significantly different between

[2] Firms with good organizational capability can better utilize the knowledge from learning. For instance, in a firm every production sector's manager can speak English, which facilitate them to understand the requirement of their international customers.

[3] A "neck and neck" industry is an industry in which firms face more similar production cost due to lacking of product differentiation.

homogeneous and heterogeneous products because they face different market competition.

Some recent papers also attempt to investigate the firm-level learning by exporting effect. Lileeva and Trefler (2010) claim that low productivity exporters invest more and gain larger productivity than more productive exporters. Andersson and Loof (2008) find that for Swedish firms, the learning takes place for persistently high exporters only. Ma and Zhang (2008) document that, in China, only domestic firms experiences TFP gains from exporting, but not the foreign affiliated firms. Girma, Greenaway and Kneller (2004) and Dai and Yu (2013) report a negative correlation between the learning–by-exporting effect and the number of years firms participate in international trade. However, to best of our knowledge, there is no paper which investigates how firms benefits from exporting varies across product differentiation.

This paper contributes to the literature several levels. Firstly, we develop an economic model to capture the potential factors affecting learning, including substitution elasticity across products, learning efficiency, and further we provide the conditions under which learning by exporting takes place. The comparative statistics of the model indicate that firms' learning incentives and capabilities differ in their export scale and product substitution elasticity. Secondly, we find not only a significant learning by exporting effect among new exporter firms, but also that the firms exporting less differentiated products (homogeneous products) or with larger export sales obtain larger TFP growth after participating in international trade. These results are consistent with the model's predictions. Thirdly, we estimate firm-level TFP in several ways and all results are robust under different TFP measures. In addition, to avoid the bias caused by self-selection, we apply propensity score matching techniques to quantify the magnitude of the effect of learning-by-exporting.

The paper proceeds as follows. The next section introduces the model and the model's predictions. Section 3 describes the data used in the empirical estimation. Section 4 and 5 present the estimation method and the empirical results. We conclude in section 6.

2. Model

In this section, we develop a model to describe learning decision in export markets. In particular, we are first interested in these conditions under which export firms decide to learn in export markets; second, we are interested in the firms' characteristics which affect their learning efforts, and hence their TFP growth.

2.1Demand

Following Melitz and Ottaviano (2008), we assume that the representative consumer's utility function is of a linear form as follows:

$$U = q_0 + \alpha \int_{q_i \in \Omega} q_i \ di - \frac{1}{2}\gamma \int_{q_i \in \Omega} (q_i)^2 \, di - \frac{1}{2}\eta \left(\int_{q_i \in \Omega} q_i \ di\right)^2 \tag{1}$$

where, q_0 and q_i represent the consumption level of the numeraire good and each variety i, respectively. The parameters α and η measure the substitution between the numeraire goods q_0 and the heterogeneous goods q_i, while γ measures the substitution elasticity across different heterogeneous goods.

The demand for each variety i implied by this utility function is:

$$q_i = \frac{\alpha L}{\eta N + \gamma} - \frac{L}{\gamma} p_i + \frac{\eta N}{\eta N + \gamma} \frac{L}{\gamma} \bar{p} \tag{2}$$

$$q_i' = \frac{\alpha L'}{\eta N' + \gamma} - \frac{L'}{\gamma} p_i' + \frac{\eta N'}{\eta N' + \gamma} \frac{L'}{\gamma} \bar{p}' \tag{3}$$

where q_i (q_i'), p_i (p_i'), and $\bar{p}(\bar{p}')$ are the demand, price of product i, and the average price level in the domestic (foreign) market, respectively. L (L') and N (N') are the population and number of firms in the domestic (foreign) market.

2.2 Production

All firms' production exhibits constant returns to scale at differing marginal costs. Labor is the only input, and the wage level is w. For nonexport firm i with productivity φ_i, the marginal production cost is $MC_i = c_i = \frac{w}{\varphi_i}$, and its total production cost, TC_i, is:

$$TC_i = c_i q_i$$

However, if firm i exports, it is able to reduce its marginal production cost (increase φ_i) by paying a learning cost:

$$TC_i = c_i q_i - b z_i q_i + \lambda_i (\theta_i z_i^2 + k) \tag{4}$$

where, z_i is the effort firm i exerts to learn from its foreign competitors or buyers. The first term on the right hand side of equation (4) is the total production cost before learning. The third term $\lambda_i(\theta_i z_i^2 + k)$ is the total learning cost firm i pays, in which λ_i is an indicator function: $\lambda_i = 1$ if firm i chooses to learn, otherwise $\lambda_i = 0$; θ_i captures firm-level learning efficiency or the marginal learning cost (Later we will interchangeably use the two terms to refer to θ_i). We allow θ_i to vary across firms, and depend on firm-level characteristics, such as export sales.[4] The learning cost is constituted by a variable component $\theta_i z_i^2$, which depends on how many efforts firm i exerts, and a fixed component k. The fixed component captures the sunk cost of learning.[5] The learning cost is assumed to be convex in z_i. The second term, $bz_i q_i$, represents the learning effect, in which bz_i is the marginal production cost reduction given the efforts, z_i. The marginal production cost, MC_i, for export firm i with learning effort z_i is given by:

$$MC_i = c_i - bz_i \tag{5}$$

Equation (5) implies that after learning from exporting, firm i's productivity becomes: $\varphi_i' = \frac{w}{c_i - bz_i} > \varphi_i$. This indicates a positive relationship between learning efforts, z_i, and total factor productivity (TFP) growth: if firm i exerts more effort to learn from their foreign competitors or buyers, it will obtain larger TFP growth.

2.3 Optimal Effort Choice

Since only firms participating in international trade have the access to learn from their foreign competitors, in the following context, we only discuss the optimal problem for exporting firms. Each exporter firm solves the optimization problem in two steps: first, each firm decides its effort level z_i which affects its marginal production cost; second, each firm chooses their prices and quantities in the domestic and foreign markets, respectively. Here, we solve the optimization problem backward: in the second step, given the choice of z_i, firm i chooses its prices and quantities to

[4] Firms with higher export sales on one hand can access more foreign buyers, and, as such they can optimally choose one to learn from. On the other hand, firms might export more because they have a more efficient organizational structure, which enhances their learning efficiency. Therefore, we assume $\frac{\partial \theta_i}{\partial Exp\_s} < 0$. This point will be discussed in detail in Section 2.5.

[5] The sunk learning cost contains the cost of setting up the learning channel, maintain the learning group, etc. We can also assume the sunk learning cost is correlated with learning efficiency, which does not change our main results.

maximize profits:

$$max(p_i \; - MC_i)q_i \; + (p_i^{'} - \tau MC_i)q_i^{'}$$

where, τ is the ice-berg transportation cost. The optimal prices and quantities in the domestic and foreign markets are as follows:

$$p_i \; = \frac{1}{2}(c_D + MC_i)$$

$$p_i^{'} = \frac{1}{2}(c_X + \tau MC_i)$$

$$q_i \; = \frac{1}{2}(c_D - MC_i)$$

$$q_i^{'} = \frac{1}{2}(c_X - \tau MC_i)$$

$$c_D = \frac{1}{\eta N + \gamma}(\gamma\alpha + \eta N\bar{p})$$

$$c_X = \frac{1}{\eta N^{'} + \gamma}(\gamma\alpha + \eta N^{'}\bar{p}^{'})/\tau$$

where c_D and c_X are the productivity cutoffs in the domestic and foreign markets, respectively. Firm profit is given by

$$\pi_i = \frac{L}{4\gamma}(c_D - MC_i)^2 + \frac{L^{'}}{4\gamma}(c_D - \tau MC_i)^2 - \lambda_{\text{i}}(\theta_i z_i^2 + k) \quad (6)$$

In the first step, the firm chooses its optimal learning effort, z_i. If it decides not to learn, $z_i=0$. In order to guarantee the nice property of the profit function,[6] we assume that all θ_i's are sufficiently large and satisfies the following condition:

$$\theta_i > \frac{b^2}{4\gamma}(L + \tau^2 L^{'}) \quad (7)$$

The intuition of this condition is that the marginal learning cost is sufficiently high for all export firms. As a result, firms need to balance the gain from TFP growth and the cost of learning.

In the first step, if firm i has decided to learn, according to maximize profit condition, its optimal effort level, z_i, will be,

$$z_i^{opt} = \frac{L(c_D - c_i)b + L^{'}(\tau c_X - \tau c_i)\tau b}{4\theta\gamma - b^2(L + \tau^2 L^h)} \quad (8)$$

Equation (8) implies that the optimal learning effort level increases in firm-level

[6]The nice property means that each firm needs to balance the gain from TFP growth and the cost of learning. If $\theta_i \leq \frac{b^2}{4\gamma}(L + \tau^2 L^{'})$, firm i will pay learning cost until learning cannot reduce its marginal production cost. In this case, the learning effect does not depend on any firm-level characteristics.

pre-export productivity. All other things equal, firms with higher pre-export productivity tend to have larger export volume. Thus the optimal learning effort increases in firm-level export volume. This is consistent with Das, et al (2007) and Aw, et al (2011). Whereas, firm i may chooses not to learn and avoids the learning cost when its learning efficiency or return from learning is low. The marginal firm is indifferent between learn or not to learn given the learning efficiency cutoff, . Exporting firms withwill choose $z_i=0$, while firms with will choose a positive z_i. The cutoff is given in equation (9):[7]

.
$$\bar{\theta} = \frac{L(c_D - c_i)b + L^{'}(\tau c_X - \tau c_i)\tau b}{16\gamma^2 k} - \frac{b^2 L + \tau^2 b^2 L^{'}}{4\gamma k} \tag{9}$$

Equation (9) implies that the learning efficiency cutoff, , is decreasing in the fixed learning cost, k. The larger the fixed cost associated with learning, the fewer the firms who choose to actively learn from exporting. It is commonly accepted that learning-by-exporting effect does not universally exist. Equation (9) tells that if the learning efficiency is sufficiently low (marginal learning cost is sufficiently high), , firms will be reluctant to learn. This implies that learning-by-exporting effects will only be significant within countries where the distribution of learning efficiency among export firms is sufficiently high.

2.4 Comparative Statistics

In this section, our primary interest is to investigate the factors which determine the optimal effort level z_i^{opt}. From equation (8), first the optimal learning effort level is decreasing in θ, the marginal learning cost.

$$\frac{\partial z_i^{opt}}{\partial \theta_i} < 0 \tag{10}$$

Inequality (10) implies that exporters with lower learning efficiency exert less effort, and gain less TFP growth.

Second, it can be proved that z_i^{opt} is also decreasing in γ, the elasticity of substitution across products:

$$\frac{\partial z_i^{opt}}{\partial \gamma} < 0 \tag{11}$$

[7] The details are in the Appendix.

Inequality (11) implies that firms in heterogeneous sectors (more differentiated sectors) tend to exert less effort towards learning than those in homogeneous sectors (less differentiated sectors). In more homogeneous sectors, each firm's product can be more easily substituted by others' products. As a result, firms in homogeneous sectors have an incentive to invest more to gain advantage in both the domestic and foreign markets.

2.5 Discussion

In this section, we discuss the implications of this model. First, equation (8) implies that firms with lower pre-export marginal cost, c_i, and hence larger export sales tend to exert more efforts to learn. The intuition is that firms with large export sales benefit more from productivity growth, and thus have more incentives to invest in learning in order to gain larger productivity growth. Second, we are interested in what firm-level characteristics affect the learning efficiency,. On one hand, Kim, Gopinath and Kim (2009) state the possible channel of learning by exporting is that exporters learn from their buyers who require specific product standards. Therefore, if an export firm reaches more foreign buyers by exporting more, it could better understand its buyers' requirements and improve its learning efficiency. In addition, Castellani (2002) indicates that firms which export more, do so because of their more sophisticated production structure, which in turn allows them to better utilize knowledge from their foreign competitors. On the other hand, the IO literature has commonly documented the risk of innovation. Du, Lu, Tao and Yu (2012) also mention that learning advanced technology takes time and continuous efforts. This implies that firms with larger export sales tend to have more stable connections with their foreign buyers and are less likely to exit from export markets. As such, they are more willing to exert learning effort. As a result, incorporating the failure probability of learning, the expected learning efficiency is higher for firms with high export sales. All the mechanisms predict a positive relationship between export sales, *EXP_s,* which measures the degree of export participation, and learning efficiency (a negative correlation between marginal learning cost and export scales), that is . Both channels imply a positive correlation between export sales and productivity growth.

Proposition 1: The learning effect is stronger for firms with larger export sales, $\frac{\partial z^{opt}}{\partial EXP\_s} > 0$.

As discussed in a number of papers, industry competitiveness has significant impact on exporters' performance (Eckel and Neary, 2006; Mayer, Melitz and Ottaviano, 2014). Varying degrees of competition changes the incentive for firms to invest in learning. Products with little differentiation can be more easily substituted by other products. Therefore, firms exporting homogeneous product, low γ, have more incentive to learn from their foreign buyers in order to survive in international markets. The competition effect leads to the following proposition.

Proposition 2: The learning by exporting effect is stronger for firms exporting homogeneous products than those exporting heterogeneous products.

Learning effort z_i is positively correlated with firm-level TFP growth: if firm i exerts more efforts to learn from their foreign competitors or buyers, it will obtain larger TFP growth. Therefore, Proposition 1 implies that upon exporting, firm-level TFP growth is positively correlated with firm-level export sales, while Proposition 2 implies that firms exporting homogeneous products experience higher TFP growth than those exporting heterogeneous products. In the next sections, we are going to use data from China to test the model's predictions.

3. Data and Statistics

Our empirical objectives include first testing the learning-by-exporting hypothesis and, second, identifying how firms' characteristics affect their TFP growth. In order to accomplish this work, we matched two important sources of data. First, we use the data of Chinese firms engaged in international trade over the period 2000-2007. These data have been collected by the Chinese Customs Trade Statistics (CCTS) and provide information about the quantities, f.o.b values, export destinations, etc of each firm's exports at the eight-digit HS code level. The customs data is carefully matched with the annual firm-level data from the Chinese Annual Survey of Industrial Firm (CASIF). Specifically, the CASIF dataset covers all state-owned enterprises(SOEs) and non-SOEs with annual sales above RMB 5 million, equivalent to around 700 thousand US dollars. More than 200 thousand firms are included in the dataset, which account for around 95% of total Chinese industrial output and 98% of industrial exports.

Rich information on financial variables listed in the main accounting statement are available from the CASIF data, such as output, value added, labor input, fixed capital, intermediate inputs, etc. However, many studies using this datasethave noticed that a large portion of the samples are quite noisy and provided some criteria to clean the data, e.g. Brandt, Biesebroeck and Zhang(2012) and Feenstra, Li and Yu(2014). Following their criteria, we delete observations where key variables are missing and where the firm reports fewer than 8 employees. Further, we also drop observations with total asset less than liquid assets, or total fixed assets or net value of the fixed assets. The filtered number of observations falls by about 50 percent in each year, where the total number of firms ranges from 83,868 in 2000 to 224,908 in 2007.

We rely on the cleaned dataset to estimate firm-level TFP which will be a key variable in our analysis. The literature proposes several ways to estimate the TFP to avoid the endogeneity problem. Olley and Pakes (1996) propose to proxy unobservable productivity using investment. Because a considerable number of firms report a zero investment, Levinsohn and Petrin (2003) instead proxy unobservable productivity using intermediate inputs. For robustness, we will use both OP and LP methods to estimate TFP in this paper. The main variables used in the estimation of productivity are constructed as follows: we first deflate each firm's value added by industry output price, and follow the procedures provided by Brandt, Biesebroeck and Zhang (2012) to get firm-level real capital stock. Since production functions may differ substantially across industries, TFP is estimated sector-by-sector at 4-digit classification level.

The Custom data records monthly export transactions which pass through Chinese Customs. Each record contains firm identifiers (name, address, ownership),eight-digit HS product codes, the value of imports and exports reported as free-on-board (f.o.b) values in US dollars, quantity of goods reported in various units depending on the nature of the goods, 18 kinds of customs regimes, means of transportation, origin, and destination country. Following Rauch(1999), we classify export products into homogeneous or heterogeneous categories according to their HS code. In order to match with CASIF data, we aggregate the monthly data to annul level, and the product level information to firm level.

A key step of the empirical analysis is to match the two datasets, but unfortunately, the firm-identifiers used in the two datasets are different. The matching method follows Yu (2014): instead of using firm-identifiers, we carefully match the two datasets using firm names, telephone numbers and zip codes. The resulting panel covers the 2000~2007 period. The successfully matched sample accounts for nearly 15% of all firms in the CASIF dataset, and about 25% of all export firms in the CCTS dataset.

Following Aw, Chung and Roberts (2000), we divide firms into four groups based on their export market participation in two adjoining years of data:

Firm Status	Year *t*	Year *t+1*
Always	Export	Export
Starter	No exports	Export
Exiter	Export	No exports
Never Exporter	No exports	No exports

Dai and Yu (2013) argue that learning effects are largest in the initial year of entry into export markets and tend to die quickly in subsequent years. To investigate the learning-by-exporting, we focus on the groups of “starters” and “never exporters” to make comparisons. This is to avoid the impact of the always export group attenuating the learning-by-exporting effect (De Locker,2007).

The definitions and summary statistics of other variables used in the study are reported in Table 1. Table 2 further reports the statistics of variables for starter and never exporter groups, respectively. Clearly, the two groups are significantly different in many aspects. In the year that the starters begin to export, these firms are, on average, of larger size, use a higher ratio of capital to labor, and are more likely to be foreign owned enterprises. Besides, the productivities estimated by OLS, LP, and OP are all higher for starters relative to never exporters. In all the following tables, we use lnOLS, lnLP, and lnOP to denote the log productivity measures estimated by OLS, LP, and OP, respectively. The results suggest a systematic difference between the starters and never exporters. However, whether the systematic difference in productivity is caused by learning or self-selection is unclear.

Table 1 Variables Definition And Summary Statistics

Variable	Name	Observations	Mean	S.D.	Definitions
export	Export status	950818	0.030	0.169	No export in period t-1, export in period t, then equal to 1; no export in both period, then equal to 0
size	Firm scale	950818	4.736	1.101	Employment in log function
KL	Capital intensity	950818	3.642	1.361	Ratio of capital to employment
FOE	Foreign dummy	950818	0.135	0.342	Foreign owned firms equals to 1, others 0
lnOLS	productivity1	950818	4.573	1.142	TFP estimated with OLS method
lnLP	productivity2	950818	6.712	1.243	TFP estimated with LP method
lnOP	productivity3	950818	3.783	1.217	TFP estimated with OP method

Data Source: Author's calculation based on the Chinese Manufacturing Survey data and custom data spanning from 2000 to 2007.

Table 2 Mean Test

	Never		Starter		Difference	*t* value
	Observations	Mean	Observations	Mean		
size	922691	4.721	28127	5.236	-0.515***	-77.61
KL	922691	3.638	28127	3.757	-0.119***	-14.42
FOE	922691	0.129	28127	0.354	-0.226***	-44.97
lnOLS	922691	4.568	28127	4.748	-0.180***	-26.02
lnLP	922691	6.697	28127	7.187	-0.490***	-65.21
lnOP	922691	3.781	28127	3.854	-0.073***	-9.92

Note: The data source and variable definitions are shown in Table 1; Significance level 0.1,0.05 and 0.01 are denoted by *, **, and ***, respectively.

Since this paper primarily studies whether learning-by-exporting effect are-stronger for firms with larger exporting or those that export homogeneous products, we further divide the starters into different categories according to their export sales and product differentiation. Specifically, we divide starters into those that export heterogeneous products (export_HE), or those that export homogeneous products (export_HO) according to the classification produced by Rauch (1999). If all of a firm's exported products are heterogeneous, it belongs to the export_HE group, and otherwise it belongs to the export_HO group. By comparing the TFP growth of these two groups of firms, we identify which group benefits more from exporting. We are aware of the fact that a considerable number of firms are multi-product exporters, and they might export both homogeneous and heterogeneous products. As a robustness check, we define the starters with export share of heterogeneous products above 90% as export_HE and the share less than 10% as export_HO. Later we also consider less restrictive critical values, such as75% and 25%, respectively. Similarly, we also divide starters into those which have small export sales (export_S) and those which have large export sales (export_L) groups in the first year of exporting to examine whether firms benefit more as initial export sales increase. In particular, firms with export revenues in the lower 25% percentile of the industry belong to export_S category (small scale exporters), and those with export revenues in upper 25% percentile of the industry belong to export_L (large scale exporter). We also use a 10% critical value as a robustness check.

4. Empirical Methodology

Endogeneity bias is a common problem associated with evaluating the potential productivity benefits from learning-by-exporting. Specifically since firms with higher productivity are likely to self-select into export markets, it is challenging to identify how to disentangle the observed higher productivity to self-selection and learning-by-exporting components. To deal with this potential selection problem, we use matching methods to compute the average treatment effect of exporting on the treated.

Let ω_{it}^{1} be the productivity of firm *i* which is a starter in year *t*, and let ω_{it}^{0} be a counterfactual value representing firm *i*'s productivity if it did not export in year *t*. Year *t* is the time firm *i* switches from a never exporter to starter, which can be any year between 2000 and 2007. The causal effect can be verified by looking at the difference: $(\omega_{it}^{1}-\omega_{it}^{0})$.This productivity gap measures the learning by exporting effect: upon exporting, firm *i's* TFP grows from ω_{it}^{0} to ω_{it}^{1} due to starting to export. Following Heckman, Ichimura, Todd (1997), we define the average export treatment effect on treated as:

$$ATT = E\left(\omega_{it}^{1}-\omega_{it}^{0}\middle|starter=1\right) = E\left(\omega_{it}^{0}\middle|starter=1\right) - E\left(\omega_{it}^{0}\middle|starter=1\right) \qquad (12)$$

Where *starter* is an export status dummy variable for new exporters. That is, if firm *i* is a starter, *starter=1*; otherwise, *starter=0*. The big problem with calculating the

ATT is that ω_{it}^{0} is not observable. The productivity of exporting firm i should it not have exported, Rosenbaum and Rubin (1983) prove that under the conditional independence assumption (CIA), propensity score matching methods can solve this problem. That is, if we can find a non-exporting firm which has a similar export propensity as firm i prior to starting to export (in year *t-1*), its productivity in year *t* can be used to approximate the counterfactual productivity, ω_{it}^{0}. As such, we have the following equation:

$$E\left(\omega_{it}^{0}\middle|p(Z_{i,t-1}), starter = 1\right) = E(\omega_{it}^{0}|p(Z_{i,t-1}), starter = 0) \tag{13}$$

where $Z_{i,t-1}$contains firm-level characteristics prior to exporting, and $p(Z_{i,t-1})$ is the export propensity. As in to De Loecker(2007), we choose pre-export period TFP ($\omega_{i,t-1}$), firm size ($size_{i,t-1}$), capital intensity ($KL_{i,t-1}$) as covariates to estimate the export propensity. Further, we also include a full set of year and 4-digit industry dummies to control for common aggregated demand and supply shocks. Finally, we compute the ATT using propensity score matching methods as follows:

$$ATT = E\left(\omega_{1i} - \omega_{0i}\middle|p\left(Z_{i,t-1}\right)\right) = E\left(\omega_{1i}\middle|p\left(Z_{i,t-1}\right)\right) - E(\omega_{1i}|p(Z_{i,t-1})) \tag{14}$$

$$p\left(Z_{i,t-1}\right) = Pr\{start = 1\} = \phi\{h(Z_{i,t-1})\} \tag{15}$$

among which $\phi(\cdot)$is the normal cumulative distribution function. Full polynomial in the elements of $h(\cdot)$ are used to allow for a flexible functional form and improve the resulting matching (Woolridge, 2002).

In sum, our estimation strategy contains four steps: first, estimate firms' export propensity score based on their characteristics in year *t-1*. Second, using the estimated propensity score to match exporting and non-exporting firms. Third, make use of the control group never exporters to construct the counterfactual value of productivities for exporting firms should they not have exported. Fourth, compare the average productivity of exporting firms and the counterfactual productivity in year *t* to identify learning-by-exporting effects.

As for testing the predictions of the economic model, we follow a similar but somewhat different strategy to make comparisons among different groups of firms.

Specifically, in order to test the model's prediction that firms exporting homogeneous products exhibit stronger learning effect, we compare the productivity difference between the group denoted by export_HE and never exporters conditional on covariates, and the difference between group denoted by export_HO and never exporters conditional on the same covariates. Lastly, we compare these two differences to find out which group experiences faster TFP growth.

One difficulty here is that while we can classify the exported products into homogenous or heterogeneous categories according to Rauch (1999), for non-exported–products, we cannot directly sort them into one of the two categories. However, when we match firms, we include 4-digit industry dummies. This is the most refined products classification in CASIF dataset, and guarantees that we are matching firms which produce similar products. Therefore, firms exporting homogeneous products are matched with non-exporting firms which also produce homogeneous products in the domestic market, while firms exporting heterogeneous products are matched with non-exporting firms which produce heterogeneous products.[8]

$$ATT = E\left(\omega_{it}^{1,HE} - \omega_{it}^{0} \middle| p(Z_{i,t-1})\right) - E\left(\omega_{it}^{1,HO} - \omega_{it}^{0} | p(Z_{i,t-1})\right) \tag{16}$$

Where $\omega_{it}^{1,HE}$ is the productivity of firm i exporting heterogeneous product (export_HE category), and $\omega_{it}^{1,HO}$ is the productivity of firm i exporting homogeneous products (export_HO category). When we use 2-digit industry classifications as covariates for matching, equation (16) can be further simplified as:

$$ATT = E\left(\omega_{it}^{1,HE} \middle| p(Z_{i,t-1})\right) - E\left(\omega_{it}^{1,HO} | p(Z_{i,t-1})\right) \tag{17}$$

This difference-in-difference boils down to comparing the productivity difference between groups of export_HE and export_HO conditional on the same propensity score. This simplification arises because for 2-digit industry classifications,

[8] After we matched the CASIF and CCTS dataset, the matched sample reports the industry code, the HS code, and where the products are homogeneous or heterogeneous. Since each industry code corresponds to several product classification in the CCST dataset, one concern is that even in the same industry, we may have some products which are homogeneous and some which are heterogeneous. This mix may potentially bias our matching results, For instance, firms which are exporting homogenous products may be matched with non-exporting firms producing heterogeneous products since they belong to the same industry. To alleviate this concern, we compute the share of industries with more than 95% products belonging to the same category over all industries, which is 96.6%. This implies that in most industries, their products belong to the same category, either homogeneous or heterogeneous.

each industry contains both homogeneous and heterogeneous products. As such, firms exporting products of different degree of differentiation but similar pre-export characteristics are matched to the same non-export firms. As a result, when compared to the difference-in-difference, the expected counterfactual productivity, $E\left(\omega_{it}^{0}\middle|p(Z_{i,t-1})\right)$, of the matched non-exporting firms cancels out. When examining the impact of export sales on learning-by-exporting, we implement the same method to make the comparison between firms which belongs to the upper and lower percentiles of the sales distribution.

5. Empirical results

A Probit model is used to estimate the probability that a firm starts exporting. Following De Loecker(2007), we choose pre-export productivity, firm size, capital-intensity as well as year and industry dummies as the determinants of starting to export. Table 3 shows that the matched samples are "well-balanced": the treated firms do not differ systematically from the controlled group before they start to export; in other words, our matching specifications generate a comparable control group.

Table 3 Balance Test

		Mean		t 检验	
	Sample	Treated	Control	t 值	$p>\lvert t\rvert$
lnOLS	Unmatched	4.582	4.453	20.01	0.00
	Matched	**4.582**	**4.580**	**0.56**	**0.57**
lnLP	Unmatched	6.982	6.582	56.15	0.00
	Matched	**6.982**	**6.966**	**1.63**	**0.10**
lnOP	Unmatched	3.706	3.670	5.02	0.00
	Matched	**3.706**	**3.704**	**0.22**	**0.82**
size	Unmatched	5.157	4.709	67.05	0.00
	Matched	5.157	**5.151**	**0.58**	**0.56**
KL	Unmatched	3.658	3.531	15.24	0.00
	Matched	3.658	**3.643**	**1.28**	**0.65**
FOE	Unmatched	0.351	0.129	106.96	0.00
	Matched	**0.351**	**0.348**	**0.68**	**0.50**

Note: The data source and variable definitions are shown in Table 1; Results of industry and province dummies are omitted to save space.

The Probit results show that, all variables are statistically significant in the full sample regression. The estimated pre-export TFP, $\omega_{i,t-1}$, has positive impact on firms' export propensity score. This positive correlation implies the self-selection effect: the pre-export productivity increases the probability of starting to export. In addition, foreign owned firms (FOE) and firms with higher capital intensity are more likely to export. This result is consistent with well-known features of Chinese manufacturing: a large part of FOE in China tends to exploit the cheap labor of China to export.

Much of China's exports can be characterized as processing trade, which is defined as importing materials and re-exporting the finished products. Processing trade firms are typically less productive, lacking incentive to do R&D, and experience slow productivity growth. Processing trade accounts for 50% of China’s total exports in many years. Although this share has declined gradually in recent years, it is still over 30% of total exports. Recent literature has pointed out that the behavior of processing trade firms differs substantially from ordinary trade firms (e.g.Dai, Maitra, and Yu, 2013). Thus, we drop processing trade sample and re-examine learning-by-exporting for ordinary trade firms alone. Hence, the propensity scores in this exercise are estimated among ordinary exporters alone. That is, the dependant variable is equal to 1 if a firm doesn't export in year *t-1*, and starts to export as an ordinary exporter in year *t*. The results exhibit similar features and as such we omit future discussion for brevity.

Table 4 Propensity Score Estimation

Explained variable	Export state					
Sample	All Sample			Ordinary trade sample		
lnOLS	0.053***			0.043***		
	(17.71)			(14.80)		
lnLP		0.052***			0.042***	
		(17.38)			(14.39)	
lnOP			0.052***			0.042***
			(17.63)			(14.60)
Size	0.178***	0.155***	0.182***	0.179***	0.162***	0.183***
	(68.90)	(51.91)	(70.76)	(72.09)	(56.10)	(73.70)
KL	0.062***	0.059***	0.068***	0.059***	0.056***	0.064***
	(26.97)	(25.45)	(30.02)	(26.67)	(25.39)	(29.24)
FOE	0.453***	0.454***	0.454***	0.528***	0.528***	0.529***
	(66.27)	(66.31)	(66.42)	(81.42)	(81.46)	(81.56)
Constant	-4.548***	-4.531***	-4.500***	-4.492***	-4.477***	-4.453***
	(-46.82)	(-46.72)	(-46.63)	(-48.15)	(-48.06)	(-48.00)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

District Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	924115	924115	924115	70357	70357	70357

Note: The data source and variable definitions are shown in Table 1; Significance level 0.1,0.05 and 0.01 are denoted by *, **, and ***, respectively.

We now turn to the estimation of the ATT. We use a nearest neighbor matching criteria through all. For each outcome, we try a series of sensitivity tests. First, we use productivity estimated by different econometric methods, including OLS, OP and LP methods. Second, we repeat the estimation for full sample and ordinary trade firms, respectively.

Panel A of Table 5 shows that the results from the matched sample of "Starters" group, which we use to determine whether there is evidence of learning-by-exporting. The full sample ATT estimates show that, for different TFP measures, export has a positive and significant treatment effect on productivity. The estimated coefficients' can be interpreted as an elasticity. Our results indicate that exporting firms become, on average, 7% ~12.2% more productive. Restricting sample to ordinary trade, we also get a positive and significant treatment effect. Thus, it can be concluded that Chinese firms experience productivity growth by exporting to foreign markets.

We next investigate the magnitude of learning-by-exporting is related to firm-level characteristics. Specifically, we are firstly interested in whether firms exporting homogenous products gain larger productivity growth than those exporting heterogeneous products. Secondly, we would like to know if firms with large export sales experience faster TFP growth than those with small export sales.

To answer the first question, we further estimate the ATT for those exporting only heterogeneous products in period *t* and the ATT for those exporting only homogenous products in period *t*, respectively. Results are shown in Panel B and Panel C in Table 5. The results indicate that all treatment effects on productivity are positive and significant among homogeneous products exporters but insignificant among heterogeneous products exporters. The results imply a stronger learning by exporting effect among homogeneous products exporters than that among heterogeneous products exporters, which are consistent with the predictions of our model. In order to further judge the significance of treatment effect between the two groups, we compare the difference based on equation (17).

Table 5 Learning By Exporting

Variables	Treated observations	ATT	S.D	*t* value
Panel A: Learning by exporting for all export firms				
		All Sample		
lnOLS	27689	0.078***	0.009	8.83
lnLP	27689	0.122***	0.010	11.87
lnOP	27689	0.070***	0.009	7.51
		Sample with Ordinary Trade		
lnOLS	31054	0.044***	0.009	5.12
lnLP	31054	0.086***	0.010	8.76
lnOP	31054	0.039***	0.009	4.33
Panel B: Learning by exporting for firms only exporting heterogeneous products				
		All Sample		
lnOLS	2353	0.020	0.031	0.66
lnLP	2353	0.061*	0.034	1.79
lnOP	2353	0.018	0.032	0.57
		Sample with Ordinary Trade		
lnOLS	2674	0.021	0.029	0.74
lnLP	2674	0.039	0.032	1.21
lnOP	2674	0.017	0.030	0.57
Panel C: Learning by exporting firms only exporting homogenous products				
		All Sample		
lnOLS	22234	0.091***	0.010	9.11
lnLP	22234	0.144***	0.011	12.57
lnOP	22234	0.079***	0.010	7.62
		Sample with Ordinary Trade		
lnOLS	25042	0.052***	0.010	5.39
lnLP	25042	0.107***	0.011	9.77
lnOP	25042	0.048***	0.019	2.50

Note: Propensity score of each specification controls for all variables appearing in table 4; standard errors are comptued using the bootstrap; significance level 0.05 and 0.01 are denoted by ** and ***, respectively. The data source and variable definitions are shown in Table1.

Table 6 reports the results for different productivity gains between firms exporting heterogeneous products (export_HE) and those exporting homogeneous products (export_HO). As pointed out in section 2, we use different critical values to divide the treated and control groups. Results show that, for all critical values used to define the export_HE and export_HO, the treated firms, on average, have lower productivity gain than the control group. In particular, the firms exporting homogeneous products obtain 3%~6% faster TFP growth than those exporting heterogeneous products. This is consistent with results reported in Table 5. However, the advantage here is that we test whether the difference is statistically significant.

The *t*-statistics of all specifications indicate that the difference in the learning effect between the two groups is statistically significant at 5% confidence level. So far, we claim that our empirical result is consistent with the model's prediction that the learning effect is, on average, stronger among firms exporting homogeneous products, all other things equal. One possible explanation is that firms exporting homogeneous products face tougher competition since their products can be more evenly substituted by their competitors' products. Therefore, they have more incentive to learn from their competitors and improve their productivity to survive.

Table 6 Learning By Exporting Effect For Export strategy

Variables	Treated observations	ATT	S.D	t value
	All Sample			
Treated: all export products are heterogeneous; Control: all export products are homogenous				
lnOLS	10108	-0.064***	0.015	-4.20
lnLP	10108	-0.064***	0.017	-3.87
lnOP	10108	-0.054***	0.016	-3.43
Treated: the share of heterogeneous products above 90%. Control: the share of heterogeneous products lower than 10%.				
lnOLS	10633	-0.064***	0.015	-4.30
lnLP	10633	-0.062***	0.016	-3.82
lnOP	10633	-0.036**	0.015	-2.34
Treated: the share of heterogeneous products above 75%. Control: the share of heterogeneous products lower than 25%.				
lnOLS	11322	-0.033**	0.014	-2.30
lnLP	11322	-0.054***	0.016	-3.47
lnOP	11322	-0.032**	0.015	-2.15
	Sample with Ordinary Trade			
Treated: all export products are heterogeneous; Control: all export products are homogenous				
lnOLS	9354	-0.049***	0.016	-3.14
lnLP	9354	-0.066***	0.017	-3.85
lnOP	9354	-0.016***	0.016	-3.01
Treated: the share of heterogeneous products above 90%. Control: the share of heterogeneous products lower than 10%.				
lnOLS	10656	-0.027*	0.014	-1.88
lnLP	10656	-0.069***	0.016	-4.30
lnOP	10656	-0.036**	0.015	-2.34
Treated: the share of heterogeneous products above 75%. Control: the share of heterogeneous products lower than 25%.				
lnOLS	9907	-0.075***	0.022	-3.40
lnLP	9907	-0.049***	0.017	-2.91
lnOP	9907	-0.055***	0.016	-3.47

Note: Propensity score of each specification controls for all variables appearing in table 4; standard errors are computed using the bootstrap; significance level 0.1, 0.05 and 0.01 are denoted by*, ** and ***, respectively. The data source and variable definitions are shown in Table1.

Finally, we examine the impact of export sales on learning. Similar to classifying firms by their exported products, we divide starters into treated group and control group according to their export sales. Firms with high export revenues are used as the control group, while firms with low export revenues are defined as the treated group. We use different critical values to divide exporting firms into different export sales groups. The results are presented in Table 7. Our results show that for all specifications, the learning effect is significantly stronger for firms with high export sales. In particular, firms with high export sales gain 10%~34% faster TFP growth than firms with low export sales. Recall, the benchmark result that exporting, on average, increases exporters TFP by 7%~12.2%, which implies that the learning effect is mainly from firms with high export sales. When for new exporters with small export sales, the learning-by-exporting effect is attenuated. A possible explanation is that firms with high export sales are more exposed to foreign markets and buyers. They can learn from their competitors or buyers more effectively and achieve higher learning efficiency. Alternatively, firms with higher export sales have more sophisticated production organizations, and so they can better utilize the knowledge from their competitors or buyers. As a result, they have higher learning potential. This result is also consistent with our model's prediction.

Table 7 Learning by exporting effect for export intensity

Variables	Treated observations	ATT	S.D	Tvalue
		All Sample		
Treated: export revenues belong to the lower 25% percentile in the industry				
Control: export revenues belong to the upper 25% percentile in the industry				
lnOLS	7013	-0.212***	0.025	-8.46
lnLP	7013	-0.241***	0.027	-8.91
lnOP	7013	-0.172***	0.025	-6.78
Treated: export revenues belong to the lower 10% percentile in the industry				
Control: export revenues belong to the upper 10% percentile in the industry				
lnOLS	2075	-0.235***	0.048	-9.08
lnLP	2075	-0.347***	0.051	-10.02
lnOP	2075	-0.231***	0.049	-8.73
		Sample with Ordinary Trade		
Treated: export revenues belong to the lower 25% percentile in the industry				
Control: export revenues belong to the upper 25% percentile in the industry				
lnOLS	7864	-0.143***	0.024	-6.05
lnLP	7864	-0.177***	0.026	-6.86
lnOP	7864	-0.115***	0.025	-4.68
Treated: export revenues belong to the lower 10% percentile in the industry				
Control: export revenues belong to the upper 10% percentile in the industry				
lnOLS	3186	-0.309***	0.042	-7.34
lnLP	3186	-0.337***	0.045	-7.42
lnOP	3186	-0.263***	0.045	-5.85

Note: Propensity score of each specification controls for all variables appearing in table 4; standard errors are comptued using the bootstrap; significance level 0.01 is denoted by ***. The data source and variable definitions are shown in Table1.

6. Conclusion

A number of papers in the literature investigate how firms' productivity growth is affected by exporting. However, current evidence remains mixed. While some papers document a trivial impact of international trade on firms' productivity growth, some others find significant learning-by-exporting effects. The mixed conclusions are possibly caused by the fact that exporting has unbalanced impacts on different firms. Without distinguishing firms, the average effect among firms who do learn from exporting could be attenuated. Therefore, in this paper, we examine how the impact of exporting depends on the firm's product structure and the degree of export participation.

We extend the model of Melitz and Ottaviano (2008) to disentangle the factors which may potentially affect firm-level learning by incorporating firm-level heterogeneity in learning efficiency. Using comprehensive manufacturing data from China, we detect that exporting has positive and significant influence on firms' TFP growth. Furthermore, by comparing the TFP growth among different groups, we first find that firms exporting homogeneous products experience higher TFP growth relative to those exporting heterogeneous products. Second, firms with large export scales experience a much faster TFP increase compared to those with small export sales. All of the results are robust and consistent with the model's predictions.

The findings imply that the export promotion programs work more effectively for firms of high export sales or those exporting homogeneous products. If export promotion programs are tailored to fit those firms, a country could potentially gain more from trade.

Appendix

The learning cutoff $\bar{\theta}$

Export firms with marginal learning cost $\bar{\theta}$ are indifferent between learn or not to learn, so we have the following equality

$$\frac{L}{4\gamma}\left(c_D - c_i + bz_i^{opt}\right)^2 + \frac{L'}{4\gamma}\left(\tau c_X - \tau c_i + \tau b z_i^{opt}\right)^2 - \left[\bar{\theta}\left(z_i^{opt}\right)^2 + k\right] = \frac{L}{4\gamma}(c_D - c_i)^2$$

$$+\frac{L'}{4\gamma}(\tau c_X - \tau c_i)^2$$

$$\Rightarrow \frac{L}{4\gamma}\left[b^2 z_i^{opt} + 2b(c_D - c_i)\right] + \frac{L'}{4\gamma}\left[\tau^2 b^2 z_i^{opt} + 2\tau b(\tau c_X - \tau c_i)\right] = \bar{\theta} z_i^{opt} + \frac{k}{z_i^{opt}}$$

$$\Rightarrow \frac{1}{2\gamma}\left[L(c_D - c_i)b + L'(\tau c_X - \tau c_i)\tau b\right] - \left(\bar{\theta} - \frac{Lb^2}{4\gamma} - \frac{L'\tau^2 b^2}{4\gamma}\right) z_i^{opt} - \frac{k}{z_i^{opt}} = 0$$

$$\Rightarrow \bar{\theta} = \frac{L(c_D - c_i)b + L'(\tau c_X - \tau c_i)\tau b}{16\gamma^2 k} - \frac{b^2 L + \tau^2 b^2 L'}{4\gamma k}$$

***Z_i^{opt}* is decreasing inγ**

To simplify the notation, we denote $c_D - c_i = k_d^i c_D$, and $c_X - c_i = k_x^i c_X$. Equation (8) can be rewritten as:

$$z_i^{opt} = \frac{bLk_d^i c_D + \tau^2 bL' k_x^i c_X}{4\theta\gamma - b^2(L + \tau^2 L')}$$

Take derivative of z_i^{opt} w.r.t. γ:

$$\frac{\partial z_i^{opt}}{\partial \gamma} = \frac{\left[bLk_d^i \frac{\partial c_D}{\partial \gamma} + \tau^2 bL' k_x^i \frac{\partial c_X}{\partial \gamma}\right]\left[4\theta\gamma - b^2(L+\tau^2 L')\right] - 4\theta\left[bLk_d^i c_D + \tau^2 bL' k_x^i c_X\right]}{\left[4\theta\gamma - b^2(L+\tau^2 L')\right]^2} \qquad (A1)$$

The sign of (A1) is determined by the numerator, in which

$$\frac{\partial c_D}{\partial \gamma} = \frac{\alpha(\eta N + \gamma) - (\gamma\alpha + \eta N\bar{p})}{(\eta N + \gamma)^2} = \frac{(\alpha - \bar{p})\eta N}{(\eta N + \gamma)^2}$$

$$\frac{\tau \partial c_X}{\partial \gamma} = \frac{\alpha(\eta N' + \gamma) - (\gamma\alpha + \eta N'\bar{p}')}{(\eta N' + \gamma)^2} = \frac{(\alpha - \bar{p}')\eta N}{(\eta N' + \gamma)^2}$$

$$sign\left(bLk_d^i \frac{\partial c_X}{\partial \gamma}(4\theta\gamma - Lb^2) - 4\theta bLk_d^i c_D\right)$$

$$= sign[-\eta NLb^2\alpha - 4\theta\gamma N\bar{p} + Lb^2\eta N\bar{p} - 4\theta\gamma^2\alpha - 4\theta\gamma\eta N\bar{p} - 4(\eta N)^2\bar{p}] < 0 \qquad (A2)$$

$$sign\left(\tau^2 bLk_x^i \frac{\partial c_X}{\partial \gamma}(4\theta\gamma - L'b^2) - 4\theta\tau^2 bL' k_x^i c_X\right)$$

$$= sign[-\eta N' L' b^2\alpha - 4\theta\gamma N'\bar{p}' + L' b^2\eta N'\bar{p}' - 4\theta\gamma^2\alpha - 4\theta\gamma\eta N'\bar{p}' - 4(\eta N)^2\bar{p}'] < 0 \quad (A2')$$

The last inequalities in equation (*A2*) and (*A2'*) are because $\theta > \frac{b^2}{4\gamma}(L + \tau^2 L^{'})$.This implies,

$Lb^2 < 4\theta\gamma; \tau^2 L^{'} b^2 < 4\theta\gamma \Rightarrow Lb^2\eta N\bar{p} < 4\theta\gamma\eta N\bar{p}; L^{'} b^2 \eta N^{'} \bar{p}^{'} < 4\theta\gamma\eta N^{'} \bar{p}^{'}$.

Finally, we have,

$$\left[bLk_d^i \frac{\partial c_D}{\partial \gamma} + \tau^2 bL^{'} k_x^i \frac{\partial c_X}{\partial \gamma}\right] [4\theta\gamma - b^2(L + \tau^2 L^{'})] - 4\theta\left[bLk_d^i c_D + \tau^2 bL^{'} k_x^i c_X\right] <$$

$$bLk_d^i \frac{\partial c_X}{\partial \gamma}(4\theta\gamma - Lb^2) - 4\theta bLk_d^i c_D + \tau^2 bLk_x^i \frac{\partial c_X}{\partial \gamma}(4\theta\gamma - L^{'} b^2) - 4\theta\tau^2 bL^{'} k_x^i c_X$$

Therefore, $\frac{\partial z_i^{opt}}{\partial \gamma} < 0$.

Reference

Aghion, P., Bloom, N., Blundell, R., Griffith, R. & Howitt, P. (2005). Competition and innovation: an inverted-U relationship. *Quarterly Journal of economics*, 120 (2), 701-728.

Aghion, P., Bechtold, S., Cassar, L., & Herz, H. (2014). The causal effects of competition on innovation: Experimental evidence. *Working Paper*.

Andersson, M.,& Loof, H. (2009). Learning-by-exporting revisited: the role of intensity and persistence.*Scandinavian Journal of Economics*, 111(4), 893-916.

Aw, B.Y., Chung, S.& Roberts,M. J. (2000). Productivity and turnover in the export market: Micro-level evidence from the republic of Korea and Taiwan.*The World Bank Economic Review*, 14(1), 65-90.

Aw, B. Y., Roberts, M. J. & Xu, Y (2011). R&D investment, exporting, and productivity dynamics. *American Economic Review*, 101 (4), 1312-1344.

Bernard, A., & Jensen, J. (1999). Exceptional exporter performance: Cause, effect or both? *Journal of International Economics*, 47 (1), 1-25.

Blalock, G.,& Gertler, P. J. (2004). Learning from exporting revisited in aless developed setting.*Journal of Development Economics*, 75(2), 397-416.

Brandt, L., Biesebroeck, J.V., & Zhang, Y.F.(2012).Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing. *Journal of Development Economics*, 97(2): 339-351.

Clerides, S., Lach, S., & Tybout, J. (1998). Is learning-by-exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco. *Quarterly Journal of Economics*, 113 (3), 903-947.

Castellani, D. (2002). Export behavior and productivity growth: evidence from Itanian manufacturing firms. *Review of World Economics*, 138 (4), 605-628.

Dai, M., & Yu, M. (2013). Firm R&D, absorptive capacity and learning by exporting: Firm-level evidence from China. *The World Economy*, 36 (9), 1131-1145.

Das, S., Roberts, M. J. & Tybout, J. R. (2007). Market entry costs, producer heterogeneity, and export dynamics. *Econometrica*, 75 (3), 837-873.

De Loecker, J. (2007). Do exports generate higher productivity? evidence from Slovenia. *Journal of International Economics*, 73 (1), 69-98.

Du, J., Lu, Y., Tao, Z., & Yu, L. (2012). Do domestic and foreign exporters differ in learning by exporting? Evidence from China. *China Economic Review*, 23(2), 296-315.

Eckel, C., Neary, P. (2010). Multi-product firms and flexible manufacturing in the global economy. *Review of Economic Studies*, 77 (1), 188-217.

Eaton,J., Eslava,M., Krugler,M.,& Tybout, J.(2007), Export Dynamics in Colombia:Firm-Level Evidence.NBER WorkingPaper,No.13531.

Feenstra, R., Li, Z.Y., & Yu, M.J. (2014).Export and Credit Constraints under Incomplete Information: Theory and Empirical Investigation from China. *Review of Economics and Statistics*, forthcoming.

Foster-Mcgregor, N., Isaksson, A., & Kaulich, F. (2014). Learning-by-exporting versus slef-selection: New evidence for 19 sub-Saharan African countries. *Economics Letters*, 125(2), 212-214.

Girma, S., Greenaway, D., & Kneller, R. (2004). Does exporting increase productivity? A microeconometric analysis of matched firms. *Review of International Economics*, 12(5), 855-866.

Haidar, I. J. (2012). Trade and productivity: self-selection or learning by exporting in India. *Economic Modeling*, 29(5), 1766-1773.

Heckman,J., Ichimura,H., Todd,P.,1997.Matching as an Econometric Evaluation Estimator. Review of Economic Studies,65, 261-294.

Kim, Soo-Il, Gopinath, M., & Kim, H. (2009). High productivity before or after exports? An empirical analysis of Korean manufacturing firms. *Journal of Asian Economics*, 20 (4), 410-418.

Levinsohn,J.,& Petrin,A. (2003).Estimating Production Functions Using Inputs to Control for Unobservables.*Review of Economic Studies*, 70,317-341.

Lileeva, Alla., & Trefler, Daniel. (2010). Improved access to foreign markets raises plant-level productivity… for some plants. *Quarterly Journal of Economics*, 125 (3), 1051-1059.

Ludema, R., & Yu, Z. (2012). Tariff pass-through, firm heterogeneity and product quality. *Working paper*.

Ma, Y., & Zhang, Y. (2008). What's different about new exporters? Evidence from Chinese manufacturing firms. *XMU-WISE working paper* 2008-May.

Mayer, T., Melitz, M. J. & Ottaviano, G. I. P. (2014). Market size, competition, and the product mix of exporters. *American Economic Review*, 104 (2), 495-536.

Melitz, M. J., & ottaviano, G. I. P. (2008). Market size, trade, and productivity. *Review of Economic Studies*, 75 (1), 295-316.

Olley, G.S. & Pakes, A. (1996).The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6), 1263-1297.

Rauch,J.,1999. Networks Versus Markets in International Trade. Journal of International Economics,48,7-35.

Van Biesebroeck, J. (2005). Exporting raises productivity in sub-Saharan African manufacturing firms. *Journal of International Economics*, 67(2), 373-391.

Woolridge,J.,2002. Econometric Analysis of Cross Sections and Panel Data.The MIT Press, Cambridge.

Yu, M.J.(2014).Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms. *Economic Journal*, Doi: 10.1111/ecoj.12127.