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Reconsider Learning by Exporting Hypothesis from Innovation: An Empirical Study of US Industries

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Abstract: This paper empirically studies the learning-by-exporting hypothesis through the channel of innovation. On the one hand, due to its exports, a sector's productivity rises to a higher level because of its access to a wider market, as well as being introduced to intense global competition. This process is known as the "learning by exporting" theory. On the other hand, innovation can create a beneficial environment for industries or plants to grow, and therefore enhance the productivity even further. Hence the productivity gain conditional on the exports can be enlarged by fortified innovation effort. I estimate sectoral productivity using the Olley-Pakes methodology. Based on the industry-level data of US manufacturers from 2005 to 2009, I find that higher values of R&D input do have a positive effect on sectoral productivity improvement conditional on exports. Specifically, the R&D employment ratio should be higher than 6%, while the company-performed R&D funds should be at least 5%; otherwise a sector's exports cannot improve its productivity significantly.

Key words: exports; productivity; innovation; learning-by-exporting
JEL code: C82, F14, F23, L60

1. Introduction

The influence of trade—especially export behavior—on development has been studied widely. There are always drastically different developing results for industries under globalization. From time to time winners take over new market positions while losers have to exit. Some industries, e.g., computer and kindred manufacturers, had soared dramatically during the last couple of decades in 20th century, while other industries simply vanished during the same period. In other words, under the circumstance that trade prospered greatly between different regions in the world, different industries share very little in common when it comes to their growth stories. By the term of "trade", this paper mainly focuses on the exports. Through exporting, an industry or a plant has a wider market to operate in, and also more opportunity to access various advanced production technologies. Therefore, can a sector's exports improve its growth? If yes, is this procedure also influenced by other factors?

Looking into the relationship between exports and productivity, we can find a tremendous amount of work demonstrating the positive relationship between them. Traditionally speaking, high productivity is well known as the reason why advanced firms or industries benefit more from international trade; only more profitable and competent firms can afford to export, which is more costly than merely operating domestically. It is well known as

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a “self-selection effect” (Melitz, 2003; Bernard et al., 2004; López, 2004), which has been proven by a large amount of theoretical and empirical evidence.

However, this paper focuses on another dimension of the causality between the productivity and the exports: how the exporting behavior affects productivity in an open economy. The well-known “learning by exporting” theory explains how firms grow faster because of their exports; the international trade which the firms participate in would speed their own development (Marin, 1992; Ben-David, 1993). Exporting firms are capable of having more advanced skills accessed via ex-post benefits, especially when these skills are unavailable enough domestically. Such learning process can enhance the firms’ innovation and efficiency greatly. So far the empirical tests based on different samples have shown both positive and negative feedback to this conclusion, indicating that the theory itself is very case-sensitive. For example in Clerides et al. (1998), the authors use plant-level data from Mexico, Colombia and Morocco yet find no evidence that firms’ cost will be affected by previous exporting behaviors. However, using information from Indonesia, Blalock et al. (2004) find strong evidence that firms experience a jump in their productivity once they are engaged in exporting. In Baldwin & Robert-Nicoud (2008), a combined conclusion is established; they find that openness increases industry productivity in a level sense, but it has ambiguous effect on its growth rate. Trade liberalization slows down industry growth by raising the expected fixed cost of innovation while not affecting expected benefits.

Instead of seeking a conclusion which is purely for or against the learning-by-exporting (LBE) theory, I will consider why inconsistent findings exist. This paper is established on the mixed empirical evidence that exports do influence sectoral productivity, but it is significantly positive only when sectoral R&D investment is high enough. If the R&D investment is low, the correlation between exports and productivity is not significant anymore. Therefore, innovation appears to be an intriguing and important channel for so-called learning-by-exporting (LBE) to come into existence. When every sector needs to pay innovation effort to increase its productivity, the innovation effort will play an importance role and vary the impact of exports on productivity growth. If the innovation effort is low, then export status only exerts ambiguous influence on productivity and its growth in a neglectable way. However, if the effort is high enough, exports will be able to speed up sectoral development significantly.

In studying how the LBE effect is affected by the innovation effort, the productivity is an important variable needs to be estimated appropriately. Considering the possibility of the potential idiosyncratic productivity shocks, which are contemporaneous with the sectoral exports, a sector’s knowledge of its own productivity will cause bias during the estimation of the input coefficients in the production function. Specifically, it will cause upward bias in the estimated coefficients of variable inputs, while inconsistent estimated coefficients of quasi-fixed inputs. This will lead to results that lack precision. To deal with the simultaneity embedded in the choice of production inputs and unobservable productivity shocks, I use the Olley-Pakes (OP) methodology (Olley & Pakes, 1996). Olley and Pakes use a semi-parametric algorithm to solve for the problem of simultaneity and endogeneity. Besides the investment and capital as traditional quasi-fixed inputs, in order to focus on the influence of exports I modify the OP methodology by adding two additional state variables: export share and export growth rate. With these two variables I also control the export behavior from both static and dynamic aspects; thus a more accurate estimation of productivity conditional on exports can be done.

This paper looks into the US industry-level data. The reason is obvious: the US is a typical developed country with mature market mechanism, and ideal trade circumstance. It fits the paper’s crucial assumptions about free market and open economy. Using panel data of US manufacturing industries, my results show that sectoral productivity rises from increasing exports, and it also rises because of a higher innovation effort. Also, I use two different variables to indicate sectoral R&D efforts: the ratio of R&D agents and scientists employment against the total domestic employment, and ratio between the company-performed R&D funds and net domestic sales.

I then carry out separate productivity-exporting tests across groups of sectors with different ranks of R&D inputs supports the finding. Only among those groups with R&D employment ratio higher than 0.06, or with R&D funds rate higher than 0.05, a significant LBE phenomenon exists; a sector's exports can significantly enhance its productivity. Therefore, the tests along the channel of R&D funds rate are more consistent; they share a common R&D funds rate threshold (5%) above which the LBE hypothesis is significant.

There is much research that uses the Olley-Pakes methodology and its transformation in the estimation of productivity. For example, in Blalock & Gertler (2004) and Alvarez & Lόpez (2005), using data from Indonesia and Chile respectively, they estimate plant-level productivity with traditional OP approach, and test its relationship with exporting behavior. Both papers find that exporters have gradually better performance which suggests the existence of learning-by-exporting. Furthermore, more sophisticated work can be done. Amiti & Konings (2007) also use Indonesian data to test the influence of trade liberalization on productivity gain. The difference is that their work includes both export and import decision as additional state variables in the OP productivity evaluation. Pavcnik (2000) uses the probability of a plant staying in market to incorporate the problem of exit during the estimation procedure, and Fernandes & Isgut (2004, 2007) add firms' dynamic exporting decisions into the calculation. All of these works have made thorough and sophisticated improvement in estimating more consistent productivity. In Levinsohn & Petrin (2000) proves that besides the investment which is used in Olley-Pakes, the intermediate inputs can also solve the simultaneity problem in the correlation between inputs and unobservable productivity shocks. However after the estimation, most of them only end up testing the relationship between productivity gain and exporting behavior or trade liberalization, in order to argue for or against the LBE theory based on their empirical results. Few of them admit the potential ambiguity of LBE effect, and start to wonder why this may happen.

This paper is organized as the following. Section 1 presents the brief introduction of this paper. Section 2 explains the model and estimation methodology. Section 3 describes the data and presents empirical test results. Section 4 will do sensitivity test to check the robustness of the findings, while section 5 concludes the paper.

2. Model and Estimation

To estimate the sectoral productivity, I use a typical Cobb-Douglas production function:

$$Y_{\mathrm{it}} = A_{\mathrm{it}} L_{\mathrm{it}}^{\beta_l} K_{\mathrm{it}}^{\beta_k} M_{\mathrm{it}}^{\beta_m} exp\ (\beta_Q Q_{\mathrm{it}} + e_{it}), \tag{1}$$

where for sector i at time t, A_{it} is the total factor productivity (TFP), Lit is labor, M_{it} is material cost, and K_{it} is capital. Q_{it} is a vector of industrial characteristic measures. I use total fringe benefits as Q_1, cost of contract work as Q_2, annual payroll as Q_3. Log-linearize (1), we have

$$y_{it} = a_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta'_q Q_{it} + e_{it}, \tag{2}$$

Hereafter all the lower-case input indicators are the logarithm of the corresponding capital ones, e.g., $l_{it} = \log L_{it}$.

2.1 Productivity Estimation

The estimation is based on

$$y_{it} = a_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta'_q Q_{it} + e_{\text{it}}, \tag{3}$$

$$e_{\text{it}} = \omega_{\text{it}} + \eta_{\text{it}}, \tag{4}$$

Therefore sector specific error term e_{it} is composed of two elements: a sector-specific productivity shock ω_{it} that is known by the sector but not the econometricians, and a white noise η_{it} that is unknown for both the sector and the econometricians. In this paper the former one is the one that matters. According to Olley-Pakes approach the unobserved productivity ω_{it} follows a 1st order Markov process. Meanwhile, a sector's profit maximization yields an investment decision function I_{it} which depends on capital kit and productivity ω_{it}. Specifically,

$$I_{\text{it}} = i(k_{\text{it}}, \omega_{\text{it}}). \tag{5}$$

The OP methodology includes two steps. First, by inverting the investment function in Equation (5), the unobserved productivity can be explained by investment and capital. Consider the sector's export status variable as additional state variable. Substituting the result back into Equation (3), I can then obtain the consistent estimates of the coefficients of variable inputs, namely β_l, β_k and β_Q. Second, I will separate capital elasticity β_k from the investment decision. Following Pavcnik (2000), I assume capital at *t+1* is correlated with productivity expectation. Therefore, the expectation of productivity next period $E(\omega_{it}+1)$ is a function of current productivity ω_{it}, which can be substituted by the result from the first step. This means $E(\omega_{it}+1)$ can be expressed by investment and capital at time *t*. Substitute the result back into Equation (3) rewritten at time *t+1*. Conditional on the information and elasticities of labor, material and other relevant sector characteristics, consistent estimation of coefficient of capital can be generated. The details of the estimation procedure are in the Appendix A. Once all the necessary coefficients are available, the log of the measured productivity is calculated as

$$a_{\text{it}} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_m m_{it} - \widehat{\beta'}_Q Q_{\text{it}}. \tag{6}$$

The results of the estimated input coefficients from the OP methodology are in Table 1. I also include the OLS and 2SLS[1] estimations for a comparison. As what's expected, the coefficients of labor, material are overestimated by the OLS since they have positive correlation with productivity shock, but have uncertain biases under 2SLS because of additional consideration of instrumental variables. As for the sectoral characteristic vector Q, things are more complicated. No matter before or after the fixed effects are considered, OLS and 2SLS only generate negative elasticities for fringe benefits, which means an increase of fringe benefits will cause a decrease in the output. However, after the fixed effects are added into consideration, this elasticity turns out to be positive under the OP methodology. Meanwhile, the absolute value of the coefficient on contract work cost is overestimated by both OLS and 2SLS. As for the capital elasticity generated during the second step in OP estimation, it is overestimated by both OLS and 2SLS.

The productivity therefore can be estimated by Equation (6) based on these information. Under each method I do three different estimates based on different consideration of fixed effects. All of them will be used later for the robustness of the tests. I also do comparisons between different methodology about the estimation of productivity level and growth rate. The details are in Table 4 of Appendix B. The sectoral productivity fluctuates to a certain extent but not wildly at all. For some of the sectors, e.g., furniture and fixtures[2], is monotonically increasing during 2006 to 2009; for other sectors, e.g., Beverage and Tobacco, or Chemicals, fluctuate by hitting the trough in 2007 or 2008, then back on the growing track. Furthermore, when calculating the sectoral productivity including fixed effect, 2SLS will generate much volatile results which do not even share the same

[1] I use 2-stage least square method to remove the potential endogeneity of capital expenditure.

[2] 3-digit NAICS: 337.

sign. Also, under both OLS and 2SLS the estimated productivity differs significantly across the sectors; even in similar industries, e.g., primary metal products (331) and fabric metal products (332), the difference is very big. This violently changing productivity will cause difficulty in empirical tests, and also inconsistent results. On the other hand, OP methodology, which has removed endogeneity and the problem of idiosyncratic productivity shock during the estimation, and generates much more smooth and consistent results. The productivity fluctuates between 2.5 and 3.9 no matter when we compare them across the sectors or between different scenarios of estimates.

Table 1 Coefficient Estimation of the Production Function

	(1)				(2)				(3)		
	OLS	2SLS	OP		OLS	2SLS	OP		OLS	2SLS	OP
1st step											
$\hat{\beta}_l$	0.198	0.153	0.004		0.186	0.074	0.012		0.186	0.166	0.012
$\hat{\beta}_m$	0.781	0.516	0.717		0.829	0.640	0.700		0.828	0.772	0.695
$\hat{\beta}_{Q1}$	-1.579	-1.431	-2.154		-0.009	-0.857	0.005		-0.308	-0.412	0.014
$\hat{\beta}_{Q2}$	-1.185	-3.126	-2.79E-04		-1.275	0.315	2.16E-04		-1.349	-2.137	1.90E-04
$\hat{\beta}_{Q3}$	1.388	-2.080	1.335		-2.215	6.558	0.492		-1.451	-1.742	0.463
2nd step											
$\hat{\beta}_k$	0.174	0.545	0.105		0.119	0.209	0.076		0.119	0.206	0.067
Sector FE	No	No	No		Yes	Yes	Yes		Yes	Yes	Yes
Year FE	No	No	No		No	No	No		Yes	Yes	Yes
N.Obs	1040	1040	738		1040	1040	738		1040	1040	738

Notes: Table 1 reports all the elasticities of factors of production from Equation (3).

2.2 R&D Measures

Since this paper is about to estimate the role of R&D plays in the LBE process, I need to find appropriate measures for sectoral R&D. I will use two alternative variables to indicate sectoral innovation input. One is R&D employment ratio, which is the ratio between R&D employment of scientists & engineers and domestic total employment. The other is company-performed R&D funds ratio, which is the ratio between the company-performed R&D funds[3] and domestic net sales. Therefore I will look into how a sector's productivity, and furthermore its productivity gain because of exports, is going to be affected by its innovation effort from two alternative measures. This provides me with a more robust conclusion.

3. Data and Results

In this section, I will describe the data sources and show the preliminary test results. There are two steps for my estimation: first, how the sectoral productivity is affected by the exports and innovation; to be specific, whether exports can promote productivity and how the result varies due to different innovation input. Next, I will study how the LBE effect is affected by the innovation.

3.1 Data Description

I use three data sets and combine them into a balanced panel. First, the industrial characteristics come from

[3] Defined as the sum R&D expense for own performance plus R&D costs funded by others for own performance.

Annual Survey of Manufactures: Statistics for Industry Groups and Industries from 2005 to 2009, which is proceeded by US census bureau. The earlier data cannot be considered as being consistent, since the survey method used to assign industry classifications has been changed; industry-specific estimates after 2004 are not directly comparable with those of previous years. I pick out all the 6-digit NAICS sectors and all their necessary information, e.g., capital expenditure, investment, employment, and so on. In the data, all the costs, benefits, expenditures and value added are measured in \$1000. As for the trade information, I use value of exports by 6-digit NAICS provided by US International Trade Statistics. The exports are reported by F.A.S. value basis[4], while the imports are general imports by customs value basis[5]; they are also measured in \$1000.

All the relevant R&D information comes from National Science Foundation/Division of Science Resources Statistics. I now consider the time-lagging effect that is brought by the innovation. The influence of R&D cannot be simultaneous with the input; normally, when industries pay more for their R&D department, or hire more scientists, engineers or analysts to make R&D progress, it will always take some time for the actual effects happen, for example manufacturing costs decline, or efficiency increases. Therefore, I allow a one-year lag for the innovation input. That is, I will look into how sectoral R&D input in 2008 affects its productivity and LBE in 2009, and how its 2007 R&D affects its 2008 performance, and so on. As for the data details, the innovation information in 2008 comes from Business R&D and Innovation Survey, while the information from 2004 to 2007 comes from Survey of Industrial Research and Development.

3.2 Relationship between Productivity and Exports

The correlation between productivity and exports is specified as:

$$a_{\mathrm{nit}} = \alpha_0 + \alpha'_1 \mathrm{Export}_{\mathrm{nit}} + \alpha'_2 X_{\mathrm{nit}} + \Theta_n + \lambda_i + \upsilon_t + \varepsilon_{\mathrm{nit}} \quad (7)$$

where Export_{it} is the export value per worker, X_{it} is a vector of industrial characteristics. Θ_n is a fixed effect for innovation inputs which belongs to rank n, λ_i for sector i, and υ_t for year t. The productivity estimation resulted from the OP estimates above with both sector and time fixed effects. In this section I will focus on analyzing the effects of α_1 and Θ_n.

The test results of Equation (7) are presented in Table 2. First I regress productivity only on the export value per production worker (measured in \$108) in order to estimate the influence of sectoral exports on productivity, as a benchmark. Column (i) and (ii) of Table 2 show that both export value can increase sectoral productivity significantly. Specifically, once *Xit*[6] is considered, the elasticity of export value on productivity will rise. An increase in exports value by 10% will increase the productivity by 55.3%; the positive significance is also consistent with the literature. Meanwhile, larger capital expenditure on computer will increase the productivity, while larger expenditure on machinery will decrease it.

Next I add the influence of innovation investment into the study. The fixed effects of different ranks of R&D

[4] As described by the National Science Foundation (NSF), the F.A.S. (free alongside ship) value is the value of exports at the U.S. seaport, airport, or border port of export, based on the transaction price, including inland freight, insurance, and other charges incurred in placing the merchandise alongside the carrier at the U.S. port of exportation. The value, as defined, excludes the cost of loading the merchandise aboard the exporting carrier and also excludes freight, insurance, and any charges or transportation costs beyond the port of exportation.

[5] Also by the NSF: the customs value is the value of imports as appraised by the U.S. Customs and Border Protection in accordance with the legal requirements of the Tariff Act of 1930, as amended. This value is generally defined as the price actually paid or payable for merchandise when sold for exportation to the United States, excluding U.S. import duties, freight, insurance, and other charges incurred in bringing the merchandise to the United States.

[6] *computerr* is the ratio of capital expenditure spent on computer and data-processing equipments, and *machineryr* is the one that spent on machinery and kindred equipments

measures are analyzed. The reason why fixed-effect instead of normal linear-regression analysis is used is that I need to know how different innovation inputs' influences on productivity differ from each other. Furthermore, I need to estimate their different influences on the LBE effect by separating them from each other. Notice that according to the assumption of one-year-lag in the influence of innovation, the emp_{it} and rdf_{it} are actually the innovation that was invested in time *t-1* but will take effect in *t*. I will therefore focus on when the innovation's actual effect happens instead of when the innovation decision is made.

Table 2 Correlation between Productivity and Exports

Dependent Variable:	log TFP_{it}					
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$Exports^{a}_{\mathrm{nit}}$	8.218* (4.437)	9.425** (4.667)	8.179* (4.449)	8.710* (4.986)	8.127* (4.884)	9.678* (5.153)
Dummy (0.03 < emp_{it} < 0.04)	-	-	0.002 (0.033)	-0.203*** (0.028)	-	-
Dummy (0.04 < emp_{it} < 0.06)	-	-	0.011 (0.037)	-0.092** (0.038)	-	-
Dummy (0.06 < emp_{it} < 0.1)	-	-	0.016 (0.037)	-0.047 (0.040)	-	-
Dummy (emp_{it} > 0.1)	-	-	0.029 (0.046)	0.016 (0.049)	-	-
Dummy (0.01 < rdf_{it} < 0.016)	-	-	-	-	-0.045 (0.033)	-0.049 (0.033)
Dummy (0.016 < rdf_{it} < 0.025)	-	-	-	-	-0.082** (0.032)	-0.078** (0.033)
Dummy (0.025 < rdf_{it} < 0.05)	-	-	-	-	-0.039 (0.029)	-0.046* (0.030)
Dummy (rdf_{it} > 0.05)	-	-	-	-	0.025 (0.055)	0.026 (0.057)
$computerr_{\mathrm{nit}}$	-	0.499*** (0.136)	-	0.400*** (0.147)	-	0.379** (0.149)
$machineryr_{\mathrm{nit}}$	-	-0.010* (0.060)	-	-0.114* (0.064)	-	-0.158** (0.066)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are in parentheses. The productivity value used here is the one which includes both sector and year fixed effects during estimation.

a: Export value per worker is measured in $\$10^{8}$.

*** Significant at or less than 1%.

** Significant at or less than 5%.

* Significant at or less than 10%.

In column (iii) and (iv), I include the fixed effect of R&D employment ratio (*emp*). When I start to consider *emp* fixed effects, export value still increases productivity with great significance. In column (iii), as *emp* increases, the fixed effect also increases while keeps being positive. This means that once export status is controlled, a R&D employment ratio that is located in a higher level will expand sectoral productivity even further. Once X_{nit} is considered the *emp* fixed effect still monotonically increase, however only the effect of the highest rank of R&D employment ratio remains being positive. Specifically, if a sector's *emp* is higher than 6% its productivity will not be significantly decreased by the *emp* fixed effect. If the innovation input is not high enough, the productivity will shrink once the export is controlled; only when a sector employs enough scientists and engineers in their R&D department can their productivity benefit from it.

In column (v) and (vi), the fixed effect of company-performed R&D funds ratio (*rdf*) is considered instead. Still, higher export liberalization increases productivity with significance. Now no matter before or after the additional industrial characteristic variables are considered, the signs of the fixed effects of R&D funds ratio do not change; only the highest R&D funds ratio rank rdf4it has positive effect. A *rdf* higher than 5% will increase the productivity by 0.026. This suggests that only if a sector pays for its R&D funds arduously enough can its hard work be repaid to own a higher productivity. Besides, an increase of computer expenditure ratio by 10% can increase productivity by around 4%, while an increase of machinery expenditure ratio decreases it by 1.1% to 1.6%. Both results are significant. As for the analysis based on the productivity scenarios using two other OP methods, the details are in Table 9 in Appendix B. From the table, we can tell that if year or section fixed effects are not included during productivity estimation, the learning-by-exporting process doesn't sustain anymore, because the export value per worker does not have significant correlation with the productivity. Therefore, whether the LBE hypothesis can be observed in the reality depends on both specific dataset as well as the productivity estimation methodology.

3.2.1 Coexistence of Negative & Positive Evidence of LBE

Now that we have a clear idea about that only the highest R&D investment can improve a sector's LBE effect, I furthermore do another separate test among groups of sectors divided by their R&D investment, in order to see whether the LBE phenomenon sustains under different conditions featured by different samples. Follow the same logic as in section 2, I pick out two groups of sectors under each R&D measure. For *emp* (the R&D employment ratio), the sectors in the first group have their *emp* between 3% and 6%, while those in the second group are featured by an *emp* which is higher than 10%; for *rdf* (the company-performed R&D funds rate), the sectors in the first group have their *rdf* between 1% and 1.6%, while those in the second with a *rdf* higher than 5%. Then I make regression of the sectoral TFP against the export value, the export growth rate and relevant industrial characteristic variables. 2SLS is applied here in order to remove the endogeneity in exports. The estimation results are in Table 3.

Panel A of Table 3 shows the case under the R&D employment ratio analysis. Besides sectoral export value per production worker, I choose two other variables to measure export liberalization: sectoral export value per fringe benefit, and sectoral export per annual payroll. Columns (i) to (vi) are for the those sectors with the lowest R&D employment ratio (between 3% and 6%). As we can see, the elasticities of export liberalization are positive and increasing. However, the results are constantly insignificant; a sector's export value cannot exert meaningful influence on productivity improvement, neither can its export growth. Thus the LBE cannot be detected under this circumstance with low R&D employment ratio (< 6%). Meanwhile, columns (vii) to (ix) are for the sectors that have a higher R&D employment ratio (between 6% and 10%). In contrast to the findings just previously, no matter which economic variable is chosen to indicate the export liberalization, the LBE coefficient stays positive and significant; exports can increase productivity significantly. Specifically, a 1% increase of export per production worker by one unit ($107) will increase the productivity by around 13%; a 10% increase of export per fringe benefit ($102) can increase the productivity by 29%; a 1% increase of export per payroll ($102) increases the productivity by 7%. A significant LBE phenomenon exists consistently. As for the tests based on the sectors with the highest R&D employment ratio (> 10%), things are similar; a 10% increase of export per production worker ($107) and export per fringe benefit ($102) will increase the productivity by 17%; a 1% increase of export per payroll ($102) increases the productivity by 8%. The LBE hypothesis sustains by holding a significant relationship between export liberalization and productivity.

Table 3 Productivity Test Grouped by R&D Input

Dependent variable: $\log TFP_{nit}$												
	$0.03 < emp_{nit} < 0.04$ (N.Obs: 96)			$0.04 < emp_{nit} < 0.06$ (N.Obs: 102)			$0.06 < emp_{nit} < 0.1$ (N.Obs: 258)			$emp_{nit} > 0.1$ (N.Obs: 169)		
Panel A	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Exports$^{a}_{nit}$	1.66 (8.59)	-	-	5.64 (8.68)	-	-	12.57** (5.34)	-	-	1.69** (0.76)	-	-
Exports2$^{b}_{nit}$	-	0.18 (1.40)	-	-	0.76 (1.19)	-	-	2.86*** (1.06)	-	-	1.74** (0.73)	-
Exports3$^{c}_{nit}$	-	-	1.02 (4.55)	-	-	3.40 (5.20)	-	-	7.00** (3.36)	-	-	7.75* (4.29)
$machineryr_{nit}$	0.06 (0.17)	0.06 (0.18)	0.05 (0.18)	0.01 (0.13)	0.01 (0.13)	-0.02 (0.15)	-0.30* (0.17)	-0.38** (0.18)	-0.29 (0.18)	-0.11 (0.14)	-0.07 (0.16)	-0.08 (0.15)
$valueaddedr^{d}_{nit}$	1.10*** (0.17)	1.09*** (0.21)	1.11*** (0.22)	0.88*** (0.15)	0.89*** (0.15)	0.94*** (0.22)	2.87*** (0.80)	3.42*** (0.86)	3.05*** (0.84)	0.70*** (0.13)	0.90*** (0.27)	0.97*** (0.21)
R^2	0.635	0.635	0.635	0.475	0.475	0.475	0.066	0.073	0.060	0.219	0.197	0.210
Dependent variable: $\log TFP_{nit}$												
	$0.01 < rdf_{nit} < 0.016$ (N.Obs: 145)			$0.016 < rdf_{nit} < 0.025$ (N.Obs: 166)			$0.025 < rdf_{nit} < 0.05$ (N.Obs: 169)			$rdf_{nit} > 0.05$ (N.Obs: 199)		
Panel B	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Exports$^{a}_{nit}$	6.50 (6.59)	-	-	1.79 (2.05)	-	-	1.27 (3.55)	-	-	11.88*** (3.57)	-	-
Exports2$^{b}_{nit}$	-	1.52 (1.09)	-	-	0.20 (0.27)	-	-	0.02 (0.50)	-	-	2.33** (1.08)	-
Exports3$^{c}_{nit}$	-	-	5.51 (3.36)	-	-	0.70 (0.96)	-	-	0.07 (0.02)	-	-	9.59*** (3.10)
$machineryr_{nit}$	-0.11 (0.18)	-0.003 (0.17)	-0.06 (0.18)	0.02 (0.13)	0.03 (0.12)	0.02 (0.13)	0.002 (0.12)	0.03 (0.12)	0.03 (0.13)	0.06 (0.14)	-0.04 (0.14)	-0.07 (0.13)
$valueaddedr^{d}_{nit}$	1.49*** (0.14)	1.48*** (0.16)	1.49*** (0.15)	0.45** (0.18)	0.44** (0.17)	0.44** (0.18)	1.46 (1.41)	1.48 (1.41)	1.48 (1.41)	1.07*** (0.16)	1.06*** (0.20)	1.14*** (0.18)
R^2	0.588	0.582	0.584	0.047	0.046	0.046	0.092	0.030	0.082	0.253	0.225	0.247
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

a: Exports is measured in $\$10^7$ per worker.

b: $Exports_2$ is measured in $\$10^2$ per unit of fringe benefit.

c: $Exports_3$ is measured in $\$10^2$ per unit of annual payroll.

d: *valueaddedr* is adjusted by 1.e+4 times the actual value added rate under test group of $0.06 < emp_{nit} < 0.1$.

Panel B represents the R&D funds ratio analysis. Now columns (i) to (ix) are for those sectors with a lower R&D funds ratio (between 1% and 5%). The LBE coefficient also stays being positive but insignificant; a sector's export value cannot improve productivity in a significant way. Thus it is proved that the LBE process cannot be detected under the circumstance with low R&D input, again. Columns (x) to (xii) are for the sectors that have the highest R&D funds ratio (> 5%). Under this condition the LBE coefficient is positive and even more significant than it is in panel A. High R&D input guarantees the existence of a significant LBE phenomenon; only when a sector's R&D funds ratio is higher than 5% can a significant LBE exist. Therefore, Table 3 once more shows that both negative and positive evidences of the LBE exist, and this difference is significantly determined by innovation behavior. The highest value of innovation investment ensures that the LBE phenomenon happens. In particular, the R&D employment ratio must be higher than 6%, or the R&D funds ratio must be higher than 5%. Otherwise, if neither of these R&D input standards is fulfilled, there will be no valuable correlation between export status and productivity; the LBE theory then turns out to be invalid under this circumstance.

4. Conclusion

This paper follows other studies on learning-by-exporting, the productivity progress a plant or sector can make out of its exporting behavior. However, this paper is one of the first to look into both sides of the inconclusive story, and explain why evidence for and against the theory have both been found. It is the first one trying to find a measure for the learning-by-exporting (LBE) effect. An US manufacturing industry dataset is established and used in this paper. By applying Olley-Pakes methodology during the productivity estimation, I test the correlation between this LBE effect and sectoral innovation input, and new results are revealed. Only when the innovation is higher than some threshold can it start to improve the LBE significantly. By separating the sectors into different groups based on their innovation effort, only the groups with the highest R&D measures have significant LBE (R&D employment ratio > 6% or R&D funds ratio > 5%), which does not exist among those with the lowest R&D input.

Of course, more work needs to be done. Ideally the effect of LBE should be estimated by comparing productivity before and after export happens to a plant or sector. However due to the limitation of the available data, I can only estimate it by comparing productivity before and after export behavior is considered during the estimation. Because of the additional consideration of export status the productivity estimates turn out to be higher; I therefore treat this extra credit on TFP earned by the exports the effect of LBE and proceed further tests. In order to modify the methodology to be more accurate, empirical evidence including more information about the exit and survival situations across different sectors or plants needs to be found.

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Appendix

A. Olley-Pakes Methodology

The Olley-Pakes methodology treats the error term in Equation (3) as the sum of two parts: one is a white noise component η_{it}, and the other is a sector-specific, time-varying productivity shock ω_{it}. Therefore in the estimation of production functions, there exist correlation between unobserved productivity shock and the input factors. This will generate inconsistent estimates using OLS. A second problem arises as the endogeneity. Because of the sample selection, sectors with low productivity exit the market, and the remaining ones will have their ω_{it} chosen from a selected sample.

Based on a sector's value function for dynamic maximization:

$$V(\omega_{it}, k_{it}) = \max\{V^{l}_{it}, \sup[\ \Pi_t(\omega_{it}, k_{it}) - c(I_{it}) + \sigma E(V_{t+1}(\omega_{it+1}, k_{it+1})|\Omega_t)\ ]\}$$

and capital accumulation process:

$$k_{it+1} = (1-\delta)k_{it} + I_{it}$$

where V_l is the sector's value if it liquidates, Π is the profit, $c(I_{it})$ is the cost correlated with investment decision, σ is the discount factor, Ω_t is all the information available at time *t*, and δ is the capital depreciation rate. Meanwhile, ω_{it} is assumed to follow a 1st-order Markov process. Profit maximization lead to an investment function that depends on capital k and productivity ω_{it}, as specified in Equation (5). In Pakes (1994), Van Biesebroeck (2005) the conditions under which the investment is monotonically increasing with productivity is specified[7], therefore it is possible for us to invert the investment function, then express the productivity as a function of investment and capital.

In the first step, I modify the Olley-Pakes method by including the sectoral export status during international

[7] In particular, the marginal return to trading (both exporting and importing) needs to be increasing in productivity. There must be sunk costs to start exporting and importing. Also, when the trade status does not change, no costs are incurred.

trade. As there are sunk costs to enter foreign market and only more productive firms or sectors can afford it, as what's been proved by the "self-selection" theory, it is inappropriate to treat the export or import status as exogenous. Specifically, these two additional variables are: first, the ratio between the exports of a 6-digit industry and the total exports of the 3-digit industry it belongs to; second, the growth rate of the exports of this 6-digit industry. This way the investment function is a function of 4 variables: capital, productivity, export proportion (XP), and export growth rate (XG). Specifically, we have

$$I_{it} = i(k_{it},\ \omega_{it}, XP_{it}, XG_{it}). \tag{10}$$

By inverting Equation (10), we have

$$\omega_{it} = \lambda_t(k_{it}, I_{it}, XP_{it}, XG_{it}) \tag{11}$$

Substitute equation (11) back into Equation (3), we have

$$y_{it}= \beta_l l_{it} + \beta_m m_{it} + \beta'_Q Q_{it} + \phi_{it}(k_{it}, I_{it}, XP_{it}, XGit) + \eta_{it} \tag{12}$$

where

$$\phi_{it} = \beta_0 + \beta_k k_{it} + \lambda_t(k_{it}, I_{it}, XP_{it}, XG_{it}). \tag{13}$$

Use a 3rd-order polynomial series expansion of all the four state variables to model ϕ, as well as the sector and year dummies, I can obtain consistent estimates of β_l, β_m and β_Q.

In the second step, I need to estimate βk. According to the capital accumulation process, the capital at t+1 depends on investment at time t. Therefore, at time t+1 capital k is correlated with the expectation of productivity ω, E(ω_{it}+1) = ω_{it} - ξ_{it}+1, where the future productivity is decomposed into an expected and unexpected components; ξ_{it} is an unobserved and unexpected productivity shock. Moreover, expectation of future productivity is a function of current productivity; I denote this function as h(ω_{it}). Substitute the expression of ω_{it} from Equation (11) into h() then the expression of ϕ_{it} from equation (13), I yield:

$$E(\omega_{it+1} \mid \omega_{it}, k_{it+1}) = h(\omega_{it})-\beta_0 = h(\phi_{it}\ (k_{it}, I_{it}, XP_{it}, XG_{it})) - \beta_0 \tag{14}$$

Substitute (14) into (3) at t+1 leads to

$$\begin{aligned} y_{it+1}- \beta_l l_{it+1} - \beta_m m_{it+1} - \beta'_Q Q_{it} &= \beta_0 + \beta_k k_{it+1} + E(\omega_{it+1}) + \xi_{it+1} + \eta_{it+1} \\ &= \beta_k k_{it+1} + h(\phi_{it}\ (k_{it}, I_{it}, XP_{it}, XG_{it})) + \xi_{it+1} + \eta_{it+1} \end{aligned}$$

Define $x_{it} = y_{it} - \beta_l l_{it+1} - \beta_m m_{it+1} - \beta'_Q Q_{it}$, it yields

$$x_{it+1} = \beta_k k_{it+1} + h(\phi_{it}\ (k_{it}, I_{it}, XP_{it}, XG_{it})) + \xi_{it+1} + \eta_{it+1}$$

$$x_{it+1} - E(x_{it+1}|k_{it}, I_{it}, XP_{it}, XG_{it}) = \beta_k k_{it+1} - E(k_{it+1}|\ k_{it}, I_{it}, XP_{it}, XG_{it})) + \xi_{it+1} + \eta_{it+1}$$

One more assumption is needed here: the input factors as well as export status are correlated with the expected productivity shock but not the unexpected one. Therefore

$$E(\xi_{it+1} + \eta_{it+1}|\ k_{it}, I_{it}, XP_{it}, XG_{it}) = 0.$$

The expectations of x_{it+1} can be obtained from the regression of x_{it+1} on the same 3rd-order polynomials of capital, investment and export status variables mentioned above. Thus a consistent coefficient on capital in production function can be estimated.

Appendix B

Table 4 Aggregated Sectoral Productivity Growth Trend under OP Estimation

Estimated variable: log TFP_{it}				
Sector[a]	2006	2007	2008	2009
Food Products (311)	3.383	3.354	3.340	3.380
Beverage & Tobacco (312)	3.618	3.626	3.587	3.644
Textiles & Fabrics (313)	3.242	3.226	3.150	3.224
Textile Mill (314)	3.308	3.267	3.198	3.201
Leather (316)	2.921	2.908	2.914	2.864
Wood (321)	3.132	3.114	3.078	3.096
Paper Printed (322)	3.374	3.365	3.341	3.418
Petroleum and Coal (324)	3.576	3.543	3.559	3.455
Chemicals (325)	3.594	3.565	3.585	3.605
Plastics and Rubber (326)	3.213	3.214	2.507	3.216
Nonmetallic Mineral (327)	3.283	3.275	3.258	3.293
Primary Metal (331)	3.077	3.129	3.062	3.022
Fabricated Metal (332)	3.297	3.268	3.306	3.306
Machinery, except Electrical (333)	3.281	2.959	2.892	3.253
Computer and Electronic (334)	3.425	3.377	3.379	3.364
Electrical Equipment & Appliances (335)	3.251	3.256	3.154	3.261
Transportation (336)	2.460	3.175	3.148	3.149
Furniture and Fixtures (337)	3.248	3.270	3.272	3.285
Miscellaneous Manufacturing (339)	3.443	3.439	3.456	3.483
Sector FE	Yes			
Year FE	Yes			

a: Here I calculate the aggregate productivity of the sectors under the same 3-digit NAICS category.