Physical Productivity and Exceptional Exporter Performance: Evidence from a Chinese Production Survey*

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Abstract

In this paper, we use a detailed production survey in the Chinese manufacturing industry to estimate both revenue and physical productivity and relate our measurements to firms' trade activity. We find that Chinese exporters for largely export oriented products like leather shoes or shirts appear to be less efficient than firms only involved on the domestic market based on the standard revenue productivity measure. However, we show strong positive export premium when we instead consider physical productivity. The simple and intuitive explanation of our results is that exporters charge on average lower prices. We focus more particularly on the role of processing trade and find that price differences are especially (and probably not surprisingly) large for firms involved in this type of contractual arrangements. We also extend our analysis to other products for which the domestic market plays a more important role like beer or rice, and our results are just the opposite.

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1 Introduction

One of the most robust stylized facts that has emerged from more than 20 years of empirical research on firm heterogeneity in international trade is that exporters appear to be more productive than firms operating only on the domestic market (see e.g. the recent survey by Bernard et al., 2015). Surprisingly, one country where this pattern has not been found is China (see Lu, 2010 for early evidence). Given the fact that China has become the biggest exporter in the world, this striking result has attracted quite a lot of attention.[1]

In this paper we want to re-examine this apparent puzzle by looking at the question from another angle. In particular we investigate the role of pricing differences between firms and distinguish between revenue productivity and physical productivity, as first suggested by Foster, Haltiwanger and Syverson (2008).

We use a detailed dataset providing physical quantities produced by Chinese firms over the period 2000-2006. We combine this production survey with standard accounting data and with customs data in order to estimate production functions using both deflated revenue and physical quantity as a measure of output. As a consequence, we obtain two different estimates of total factor productivity: the standard revenue based productivity (TFPR) and the physical productivity (TFPQ). We then relate our two measures of productivity to export behavior of firms.

In line with the previous literature, we find that the standard measure of revenue based productivity is negatively correlated with export behavior. However, when we use physical productivity, we find that exporters benefit from a large premium. Our result is therefore explained by the fact that exporters have lower prices than non exporters and are most likely selected due to this superior physical efficiency.

We then relate our finding to the literature on the importance of processing vs ordinary trade in Chinese manufacturing (see e.g. Dai, Maitra and Yu, 2015; Yu, 2015). Given that a significant share of processing trade involves that the assembler received their inputs for free, this will by definition reduce the material costs incurred by the firm and affect the measurement of productivity.

For this reason, we use the Chinese customs data to identify firms involved in processing trade and control for this specific regime in our analysis. In line with our prior, we find that firms involved in processing trade have lower revenue productivity, charge lower prices and have higher physical productivity.

[1] Several explanations have been provided for this result, varying from the presence of export subsidies or easy access to financing or the fact that many Chinese manufacturers engage in processing trade. See below for more details.

We focus our analysis on a subset of products in footwear and apparel that have become largely dominated by Chinese firms. These sectors have grown in a dramatic way to a large extent thanks to the existence of this institutional feature of processing trade. We discuss how our results can be extended to other products which are not focused on exports but instead more oriented towards the domestic market, like beer or rice. For these products, we have the opposite relationship that exporters charge higher prices and therefore their measure of revenue productivity is more closely related to export than their physical productivity. Based on these observations, we suggest a typology based on the importance of the domestic market and product differentiation.

We contribute to a growing literature investigating the role of pricing heterogeneity bias on the measurement of productivity (e.g. Klette and Griliches, 1996; Levinsohn and Melitz, 2001; Kugler et al., 2004; Foster Haltiwanger and Syverson, 2008; De Loecker, 2011). Our results are closely related to recent papers that show that export premium and learning by exporting are estimated with a different magnitude when looking at physical rather than revenue productivity (Smeets and Warzynski, 2013; Garcia-Marin and Voigtlander, 2013). It is also related to Kugler and Verhoogen (2012) who show that more productive firms are more likely to buy higher quality inputs and produce higher quality products when there is scope for product differentiation.

Our paper is also related to a more recent body of research investigating the implications of input price heterogeneity bias. When firms produce goods of different level of quality within the same product market, they are likely to use inputs of different level of quality as well. This might bias our productivity estimates if we use a common deflator for materials. To deal with this issue, we follow De Loecker et al. (2016) who provide a simple and elegant framework to control for input price heterogeneity. We apply their algorithm to our sample of Chinese firms and show that taking into account input price differences significantly affects the coefficients of our production function.

The rest of the paper is organized as follows. Section 2 describes the datasets that we use with a special emphasis on the production survey which is relatively unknown. Section 3 presents our simple empirical methodology based on Foster, Haltiwanger and Syverson (2008). In section 4, we discuss our results. We first comment on the estimation of the production function using physical quantity as measure of output and how the resulting physical productivity estimates differ from standard revenue based measures. We then relate our productivity measures to export and price behavior, as well as we test the robustness of our findings. Section 5 concludes.

2 Data

We use three data sources to conduct our study: (i) the NBSC firm-level accounting data that reports revenue-based information on inputs and outputs of production, (ii) the NBSC (National Bureau of Statistics of China) firm-product level production survey that contains physical output quantity information, and (iii) the Chinese Customs data. The first two databases use the same firm identity code while the last one adopts a different firm ID system. We managed to merge these two sets of firm identification codes based on the contact information of manufacturing firms, as no consistent coding system of firm identity is available for these two databases. Our matching procedure is carried out in three steps: (1) by company name, (2) by telephone number and zip code, and (3) by telephone number and contact person name (see a detailed description of the matching process in Fan, Li, and Yeaple, 2015). Now we discuss each of the three databases in turn.

2.1 Accounting data

This now standard dataset has been used in many papers about firm productivity in China. The NBSC firm-level accounting data are drawn from Annual Surveys of Industrial Firms (ASI) for all state-owned enterprises (SOEs) and non-state-owned enterprises with annual sales of at least five million RMB. The NBSC accounting database contains detailed firm-level accounting information on Chinese manufacturing enterprises, including employment, capital stock, gross output, value added, and firm identification information (e.g., company name, telephone number, zip code, contact person, etc.).[2] With regard to misreporting cases, we use the following protocols to remove unsatisfactory observations in accordance with the previous literature and General Accepted Accounting Principles: (i) total assets must be higher than liquid assets; (ii) total assets must be higher than total fixed assets; (iii) total assets must be higher than the net value of fixed assets; (iv) a firm's identification number cannot be missing and must be unique; and (v) the established time must be valid.

2.2 Production Survey

This quantity production survey dataset is collected and maintained by the NBSC, for the purpose of monitoring the production of major industrial products by all state-owned enterprises (SOEs) and above-scale non-state-owned manufacturing firms in China.[3] Our

[2]This firm identification information is used to match the NBSC database with the customs database.

[3]During the sample period 2000-2006, the above-scale manufacturing firms refer to those with annual sales of at least 5 million RMB (Chinese currency).

sample contains more than 800 5-digit product codes that are listed as main industrial product and approximately 186,000 manufacturing firms.

The survey covers roughly the same firms in manufacturing than in the accounting dataset. Firms are asked to name the products that they make and the physical quantity produced. The survey is monthly (except in January) but firms are also asked about their cumulative production over the year. Given that our accounting dataset provides yearly information about nominal sales and input use, we only consider the cumulative quantity produced provided at the end of December of each year.

A product is defined at a slightly more aggregated level than what is done in the US or in Europe. We consider more specifically a series of products that can be matched relatively easily to HS2 categories. We use leather shoes as our key product (product code 5901), although we will also experiment with various alternative products. Leather shoes span over several HS4 categories: 6401 to 6405.

2.3 Customs data

To identify firms involved in processing or ordinary trade, we use the commonly used Chinese customs data (see e.g. Manova and Zhang, 2012; ...). The Chinese Customs Database covers the universe of all Chinese trade transactions for the years 2000-2006, including import and export values, quantities, product classifications, source and destination countries, custom's regime (e.g. "Processing and Assembling" and "Processing with Imported Materials"), type of enterprise (e.g. state owned, domestic private firms, foreign invested, and joint ventures), and contact information for the firm (e.g., company name, telephone, zip code, contact person).[4]

The initial customs data at the HS 8-digit product level are aggregated to the HS 6-digit level so as to be able to concord it consistently over time because the concordance for HS 8-digit codes in China is not available to us. To ensure the consistency of the product categorization over time, we adopt HS 6-digit codes maintained by the World Customs Organization (WCO) and use the conversion table from the UN Comtrade to convert the HS 2002 codes into the HS 1996 codes.

We aggregate exports (and imports) at the firm-HS6-year level and by type of transaction (processing, ordinary or hybrid trade). We then categorize firms according to two dimensions: 1) whether the firm is involved only in processing trade, ordinary trade or a mix of the two (hybrid); 2) whether the firm is only exporting products that it declares to be producing or not. Through the first dimension, we want to deal with how firms

[4]Note that the Chinese Customs data we use in this paper contain only realized transactions rather than the "reported" transactions from invoice records. Thus, we are not concerned about the possibility of fake invoicing.

involved in processing trade might have different production functions but also different prices. Through the second dimension, we want to address the issue of carry along trade (CAT) and its implications for our measurement.

2.4 Processing, ordinary and hybrid trade

Table 1 provides summary statistics about the export behavior of firms in our sample and the mode of export. We observe that a large proportion of firms in the leather shoes industry export at the beginning of the period, but the share of exporters is declining over the years, possibly as the domestic market becomes more important.

Regarding the mode of export, we see that the share of processing trade remains relatively constant (declining slightly from 26% to 22%), while the share of ordinary trade goes down dramatically from 59% to 35%, implying a large increase in the relative share of hybrid trade.

2.5 Carry along trade

In our analysis, we focus on single product firms, i.e. those firms that report producing only one product. When comparing the information from the production survey and the customs dataset, we realized that firms sometimes export products that they do not necessarily (report they) produce. This has been labeled in the literature as carry along trade (Bernard et al., 2012). This might be problematic if firms employ part of their inputs for exporting goods they do not produce, as we would wrongly allocate these inputs to production.[5] In our sample, more than 75% of firms only export shoes and 95% of firms only export shoes and part of shoes.

3 Methodology

Our aim is to show that the productivity measure commonly used in the literature suffers from a measurement bias referred to as pricing heterogeneity bias. Once we are able to define a measure that corrects for this bias, we obtain a very different message about the link between productivity and exporting.

To illustrate the problem, consider a production function:

$$Q_{it} = \Theta_{it} f(X_{it})$$

where Q is a measure of output, X is a vector of inputs, Θ is an index of technical progress, i is a firm index and t a time index.

[5] See Smeets and Warzynski (2014) for similar discussion about subcontracting and offshoring.

Assuming a Cobb-Douglas function and taking logs:

$$q_{it} = \alpha x_{it} + \vartheta_{it}$$

where lower cases denote logs, α is a vector of parameters to be estimated, $\vartheta_{it} = \omega_{it} + \epsilon_{it}$, ω is a measure of "true" (observed by the manager but not by the econometrician) productivity and ϵ is a true noise (unexpected shock to productivity).

Most researchers use deflated revenue as a proxy for Q ($\widetilde{R}_{it} = R_{it}/P_{jt}$ where $R_{it} = P_{it}Q_{it}$ is firm revenue, P_{it} is the price set by the firm, or a firm-specific price index; and P_{jt} is an industry-level deflator, i.e. a price index in industry j at time t, typically provided by the statistical office based on micro-surveys such as the one we use in this study) so that our typical regression will be:

$$\widetilde{r}_{it} = \alpha x_{it} + (p_{it} - p_{jt}) + \omega_{it} + \epsilon_{it}$$

where $(p_{it} - p_{jt})$ measures the difference between the log of the firm-level price index and the industry level price index. We refer to this difference as the price bias. Its presence implies that productivity will be badly measured as the price bias will be part of the error term and will include a (possibly firm-specific) demand shock. This bias is stronger the more there is pricing heterogeneity in the market. In addition, if pricing varies systematically depending on firm characteristics such as exporting status or the type of export (processing vs ordinary), not accounting for it would lead to the wrong conclusions.

We refer to the previous measure as revenue productivity ($TFPR$). Following Foster, Haltiwanger and Syverson (2008), we use our production survey to compute a measure of physical productivity ($TFPQ$) that results from the estimation of the alternative regression:

$$q_{it} = \alpha x_{it} + \omega_{it} + \epsilon_{it}$$

where q_{it} is the physical quantity reported by the firm in the survey. It is obvious that, in this case, the measure does not suffer from the pricing heterogeneity bias.

As discussed in De Loecker et al. (2016), a similar concern affects our input variables, in particular materials. We follow their suggestion and add price and market share in our control function when estimating the production function. To address the well known endogeneity concern, we follow their modified version of Wooldridge (2009). (See appendix for more details.) The technique is applied using both deflated revenue and physical quantity as left hand side variable.

In the rest of our analysis, we look at how our two measures of productivity relate to exporting behavior and try to explain why we observe dramatic differences.

4 Results

4.1 Production function estimation

Table 2 shows the coefficients of our production function using various estimation algorithm (we focus on OLS and the DLGKP version of WLP; we also use a CD version of WLP and WOP) for all single product firms producing leather shoes. The upper panel shows the results of the estimation using physical quantity from the production survey, while the bottom panel uses deflated turnover from the accounting dataset as left hand side variable.

Following the suggestion of DLGKP, we define a proxy for output price using the information available by combining our datasets and include it in our polynomial to control for input price heterogeneity bias.[6] While we do not observe value in the production survey, we have turnover from the accounting data. Our price proxy is simply turnover divided by physical quantity. Since we only consider single product firms in our analysis, we make the explicit assumption that firms report their product portfolio accurately and also that most of the firm revenue comes from product sales (probably not a bad assumption for the subset of firms that we consider). We will provide several tests for this assumption using the customs data to double check the validity of our proxy.

Looking at the OLS coefficients, we observe that the coefficient of material is higher with deflated revenue than with physical quantity. The coefficient of capital is low in both cases but significant with deflated revenue. Once we move to our different methods to deal with endogeneity, the coefficients become more similar between the top and bottom panels.

4.2 Export Premium

The bottom part of both panels in table 2 shows the export premium under all the various specifications chosen. We find robust positive exporter premium when we consider physical productivity but negative ones when we use revenue TFP. Looking at TFPQ, it looks like the size of the premium is larger when using more sophisticated methods dealing with endogeneity. The method does not appear to matter for revenue TFP. The negative coefficient is small and around 2%-4%.

This result can be explained by looking at pricing behavior by export status. Exporters on average charge prices 20% lower than non exporters.

[6]The measurement of material costs has been shown to be especially problematic with Chinese data see Feenstra, Li and Yu (2014); on the importnce of input price bias, see also Zhang et al (IER) and Attalay (JEEA).

4.3 Processing and Regular Trade

We then match our production and accounting data with the customs data information in order to assess whether productivity is related to exporting depending on the mode of exports, as has been suggested by Dai, Maitra and Yu (2015). Table 3 shows the relationship between our various measures of TFP and the mode of export. Looking at TFPR fist, it looks like firms involved in ordinary trade are less productive, followed by firms only doing processing trade. Both types have lower revenue productivity than non exporters. Firms involved in hybrid have a slightly higher TFPR than domestic firms. Turning to TFPQ, the reverse is true. Firms involved in regular trade and only processing trade outperform non exporters and firms doing hybrid trade. Again, these results can be explained by how these different modes of transaction are related to firms' price. Firms involved in processing trade have prices that are 42% lower than domestic firms. For firms doing ordinary trade, prices are 32% lower, while firms doing hybrid trade do not differ from domestic firms in terms of pricing.

4.4 A Look at Other Products

As a next step, we investigate how these results for just one product can be generalized to a larger subset of goods. We consider two types of products: those intended for exports and those focused on the domestic market. As another example of a good mostly produced for exports, we look at the production of shirts. For domestic goods, we consider beer and rice. Only a few firms are engaged in the export market for these goods. Also, as should be obvious, processing and hybrid trade mostly takes places in the first category of products.

We observe that the relationship between TFP and export for shirts follows a similar pattern than in the case of leather shoes (see table 7). On the other hand, when we focus on goods mostly produced for the domestic markets, things change in the expected way. Looking at beer production, we notice than exporters have higher TFPR but lower TFPQ (see table 8). The logic is exactly the opposite: exporters have 31% higher prices than non exporters and only a few firms export. In the case of rice, interestingly, we see no big difference regarding the link between both TFPQ and TFPR and export (table 9). This striking difference between these two goods can most likely be attributed to market power and product differentiation through advertising in the beer industry (*to be elaborated*). Indeed, in the case of rice, the price of exporters is not statistically different than the one of domestic producers.

5 Conclusion

Using a rich data about physical production of Chinese firms, we estimate revenue and physical productivity for firms engaging in the production of export oriented goods, with a particular focus on leather shoes producers. We find that exporters appear less efficient when looking at revenue productivity, but are actually much more efficient when we consider physical productivity. This difference is explained by pricing differences between firms: exporters charge on average lower prices by a margin of around 20%.

We relate our findings to an important institutional feature of Chinese manufacturing that has facilitated the development of exporting capabilities over the last twenty years: processing trade. In this type of contractual agreements, Chinese firms compete in price to assemble final goods for their clients and use their competitive advantage coming from lower labor costs.

For other type of products turned relatively more towards the domestic market, pricing differences do not necessarily show the same pattern. Beer exporters charged higher prices and have higher revenue TFP, but have lower physical TFP. For rice exporters, prices do not appear to depend on the export status, so that we find no major difference in terms of export premium between our two measures.

While our work unveils interesting stylized facts related to well known difficulties in the productivity estimation literature, we are planning to expand our analysis in two directions. First, while we focus our attention in this paper to single product firms in order to keep the estimation simple, we plan to integrate multi-product firms in our framework as they constitute a group of firms of particular interest during the expansion of the manufacturing sector in China. Second, evidence of large pricing differences between firms suggests that more attention should be devoted to quality differences. Recent work appears to indicate that Chinese firms have engaged in quality upgrading (see e.g. Schott, 2008) and this could significantly affect our analysis. A joint estimation of productivity and quality would contribute to our understanding of the evolution of the role of China on global markets.

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Table 1: Summary statistics on export behavior (leather shoes producers)

			among matched exporters: mode of export		
	share exporters	share matched exporters	share processing	share hybrid	share ordinary
2000	65.55%	57.69%	25.78%	15.11%	59.11%
2001	62.67%	55.69%	26.28%	20.44%	53.28%
2002	65.74%	53.59%	26.52%	29.57%	43.90%
2003	62.56%	55.52%	25.94%	37.46%	36.60%
2004	71.07%	51.81%	21.68%	44.52%	33.80%
2005	62.82%	56.59%	23.47%	43.13%	33.40%
2006	56.96%	59.58%	22.20%	42.81%	34.99%

Table 2: Production function estimation: leather shoes

Dep. var.: logQ	OLS (coeff)	correcting for price WOP (coeff)	correcting for price WLP (coeff)	DLGKP - translog (median elasticity)
logM	0.639*** (0.012)	0.857*** (0.018)	0.840*** (0.211)	0.856
logL	0.178*** (0.011)	0.129*** (0.015)	0.138*** (0.037)	0.109
logK	0.003 (0.007)	0.013* (0.006)	0.016 (0.022)	0.012
# obs.	6,333	1,675	2,181	3,754
Dep. var.: TFPQ				
EXP	0.133*** (0.017)	0.217*** (0.043)	0.214*** (0.038)	0.209*** (0.028)
logL	-0.020*** (0.007)	-0.130*** (0.016)	-0.103*** (0.015)	-0.106*** (0.011)
Dep. var.: logDefRev	OLS	correcting for price WOP	correcting for price WLP	DLGKP
logM	0.820*** (0.004)	0.858*** (0.018)	0.849*** (0.213)	0.855
logL	0.151*** (0.004)	0.129*** (0.015)	0.137*** (0.037)	0.115
logK	0.025*** (0.003)	0.013** (0.006)	0.015 (0.022)	0.010
# obs.	6,333	1,675	2,181	3,754
Dep. var.: TFPR				
EXP	-0.034*** (0.007)	-0.033*** (0.012)	-0.040*** (0.012)	-0.020*** (0.007)
logL	0.005* (0.003)	0.015*** (0.004)	0.034*** (0.005)	0.022*** (0.003)

Table 3: Link between TFP and mode of export: leather shoes

	OLS	WOP correcting for price	WLP correcting for price	DLGKP
Dep. var.: TFPQ				
Ordinary	0.277*** (0.027)	0.199*** (0.054)	0.208*** (0.048)	0.236*** (0.039)
Processing	0.110*** (0.035)	0.395*** (0.078)	0.392*** (0.068)	0.333*** (0.053)
Hybrid	-0.029 (0.031)	0.137** (0.062)	0.138** (0.057)	0.051 (0.045)
Dep. var.: TFPR				
Ordinary	-0.055*** (0.009)	-0.055*** (0.012)	-0.055*** (0.014)	-0.030*** (0.009)
Processing	-0.036*** (0.012)	-0.044*** (0.017)	-0.042** (0.020)	-0.037*** (0.013)
Hybrid	0.019* (0.011)	0.008 (0.014)	0.013 (0.017)	0.021* (0.011)

Note: default category, non exporters; the specification controls for year dummies and log of firm size

Table 4: Production function estimation: shirts

Dep. var.: logQ	OLS	DLGKP
logM	0.440*** (0.019)	0.794
logL	0.453*** (0.026)	0.135
logK	-0.116*** (0.015)	0.022
# obs.	3,349	1,565
Dep. var.: TFPQ		
EXP	0.210*** (0.033)	0.211*** (0.032)
logL	-0.022 (0.019)	0.012 (0.018)
Dep. var.: logDefRev	OLS	DLGKP
logM	0.818*** (0.005)	0.794
logL	0.139*** (0.007)	0.141
logK	0.035*** (0.004)	0.024
# obs.	3,349	1,565
Dep. var.: TFPR		
EXP	0.005 (0.009)	-0.029*** (0.011)
logL	-0.001 (0.005)	0.051*** (0.006)

Table 5: Production function estimation: beer

Dep. var.: $logQ$	OLS (coeff)	DLGKP (median elasticity)
$logM$	0.610*** (0.013)	0.860
$logL$	0.384*** (0.019)	0.037
$logK$	0.058*** (0.010)	0.039
# obs.	2,251	1,489
Dep. var.: TFPQ		
EXP	0.001 (0.012)	-0.197*** (0.057)
$logL$	-0.020*** (0.007)	0.098*** (0.010)
Dep. var.: $logDefRev$	OLS	DLGKP
$logM$	0.890*** (0.007)	0.862
$logL$	0.087*** (0.011)	0.035
$logK$	0.047*** (0.005)	0.041
# obs.	2,251	1,489
Dep. var.: TFPR		
EXP	0.081*** (0.024)	0.137*** (0.034)
logL	-0.003 (0.006)	0.097*** (0.010)

Table 6: Production function estimation: rice

Dep. var.: logQ	OLS (coeff)	DLGKP (median elasticity)
logM	0.684*** (0.011)	0.904
logL	0.125*** (0.017)	0.098
logK	0.018 (0.011)	-0.001
# obs.	3,954	1,510
Dep. var.: TFPQ		
EXP	0.269*** (0.054)	0.184** (0.080)
logL	-0.007 (0.013)	-0.022 (0.019)
Dep. var.: logDefRev	OLS	DLGKP
logM	0.808*** (0.006)	0.902
logL	0.129*** (0.009)	0.099
logK	0.022*** (0.006)	-0.003
# obs.	3,954	1,510
Dep. var.: TFPR		
EXP	0.273*** (0.007)	0.224*** (0.044)
logL	-0.007 (0.007)	-0.005 (0.011)