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Measuring Chinese Firms' Performance – Experiences with Chinese firm level data

Yue Ma & Yifan Zhang

Economics Department
Lingnan University
Hong Kong

Corresponding author: Prof. Yue Ma,
yuema@ln.edu.hk
www.ln.edu.hk/econ/staff/yuema

Introduction

Introduction (1)

A growing body of empirical literature has documented the superior performance of exporters relative to non-exporters. Two mechanisms may explain a positive correlation between exporting and productivity.

The first is related to self-selection (e.g., Clerides, Lach, and Tybout, 1998, QJE; Bernard, Eaton, Jensen, and Kortum, 2003, AER; Melitz, 2003, Econometrica): only the best firms are able to compete in the international markets.

The second explanation is "learning-by-exporting" (e.g., Van Biesebroeck, 2005, JIE; De Loecker, 2007, JIE): after firms enter the export markets, they gain new knowledge and expertise that improve their productivity.

Introduction (2)

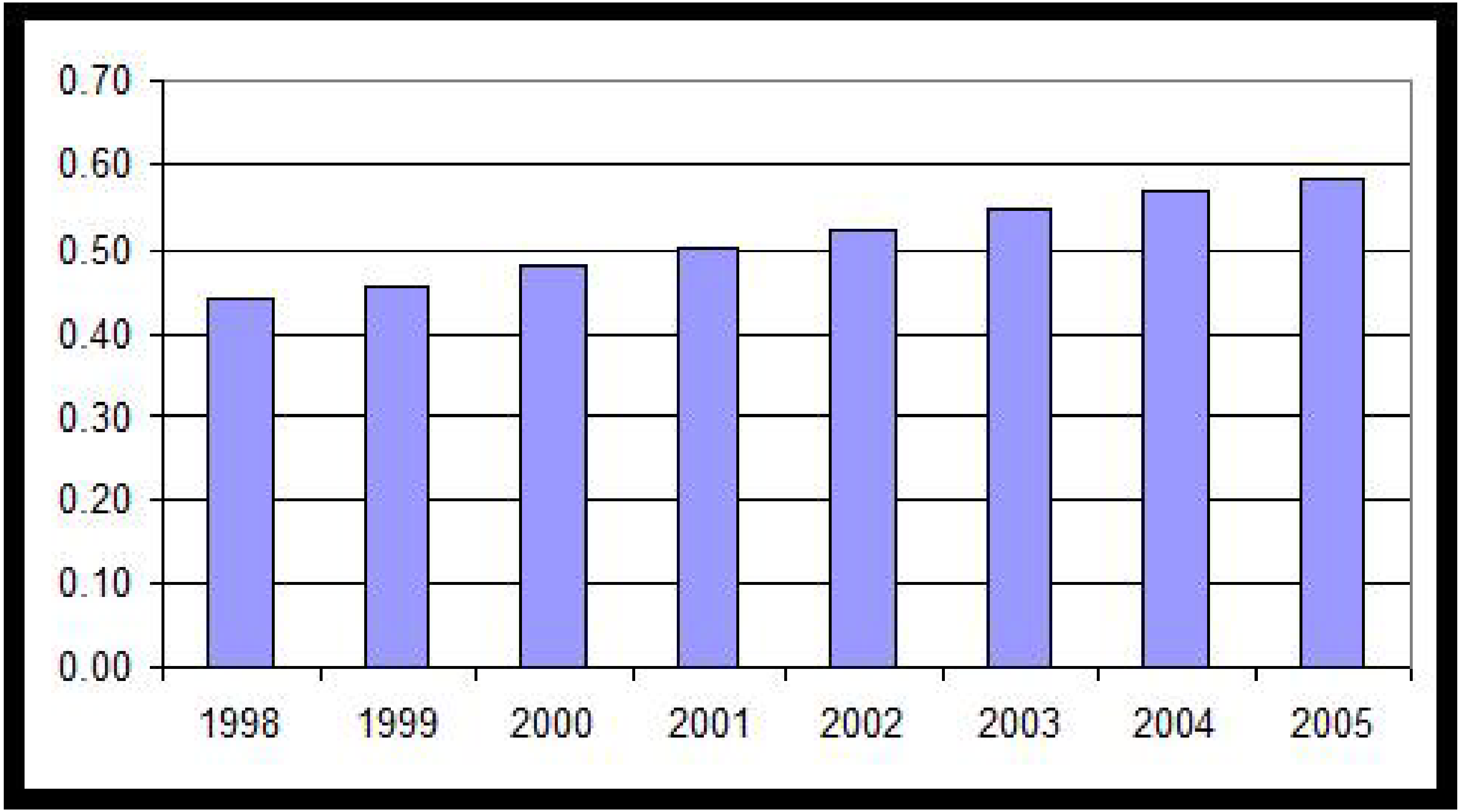
Being a major world exporter, the case of China is of considerable interest in this context.

Since the economic reforms started in the late 1970s, the Chinese government has actively promoted exports (Branstetter and Lardy, 2008).

After three decades of rapid growth, China overtook Japan as the world's third largest trading economy (behind the United States and Germany) in 2006.

However, the contribution of foreign-invested firms to total Chinese exports has been consistently above 50% in recent years (see Figure 1).

Fig 1. Foreign Firms’ Share of Total Exports of China



Source: China Statistical Yearbook, 2006.

Introduction (4)

This paper analyzes the relationship between the performance and export behavior of Chinese manufacturing firms during the period 1998-2005.

When estimating total factor productivity, we implement a modified Levinsohn and Petrin (2003) procedure with export status as an additional control in the dynamic problem.

In searching for causal links between exporting and firm productivity, we use the difference-in-difference (DID) matching technique developed by Heckman, Ichimura, and Todd (1997, Econometrica). This method can determine the changes in productivity of exporters attributed to exporting activities.

Main Findings

Main Findings (1)

The Chinese domestic firms self-selected into the export market through higher productivity and paying a higher than average wage.

However, being closer to the world technology frontier and having more international experience before coming to China, foreign firms that start to engage in export sales do not show any significant difference in TFP ex ante to their matched non-exporting counterparts, neither do they exhibit a significant learning effect ex post.

Main Findings (2)

We find that the learning-by-exporting effect for domestic firms is via the more usual channel of exporting to developed markets.

In addition, the learning-by-exporting effect of Chinese domestic firms is positively related to the firms’ absorptive capacity.

Literature Review

Literature Review (1)

Most of the empirical studies on exporting and productivity are based on firm-level panel data.

A recent study by a group of economists (International Study Group on Exports and Productivity, 2007) uses comparable firm panel data for 14 countries and an identical method to investigate the relationship between exports and productivity.

They find strong evidence of self-selection to export but no evidence of learning-by-exporting.

Note: Foreign and domestic firms were pooled together in this study.

Literature Review (2)

Some recent studies find some evidence to support the learning-by-exporting theory:

Wagner (2002) for Germany;

Girma, Greenway, and Kneller (2003) for the United Kingdom;

Alvarez and Lopez (2005) for Chile;

Van Biesebroeck (2005) for sub-Saharan African countries; and

De Loecker (2007) for Slovenia.

Research Method

Research Method (1)

An important performance indicator of firms is the unobserved total factor productivity (TFP).

The ordinary-least-squares (OLS) estimator is biased when estimating the production function and TFP because

(1) inputs are endogenous since they are chosen by firms after productivity is observed (Griliches and Mairesse, 1998), and

(2) a firm exits from the sample endogenously when its productivity falls below a threshold.

Research Method (2)

Olley and Pakes (1996, Econometrica) propose a semi-parametric estimation procedure to correct both endogeneity biases.

However, the Olley-Pakes procedure requires investment information, which is not available in our dataset.

We opted for the Levinsohn and Petrin (2003, REStud) procedure, which uses intermediate inputs rather than investment as a proxy for the unobservable productivity shock to address the underlying input endogeneity issue.

Research Method (3)

We supplement the Levinsohn-Petrin procedure with the Olley-Pakes approach to model the firm's exit decision in order to control for the self-selection bias:

$$\ln TFPt = \ln Yt - \beta 1 \ln Lt - \beta 2 \ln Kt$$

where $\beta 1$ and $\beta 2$ are estimated based on the firm's decisions to continue to operate or not, and the firm's target market(s).

Research Method (4)

Difference-in-difference (DID) the propensity score matching technique developed by Heckman, Ichimura, and Todd (1997, Econometrica):

$$DID = [\Sigma(\ln TFP_{1,t,i} - \ln TFP_{0,t-1,i})$$

$$- \Sigma W(i,j)(\ln TFP_{0,t,j} - \ln TFP_{0,t-1,j})]/n1$$

where 1 and 0 for exporter and non-exporter, respectively, W() is nonparametric weight.

Data Source

Data Source (1)

The firm-level data come from the annual surveys of industrial firms by the China National Bureau of Statistics between 1998 and 2005.

The surveys cover all state-owned firms, and all non-state-owned firms with sales above 5 million yuan.

The industry section of the China Statistical Yearbook is compiled based on this dataset.

The dataset contains detailed information for about 100 variables, including firm ID, address, ownership, output, value added, four-digit industry code, six-digit geographic code, exports, employment, capital stock, and intermediate inputs

Data Source (2)

The firms in our sample account for 57% of the total industrial value added in 1998 and 94% in 2005.

Since we focus on manufacturing, we exclude mining and utility industries. Moreover, we delete those observations with missing values and those that fail to satisfy some basic error checks.

We deflate firm value-added with industry-specific ex-factory price index. The capital stock is the net value of fixed assets deflated by investment price index.

The deflators of output and capital stock are calculated based on the price information in China Statistical Yearbook (2006).

Empirical Results

Empirical Results
Table 1. Firm level export information 1999-2005

	1999		2005	
Ownership	Domestic	Foreign	Domestic	Foreign
Total no. of firms	118,251	25,272	192,325	53,661
Non-exporters	97,079	9,209	141,016	14,140
share	(0.82)	(0.36)	(0.73)	(0.26)
Existing Exporters	18,394	14,742	42,820	38,154
share	(0.16)	(0.58)	(0.22)	(0.71)
New exporters	2,778	1,321	8,489	1,367
share	(0.02)	(0.05)	(0.04)	(0.03)

Table 2. The self-selection decision to start exporting
Dependent variable: New-exporter indicator

Probit estimation	Domestic firms	Foreign firms
ln TFP	0.098	-0.012
	[0.000]***	[0.162]
Wage per worker	0.029	0.008
	[0.002]***	[0.542]
New product share in sales	0.502	0.065
	[0.000]***	[0.240]
Pseudo R-squared	0.079	0.088
Observations	519,481	53,949

Note: The sample period is 1999-2005. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions include firm characteristics, and a full set of industry and provincial dummies. P-values are in brackets, are based on Huber-White heteroskedasticity-consistent standard error, and are corrected for industry-province clustering.

Table 3. Difference-in-difference matching estimation exporting effects on lnTFP of the new exporters

Domestic	DID_x	pv		Foreign	DID_x	pv
1999	0.113	0.01	**	1999	0.011	0.932
2000	0.113	0.011	**	2000	0.08	0.432
2001	0.084	0.011	**	2001	0.019	0.914
2002	0.087	0.008	***	2002	-0.036	0.779
2003	0.085	0.006	***	2003	0.049	0.601
2004	0.037	0.008	***	2004	0.018	0.854
2005	0.199	0.001	***	2005	0.089	0.336
Pooled	0.112	0.000	***	Pooled	0.034	0.479

Notes: Firms are matched using the propensity score method. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. pv is the p-value based on bootstrapped standard errors

Table 4. Learning channels of exporting for domestic firms: OLS estimation

Explanatory variables	OLS
New product share in sales	0.115
	[0.014]***
Log of Export to OECD	0.034
	[0.000]***
Adjusted R^2	0.131
# of obs	18,675

Notes: The dependent variable is the lnTFP gap between the new exporters and the non-exporters, estimated by the difference-in-difference matching estimator.*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The regression includes a full set of year, industry, and provincial dummies. P-values are in brackets, are based on White heteroskedasticity-consistent standard error, and are corrected for industry-province clustering.

Conclusion

Conclusion (1)

This paper analyzes the relationship between firm performance and export behavior in China's manufacturing firms.

We find that only the Chinese domestic-owned firms that enter export markets show superior initial performance compared to domestic non-exporters; in other words, we discover evidence consistent with the self-selection theory.

Conclusion (2)

To determine the direction of causality between exporting and productivity, we use the difference-in-difference (DID) propensity score matching technique to construct a counterfactual control group.

The matching method controls for the non-random selection of exporting firms in our sample, and allows us to interpret our results as causal effects.

Our findings suggest that exporting leads to better performance of domestic firms only. They become on average 3.7% to 19.9% more productive after they start to export, which gives support to the learning-by-exporting hypothesis.

Conclusion (3)

The results of this study are broadly consistent with the idea that increasing access to export markets boosts productivity for domestic-owned firms in developing countries.

From an industrial policy perspective, there is good reason to promote foreign sales over domestic sales because firms improve once they are active in export markets.

On the other hand, it would also be a good policy to attract foreign firms to a developing country to exploit its comparative advantage of cheap labor.

We find that it is important to have a separate analysis for the foreign-owned firms operating in a developing economy, as they start from a relatively strong position and may have quite different motivation and behavior in selecting into which markets to sell.

Unfinished story: A puzzle ???

Table A. Difference-in-difference matching estimation exporting effects on capital intensity [ln(K/L)] of the new exporters

Domestic	DID_x	pv		Foreign	DID_x	pv	
1999	-0.042	0.36		1999	-0.135	0.017	**
2000	-0.004	0.955		2000	-0.103	0.038	**
2001	-0.005	0.996		2001	-0.115	0.03	**
2002	-0.029	0.613		2002	-0.005	0.958	
2003	-0.037	0.039	**	2003	-0.098	0.026	**
2004	-0.066	0.013	**	2004	-0.094	0.044	**
2005	-0.06	0.027	**	2005	-0.016	0.745	
Pooled	-0.046	0.035	**	Pooled	-0.08	0.028	**

Notes: Firms are matched using the DID propensity score method. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. pv is the p-value based on bootstrapped standard errors

Data Problems

(We thank Prof Harry Wu who provided many critical comments on the data problem in this section)

Data Problems (1)

The surveys cover all state-owned firms, and all non-state-owned firms with sales above 5 million yuan.

=> This may create sample-selection bias.

The dataset contains detailed information for about 100 variables, including firm ID, address, ownership, etc…

=> The raw data is not a panel data, we have to match the firm over time to make a panel data ourselves. Mismatch could happen.

Data Problem (2)

We deflate firm value-added with industry-specific ex-factory price index. The capital stock is the net value of fixed assets deflated by investment price index.

⇒These deflators are not satisfactory as they are not at the firm level.

⇒ More fundamentally, NBS capital stock data (end-year fixed assets) is not proper indicator for K, and deflating it does not help because it is in historical costs (mixed of prices). There is also an initial stock problem.

⇒ We used intermediate inputs rather than investment as a proxy for the unobservable productivity shock due to missing information on investment.

Data Problem (3)

$\Rightarrow$ Firms output (value added) should be derived by double deflation. It is inappropriate to assume different industries, exporting or not-exporting, have the same input prices as their outputs.

$\Rightarrow$ What if the output is exaggerated?

There are problems of data fabrication and double counting, which have mainly affected output indicator. That is why the NBS has stopped reporting industry level value added recent years.

Comments/suggestions are welcome

Thank you!