Physical productivity and exceptional exporter performance: Evidence from a Chinese production survey*

Yao Amber Li† Valérie Smeets‡ Frédéric Warzynski§

December 24, 2020

Abstract

In this paper, we use a detailed production survey covering a large subset of firms 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 large for firms involved in this type of contractual arrangements. Our results are helpful to solve the "missing exporting premium puzzle" in China and can also shed light on similar processing trade institutions in other developing countries, where this type of trade regime is relatively widespread and can be seen as a fast track to industrial development.

*This paper previously circulated under the title "Processing trade, productivity and prices: Evidence from a Chinese production survey". We thank Andrew Bernard, Simeon Djankov, Edwin Lai, Peter Morrow, Marc-Andreas Muendler, Sandra Poncet, Chad Syverson, Stephen Yeaple, Miaojie Yu, Yuan Zi and seminar participants at Aarhus, NOITS2016, ADI2016, Beijing Forum 2016, EITI 2017, ATW 2017, AMES 2017, CAED 2017, CUHK 2018, RIETI 2019, HKUST 2019, PKU HSBC 2020 and the Melbourne Trade Workshop 2020, for useful comments and discussions. All errors are ours.

† Hong Kong University of Science and Technology, email: yaoli@ust.hk

‡ Aarhus University, email: vas@asb.dk

§ Aarhus University, email: fwa@asb.dk

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. Bernard and Jensen, 1999 and the discussion in Bernard et al., 2018). Surprisingly, one country where this pattern has not been found is China (see Lu, 2010 for early evidence). Given the fact that China is the largest exporter in the world, this striking result has attracted quite a lot of attention.

In this paper we want to re-examine this apparent puzzle by looking at the question from another angle. More specifically, we investigate the role of pricing differences between firms and distinguish between revenue productivity and physical productivity, following the seminal contribution of Foster, Haltiwanger and Syverson (2008). We use a novel detailed dataset providing physical quantities produced by Chinese firms over the period 2000-2006, a period during which China dramatically opened up to the world economy.[1] 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). The latter allows us to separate pricing heterogeneity from technical efficiency.

Using these two measures of productivity, we analyze their relationship with the export behavior of firms. We first show (in line with several previous studies, see e.g. Lu, 2010 and Dai, Maitra and Yu, 2016) that Chinese exporters appear to be less productive than firms operating only on the domestic market when we use revenue based productivity; however, the opposite is true when we instead look at physical productivity. Intuitively, the difference comes from the fact that exporters charge lower prices than non exporters, and we provide evidence supporting this explanation.

We then relate our findings to an important institutional feature of the Chinese globalization strategy: the role of processing trade (see e.g. Dai, Maitra and Yu, 2016). Firms trading under processing trade regime are shielded from tariffs and also directly receive their inputs for assembly from their foreign clients. This arrangement potentially leads to the reduction of the material costs incurred by the firm and also affects 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,

[1] See e.g. Naughton (2018) for a description of the gradual nature of China's reform process.

charge lower prices and have higher physical productivity.

We end our empirical exercise by discussing the various potential channels of pricing differences between trade regimes. First, as mentioned previously, inputs and outputs of processing trade firms are exempted from tariffs, giving them a cost advantage. There are also additional fiscal benefits such as VAT exemption. Second, a special type of processing trade involves the free provision of inputs to the assembly firm. This mechanically reduces the material costs and can affect the price charged for the final good. Third, foreign firms involved in FDI might use transfer pricing and strategically charge lower prices to shift profit between locations. We argue that the third explanation appears the most convincing to explain the patterns that we document.

Our research builds on a growing literature investigating the role of output pricing heterogeneity bias on the measurement of productivity (e.g. Klette and Griliches, 1996; Levinsohn and Melitz, 2001; Eslava 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 Voigtländer, 2019).

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) and show that taking into account input pricing heterogeneity significantly affects productivity measurement.

Aside from shedding light on the consequences of processing trade for productivity measurement and pricing, we contribute to the debate about the surprising fact found in previous papers that exporters in China appear to be less productive than domestic firms, in particular in low tech industries (see Lu, 2010 for early evidence). While several explanations have been provided for this result, varying from the presence of export subsidies (Defever and Riaño, 2017) or easy access to financing; or the fact that many Chinese manufacturers engage in processing trade (e.g. Dai, Maitra and Yu, 2016), none have stressed the implications for productivity measurement of pricing differences between regimes of trade.

Last, our results also have implications for similar contractual arrangements taking place in other developing countries, so that our findings could be generalized outside of the Chinese context. Indeed, the WTO estimated that processing trade accounted for around one fifth of total exports from developing countries between 2000 and 2008 (Maurer and Degain, 2010). By 2006, based on an ILO estimate, 130 countries had established more than 3,500 export processing zones where firms benefit from special tariffs and tax regime (Singa Boyenge, 2007). Multinational enterprises (MNEs) are major players in these special economic zones and are using their own internal prices for these intra-firm transactions. Our paper provides a simple framework to assess the effects of MNEs' pricing strategies on productivity measurement.

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, and discuss the robustness of our findings. Section 5 concludes.

2 Data

We use three data sources to conduct our study: (i) the National Bureau of Statistics of China firm-level accounting data that reports revenue-based information on inputs and outputs of production, (ii) the 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 follow the now standard procedure to merge these two sets of firm identification codes based on the contact information of manufacturing firms. 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).

2.1 Accounting data

This now standard dataset has been used in many papers about firm productivity in China (see e.g. Brandt et al., 2017). The National Bureau of Statistics of China 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 National Bureau of Statistics of China, 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 sample contains more than 800 5-digit product codes that are listed as main industrial product and approximately 186,000 manufacturing firms.[4] 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 within 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.[5]

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

[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).

[4]A few papers have used this dataset to analyze markup dynamics but have not focused on productivity measurement and pricing heterogeneity; see Lu and Yu (2015); Fan et al. (2018); Zhang and Zhu (2017).

[5]Roberts et al. (2018) also use the more broadly defined footwear industry for their analysis of the determinants of firm heterogeneity. They justify their choice by the relative importance of the industry in terms of export.

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).[6]

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 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

Panel A of 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. The last column shows the quality of the match between accounting and customs in our subsample of leather shoes producers. We can see that the proportion is relatively high, in line with previous studies and appears to improve over the years.

We then classify firms based on their main mode of export. According to the most extreme definition, we define as firm as pure processing (or ordinary) trade exporter if all their export transactions follow the processing (or ordinary) trade mode. If they export under both modes of export, we define them as hybrid exporters. We see from panel B that the share of processing trade remains relatively constant (declining slightly from

[6] 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.

26% to 22%), while the share of hybrid trade goes down dramatically from 59% to 35%, implying a large increase in the relative share of ordinary trade.

We also followed a different (less extreme) definition of modes by redefining firms as mainly processing (or ordinary) if the total value of exports under that mode was larger than 90%. Under this alternative classification, shown in panel C, the number of processing trade exporters falls from 60% to 37% and the number of ordinary trade firms increases from 16% to 48%.[7] In our empirical analysis, we use this alternative definition, but our results are robust and very similar when using the strict definition.

We should however make a distinction between the main mode of export that firms are using, and the absolute value of the different trade modes in the customs data. Looking at the aggregate figures in the customs data, the share of export transactions under the mode of processing trade has declined in value from 92% in 2000 to around 73% in 2006. This suggests that a large proportion of the export value generated by hybrid firms follows the processing trade mode. On the other hand, the share of import transactions under the regime of processing trade is stable and around 95%.

2.5 Carry along trade

In our analysis, we focus on single product firms, i.e. those firms that report producing only one product. More than 90% of the firms in our sample that are involved in the leather shoes industry belong to that category, suggesting substantial amount of specialization. When comparing the information from the production survey and the customs dataset, researchers have 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., 2019). 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.[8] This does not appear to be the case in the Chinese leather shoes industry. In our sample, more than 95% of firms only export shoes and part of shoes, i.e. items in the 64 2-digit HS category.

[7] This relative decline in the share of processing trade in total exports is in line with Brandt and Morrow (2017) and also the evidence in Naughton (2018).

[8] See Smeets and Warzynski (2019) for a similar discussion about subcontracting and offshoring.

3 Methodology

Our aim in this section is to briefly explain how the productivity measure commonly used in the literature suffers from a measurement bias referred to as pricing heterogeneity bias.[9] We then show how this bias can affect 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. 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 mode 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:

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

[9] The discussion is based on Klette and Griliches (1996), Foster, Haltiwanger and Syverson (2008), De Loecker (2011), and De Loecker and Goldberg (2014).

where q_{it} is the log of 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 pricing heterogeneity concern affects our input variables, in particular materials (intuitively, if firms produce higher quality output, they might also use higher quality and more expensive inputs). We follow their suggestion and add price and market share in our control function when estimating the production function. Finally, to address the well known endogeneity concern, we follow their modified version of Wooldridge (2009).

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.[10] 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.

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 Main results

The top panel of Table 2 shows the estimated output elasticity of our production function using OLS and DLGKP for all single product firms producing leather shoes. The first two columns use deflated turnover from the accounting dataset as left hand side variable, while the last two columns show the results of the estimation using physical quantity from the production survey.

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. Using a translog, and controlling for output price in the control function, the DLGKP method generates similar output elasticities for all three inputs whether we use log of deflated revenue or log of physical quantity as left hand side variables.

[10] The measurement of material costs has been shown to be especially problematic with Chinese data see Feenstra, Li and Yu (2014); on the importance of input price bias, see also Grieco, Li and Zhang (2016) and Atalay (2014).

Panel B 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. As we show in more details later, this result can be explained by differences in pricing behavior by export status (in these specifications, exporters on average charge prices 28% lower than non exporters for the OLS subsample and 23% for the DLGKP subsample, as shown in Appendix Table A1, columns 1 and 2).

We next match our production and accounting data with the customs data information in order to assess whether productivity is related to the mode of exports, as has been suggested by Dai, Maitra and Yu (2016). Panel C of Table 2 shows the relationship between our various measures of TFP and the mode of export. Looking first at TFPR, it looks like firms involved only in ordinary trade and only doing processing trade have lower measures of revenue productivity, while firms involved in hybrid have a slightly higher TFPR relative to non exporters. 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. Using the DLGKP subsample, firms involved in processing trade have prices that are 33% lower relative to non exporters; for firms doing ordinary trade, prices are 25% lower, while firms doing hybrid trade have slightly higher prices (around 10%).[11]

4.2 Additional findings and robustness

4.2.1 Controlling for ownership and location

The decision to engage in processing is intrinsically related to both the location decision and the ownership type (nationality of the owner). Indeed, many foreign firms were attracted in export processing zones (EPZs) through the direct fiscal (and other) advantages that they convey, in addition to low Chinese labor cost. Our dataset contains information about both firms' location and ownership. Location is provided though a 6-digit district code. Ownership is divided into several categories: state owned enterprise (SOE), domestic private, joint venture, multinational enterprise (MNE) and other. The Chinese data also makes a distinction between MNE's from Hong Kong, Macau and Taiwan (HKMTW) on the one hand, and from OECD countries on the other. Since there are only a few SOE's involved in the leather shoes market, we omit them from our analysis.

Table 3 shows the distribution of the various ownership types for our sample of matched

[11]See columns 3 and 4 of Appendix Table A1.

exporters. It clearly shows that MNEs are more likely to be using processing trade than domestic firms, and the use of processing trade is most widespread for firms based in Hong Kong, Taiwan and Macau.

In Table 4, we replicate our results from Table 2 (panels B and C) with these additional variables as control. Controlling for location might capture several other aspects such as the benefits to be located in clusters or the effect of local competition. The main results remain relatively robust to the introduction of these additional variables. Exporters have higher physical productivity but lower prices (Table 4 panel A), and this relationship is entirely driven by firms doing processing trade (Table 4 panel B). We also provide additional findings about the link between productivity and ownership. In particular, MNE's from Hong Kong, Macau and Taiwan have higher TFPQ but much lower prices.

As noted in previous research (e.g. Dai, Maitra and Yu, 2016), processing trade can itself be divided in two separate modes: firms receiving inputs for free (pure assembly firms) and firms involved in processing trade but acquiring inputs themselves on the market. Our hypothesis is that the former group of firms will experience a stronger distortion in the price they charge than the latter. We test it in Table 5. Indeed, we observe that pure assemblers have much higher physical productivity than non exporters and firms involved in other types of trade modes, but they are also charging lower prices in the same proportion (around 60%). We should be aware though that pure assembly is much less common than processing with import in our sample.

4.2.2 Export and domestic prices

Customs data also provide value and quantity at the HS6 level, so we can compute a proxy for export price. We use this proxy to understand the role of processing trade and to look at the relationship between export price and production price. This is also a way to validate our production price proxy. Table A2 shows the results. In line with our previous findings, export prices under the processing trade regime are around 9.4% lower than under other transaction modes. We also observe that our two price proxies correlate very well.

4.2.3 Subsidies

Another reason why firms might have lower prices is because they receive subsidies from the state, especially in relationship with export share requirement. These types of subsidies have often been claimed in the literature but are typically hard to observe in accounting data (see the discussion in Defever and Riaño, 2017).

Our accounting data actually contains some information about subsidies, although it does not distinguish between types of subsidies. Not surprisingly, most firms report no subsidies at all. However, some do, even though the amount reported is very tiny in most cases. Based on this information, we compute two dummy variables: one equal to 1 if the firm received a subsidy (and 0 otherwise); and another one equal to 1 if the firm receives a subsidy at least equivalent to 1% of its turnover (and 0 otherwise). For around 11% of our observations, firms report having received a subsidy, but this rate is much higher for exporters (14.1%) than for non exporters (4.17%). The number is much lower if we use the more constraining definition (around 1.4%) and does not vary as much by exporting status. Perhaps more surprisingly, among exporters, firms doing ordinary trade and hybrid firms are more likely to be recipient of these subsidies. This might suggest that direct export subsidies are not included in the subsidy variable and our variable measures other types of subsidies. When we include subsidies in our estimation, our results remain robust (see Table A3). Subsidies do not appear to be strongly related to productivity or prices once we control for mode of transaction.

4.2.4 Other similar apparel products

Our results that pricing differences are important to explain differences in revenue TFP are validated when we look at the subsample of single product producers of shirts and suits. For these two other product markets, exporters have higher TFPQ and charge lower prices (see Tables A4 and A5 that replicate Table 2 for these two products).

4.2.5 Shielded from tariffs and transfer pricing

In order to better understand the origin of pricing heterogeneity, we try to disentangle the various explanations why prices charged by processing trade firms might be lower. We identified three main reasons that may drive large pricing differences among Chinese exporters, especially for firms involved in processing trade. First, lower prices may simply be due to a mechanical effect as processing trade products are not subject to tariffs nor have to pay VAT. Second, some types of processing trade activities entail that the processing trade firm receives the inputs for free from the contracting firm. This will artificially depress the values of inputs or materials used for the firm's production, but should also automatically be reflected in the negotiated price. Third, lower prices may also reflect transfer pricing, or more generally strategic pricing considerations of multinational enterprises when offshoring to China.

To distinguish the first set of explanations from the second, we artificially inflate the material costs of processing trade firms by the amount of the tariffs they are supposed to be shielded from on their main inputs (mostly leather). We find that this artificial increase in costs reduces the TFPQ premium of processing trade exporters by around 5% (see Table A6), but does not change the results of our paper otherwise, suggesting strategic pricing plays a significant role in these product markets.

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, or also lower input costs, especially in the case of pure assemblers.

Our analysis therefore provides a solution to the so called "missing exporting premium puzzle" in China and shows the importance of strategic pricing in processing trade regimes. Our approach can also be applied to other developing countries, where processing trade is widely used, as documented by international institutions like the WTO or the ILO.

In future work, 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 for an early discussion and Fan, Li and Yeaple, 2018 for more recent evidence) 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.

References

Atalay, Enghin. 2014. "Materials Prices And Productivity." *Journal of the European Economic Association*, 12(3): 575–611.

Bernard, Andrew B., and J. Bradford Jensen. 1999. "Exceptional exporter performance: cause, effect, or both?" *Journal of International Economics*, 47(1): 1–25.

Bernard, Andrew B, Emily J Blanchard, Ilke Van Beveren, and Hylke Vandenbussche. 2019. "Carry-Along Trade." *The Review of Economic Studies*, 86(2): 526–563.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott. 2018. "Global Firms." *Journal of Economic Literature*, 56(2): 565–619.

Brandt, Loren, and Peter M. Morrow. 2017. "Tariffs and the organization of trade in China." *Journal of International Economics*, 104(C): 85–103.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Dai, Mi, Madhura Maitra, and Miaojie Yu. 2016. "Unexceptional exporter performance in China? The role of processing trade." *Journal of Development Economics*, 121(C): 177–189.

Defever, Fabrice, and Alejandro Riaño. 2017. "Subsidies with export share requirements in China." *Journal of Development Economics*, 126(C): 33–51.

De Loecker, Jan. 2011. "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity." *Econometrica*, 79(5): 1407–1451.

De Loecker, Jan, and Pinelopi Koujianou Goldberg. 2014. "Firm Performance in a Global Market." *Annual Review of Economics*, 6(1): 201–227.

De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. 2016. "Prices, Markups, and Trade Reform." *Econometrica*, 84: 445–510.

Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler. 2004. "The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia." *Journal of Development Economics*, 75(2): 333–371.

Fan, Haichao, Xiang Gao, Yao Amber Li, and Tuan Anh Luong. 2018. "Trade liberalization and markups: Micro evidence from China." *Journal of Comparative Economics*, 46(1): 103 – 130.

Fan, Haichao, Yao Amber Li, and Stephen R. Yeaple. 2015. "Trade Liberalization, Quality, and Export Prices." *Review of Economics and Statistics*, 97(5): 1033–1051.

Fan, Haichao, Yao Amber Li, and Stephen R. Yeaple. 2018. "On the relationship between quality and productivity: Evidence from China's accession to the WTO." *Journal of International Economics*, 110(C): 28–49.

Feenstra, Robert C., Zhiyuan Li, and Miaojie Yu. 2014. "Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China." *The Review of Economics and Statistics*, 96(4): 729–744.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394–425.

Garcia-Marin, Alvaro, and Nico Voigtländer. 2019. "Exporting and Plant-Level Efficiency Gains: It's in the Measure." *Journal of Political Economy*, 127(4): 1777–1825.

Grieco, Paul L. E., Shengyu Li, and Hongsong Zhang. 2016. "Production Function Estimation With Unobserved Input Price Dispersion." *International Economic Review*, 57: 665–690.

Klette, Tor Jakob, and Zvi Griliches. 1996. "The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous." *Journal of Applied Econometrics*, 11(4): 343–361.

Levinsohn, J., and M. Melitz. 2001. "Productivity in a Differentiated Products Market Equilibrium." Mimeo.

Lu, Dan. 2010. "Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms." Mimeo.

Lu, Yi, and Linhui Yu. 2015. "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession." *American Economic Journal: Applied Economics*, 7(4): 221–53.

Manova, Kalina, and Zhiwei Zhang. 2012. "Export Prices Across Firms and Destinations." *The Quarterly Journal of Economics*, 127(1): 379–436.

Maurer, Andreas, and Christophe Degain. 2010. "Globalization and trade flows: What you see is not what you get!"

Naughton, Barry J. 2018. *The Chinese Economy: Adaptation and Growth, second edition.* Vol. 1 of *MIT Press Books*, The MIT Press.

Roberts, Mark J, Daniel Yi Xu, Xiaoyan Fan, and Shengxing Zhang. 2018. "The Role of Firm Factors in Demand, Cost, and Export Market Selection for Chinese Footwear Producers." *Review of Economic Studies*, 85(4): 2429–2461.

Schott, Peter K. 2008. "The relative sophistication of Chinese exports." *Economic Policy*, 23: 5–49.

Singa Boyenge, Jean-Pierre. 2007. "ILO database on export processing zones (Revised)." International Labour Organization ILO Working Papers 993989593402676.

Smeets, Valerie, and Frederic Warzynski. 2013. "Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade." *Journal of International Economics*, 90(2): 237–244.

Smeets, Valerie, and Frederic Warzynski. 2019. "Multi-Product Firms in French Manufacturing and the Rise of Subcontracting." Aarhus University Mimeo.

Wooldridge, Jeffrey M. 2009. "On estimating firm-level production functions using proxy variables to control for unobservables." *Economics Letters*, 104(3): 112–114.

Zhang, Hongyong, and Lianming Zhu. 2017. "Markups and exporting behavior of foreign affiliates." *Journal of Comparative Economics*, 45(3): 445–455.

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

Panel A: number of firms by year and exporting status;
match quality between production and customs datasets

Year	# Firms	Non exporters	Exporters	% match between production and customs for exporters
2000	595	205	390	77.3%
2001	785	293	492	75.2%
2002	931	319	612	83.3%
2003	999	374	625	83.3%
2004	1,165	337	828	81.8%
2005	1,474	548	926	88.0%
2006	1,659	714	945	87.0%
All	7,608	2,790	4,818	83.0%

Panel B: Shares of processing, hybrid and ordinary trade among leather shoes exporters
(STRICT DEFINITION)

Year	Share of firms by main export mode:			Share of trade value by main export mode:		
	Processing trade	Ordinary trade	Hybrid trade	Processing trade	Ordinary trade	Hybrid trade
2000	25.8%	15.1%	59.1%	20.2%	2.5%	73.4%
2001	26.3%	20.4%	53.3%	24.8%	4.9%	69.2%
2002	26.5%	29.6%	43.9%	33.2%	11.8%	54.1%
2003	25.9%	37.5%	36.6%	33.7%	14.4%	51.4%
2004	21.7%	44.5%	33.8%	27.2%	14.7%	56.9%
2005	23.5%	43.1%	33.4%	31.5%	15.9%	52.3%
2006	22.2%	42.8%	35.0%	32.2%	16.4%	51.3%

Panel C: Shares of processing, hybrid and ordinary trade among leather shoes exporters
(ALTERNATIVE DEFINITION)

Year	Share of firms by main export mode:			Share of trade value by main export mode:		
	Processing trade	Ordinary trade	Hybrid trade	Processing trade	Ordinary trade	Hybrid trade
2000	60.7%	16.2%	23.1%	78.4%	3.5%	18.1%
2001	56.1%	21.6%	22.3%	75.3%	5.5%	19.2%
2002	50.5%	30.9%	18.6%	73.1%	12.6%	14.2%
2003	44.1%	39.3%	16.6%	72.6%	17%	10.4%
2004	40.6%	46.1%	13.4%	72.9%	18.2%	8.9%
2005	37.8%	46.5%	15.7%	69.4%	19.2%	11.5%
2006	36.8%	48.0%	15.2%	68.1%	21.2%	10.7%

Table 2: Production function estimation: leather shoes

Panel A: production function estimation

	Using deflated revenue, dep. var.: $logDefRev$		Using physical quantity, dep. var.: $logQ$	
	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)
$logM$	0.820*** (0.004)	0.855	0.639*** (0.012)	0.856
$logL$	0.151*** (0.004)	0.115	0.178*** (0.011)	0.109
$logK$	0.025*** (0.003)	0.010	0.003 (0.007)	0.012
# obs.	6,333	3,754	6,333	3,754

Panel B: link between productivity estimates and export

	Dep. var.: $TFPR$		Dep. var.: $TFPQ$	
Exporter	-0.033*** (0.007)	-0.018** (0.007)	0.133*** (0.017)	0.211*** (0.028)
$logL$	0.005* (0.003)	0.022*** (0.003)	-0.020*** (0.007)	-0.106*** (0.011)
Year dummies	YES			
Adj. R2	0.025	0.032	0.015	0.033
# obs.	6,333	3,754	6,333	3,754

Panel C: link between productivity estimates and mode of export

	Dep. var.: $TFPR$		Dep. var.: $TFPQ$	
	OLS - Cobb Douglas	DLGKP - translog	OLS - Cobb Douglas	DLGKP - translog
Processing	-0.019* (0.011)	-0.017 (0.011)	0.080*** (0.030)	0.317*** (0.046)
Ordinary	-0.054*** (0.009)	-0.029*** (0.009)	0.267*** (0.026)	0.216*** (0.038)
Hybrid	0.041*** (0.014)	0.035** (0.014)	-0.071* (0.039)	-0.065 (0.058)
$logL$	-0.001 (0.003)	0.021*** (0.004)	-0.013 (0.010)	-0.134*** (0.015)
Year dummies	YES			
Adj. R2	0.036	0.047	0.035	0.049
# obs.	4,292	2,569	4,292	2,569

Table 3: Distribution of ownership type by mode of export (matched exporters only)

	# firms (%)	share processing
dom priv	412 (18.25%)	1.46%
Other	299 (13.24%)	6.69%
Joint venture	780 (34.54%)	20.26%
MNE OECD	274 (12.13%)	36.86%
MNE HKMTW	493 (21.83%)	46.86%

Table 4: Export and export mode premia (with controls for ownership and location)

Panel A: Link between TFP and export behavior

Dep. var. :	TFPQ	logp	TFPR
Exporter	0.086*** (0.023)	-0.085*** (0.023)	0.001 (0.008)
Joint venture	-0.069* (0.031)	0.084*** (0.031)	0.015 (0.010)
Other	-0.040 (0.027)	0.049 (0.027)	0.010 (0.009)
MNE OECD	-0.099** (0.043)	0.104* (0.044)	0.006 (0.015)
MNE HKMTW	0.108*** (0.038)	-0.116** (0.039)	-0.009 (0.013)
logL	-0.105*** (0.010)	0.123*** (0.011)	0.018*** (0.004)
Location dummies		YES	
Year dummies		YES	
Adj. R2	0.515	0.529	0.150
# obs.	3,731	3,731	3,731

Panel B: Link between TFP and mode of transaction

Dep. var. :	TFPQ	logp	TFPR
Processing	0.132*** (0.050)	-0.090* (0.051)	0.044*** (0.016)
Ordinary	-0.014 (0.032)	0.002 (0.032)	-0.012 (0.010)
Hybrid	0.012 (0.052)	0.045 (0.052)	0.058*** (0.017)
Joint venture	-0.001 (0.037)	-0.007 (0.038)	-0.010 (0.012)
Other	-0.038 (0.033)	0.032 (0.033)	-0.005 (0.011)
MNE OECD	0.037 (0.052)	-0.038 (0.053)	-0.001 (0.017)
MNE HKMTW	0.197*** (0.047)	-0.225*** (0.048)	-0.030* (0.015)
logL	-0.104*** (0.012)	0.121*** (0.013)	0.017*** (0.004)
Location dummies		YES	
Year dummies		YES	
Adj. R2	0.554	0.564	0.149
# obs.	2,559	2,559	2,559

Table 5: Link between TFP and mode of transaction (with controls for ownership and location and distinguishing by regime of processing trade)

Dep. var. :	TFPQ	logp	TFPR
Processing with imp. inputs	-0.048	0.098*	0.053***
	(0.053)	(0.054)	(0.018)
Pure assembly	0.645***	-0.628***	0.016
	(0.073)	(0.074)	(0.024)
Ordinary	-0.028	0.016	-0.011
	(0.032)	(0.032)	(0.011)
Hybrid	0.011	0.047	0.058***
	(0.051)	(0.051)	(0.017)
Joint venture	0.001	-0.009	-0.010
	(0.037)	(0.037)	(0.012)
other	-0.040	0.035	-0.005
	(0.033)	(0.033)	(0.011)
MNE OECD	0.056	-0.058	-0.002
	(0.052)	(0.052)	(0.017)
MNE HKMTW	0.219***	-0.248***	-0.031**
	(0.047)	(0.047)	(0.016)
$logL$	-0.092***	0.107***	0.016***
	(0.012)	(0.013)	(0.004)
Location dummies		YES	
Year dummies		YES	
Adj. R2	0.571	0.581	0.150
# obs.	2,559	2,559	2,559

Table A1: the link between price, export and mode of export transaction

Dep. var.: logp	(1)	(2)	(3)	(3)
Exporter	-0.282***	-0.229***		
	(0.023)	(0.029)		
Processing			-0.334***	-0.333***
			(0.038)	(0.047)
Ordinary			-0.303***	-0.246***
			(0.034)	(0.039)
Hybrid			0.085*	0.100*
			(0.051)	(0.059)
logL	0.092***	0.127***	0.115***	0.156***
	(0.010)	(0.012)	(0.013)	(0.015)
Year dummies		YES		
Adj. R2	0.038	0.038	0.052	0.056
# obs.	6,333	3,754	4,292	2,569

Note: Column 1 uses the OLS subsample used in the first column of table 2 panels A and B; column 2 uses the DLGKP subsample used in the second column of table 2 panels A and B; olumn 3 uses the OLS subsample used in the first column of table 2 panel C; column 4 uses the DLGKP subsample used in the second column of table 2 panel C

Table A2: Export price, mode of transaction and production price (matched exporters only)

Dep. var.: *logpexp*	(1)	(2)	(3)
processing	-0.094***	-	-0.026*
	(0.018)		(0.015)
logp	-	0.416***	0.414***
		(0.008)	(0.008)
cons	1.376***	-1.181***	-1.153***
	(0.033)	(0.057)	(0.059)
HS6 dummies		YES	
Year dummies		YES	
Adj. R2	0.243	0.460	0.461
# obs.		5,992	

Table A3: Link between TFP and mode of transaction (with controls for ownership, location and subsidies)

Dep. var. :	TFPQ	logp	TFPR
Processing with imp. inputs	-0.049	0.098*	0.053***
	(0.053)	(0.054)	(0.018)
Pure assembly	0.653***	-0.629***	0.016
	(0.073)	(0.074)	(0.024)
Ordinary	-0.028	0.016	-0.011
	(0.032)	(0.032)	(0.010)
Hybrid	0.011	0.046	0.058***
	(0.051)	(0.051)	(0.017)
Joint venture	0.001	-0.008	-0.010
	(0.037)	(0.037)	(0.012)
Other	-0.040	0.035	-0.005
	(0.033)	(0.033)	(0.011)
MNE OECD	0.056	-0.057	-0.002
	(0.052)	(0.052)	(0.017)
MNE HKMTW	0.219***	-0.248***	-0.031**
	(0.047)	(0.047)	(0.016)
$logL$	-0.092***	0.107***	0.016***
	(0.012)	(0.013)	(0.004)
Pos subs > 1%	0.056	0.032	0.002
	(0.109)	(0.034)	(0.036)
cons	10.466***	-3.971***	13.473***
	(0.079)	(0.080)	(0.026)
Location dummies		YES	
Year dummies		YES	
Adj. R2	0.602	0.613	0.214
# obs.	2,559	2,559	2,559

Table A4: Production function estimation: shirts

Panel A: production function estimation

	Using deflated revenue, dep. var.: $logDefRev$		Using physical quantity, dep. var.: $logQ$	
	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)
$logM$	0.820*** (0.004)	0.768	0.440*** (0.020)	0.769
$logL$	0.151*** (0.004)	0.128	0.453*** (0.026)	0.126
$logK$	0.025*** (0.003)	0.021	-0.116*** (0.015)	0.022
# obs.	3,349	2,035	3,349	2,035

Panel B: link between productivity estimates and export

	Dep. var.: $TFPR$		Dep. var.: $TFPQ$	
EXP	-0.033*** (0.012)	-0.006 (0.011)	0.210*** (0.033)	0.236*** (0.043)
$logL$	0.005* (0.003)	0.095*** (0.007)	-0.022 (0.019)	-0.054** (0.025)

Table A5: Production function estimation: suits

Panel A: production function estimation

	Using deflated revenue, dep. var.: $logDefRev$		Using physical quantity, dep. var.: $logQ$	
	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)	OLS - Cobb Douglas (coeff)	DLGKP - translog (median elasticity)
$logM$	0.810*** (0.006)	0.816	0.414*** (0.024)	0.811
$logL$	0.161*** (0.009)	0.135	0.595*** (0.034)	0.142
$logK$	0.034*** (0.005)	0.080	-0.161*** (0.020)	0.032
# obs.	2,665	1,446	2,576	1,446

Panel B: link between productivity estimates and export

	Dep. var.: $TFPR$		Dep. var.: $TFPQ$	
EXP	0.011 (0.014)	0.002 (0.014)	0.665*** (0.048)	0.806*** (0.066)
$logL$	-0.002 (0.007)	-0.000 (0.008)	-0.127*** (0.026)	-0.182*** (0.035)

Table A6: Link between TFP and mode of transaction (with controls for ownership, location and assuming higher material costs for processing trade firms)

Dep. var. :	TFPQ
Processing with imp. inputs	-0.059
	(0.053)
Pure assembly	0.615***
	(0.073)
Ordinary	-0.025
	(0.032)
Hybrid	0.009
	(0.051)
Joint venture	0.001
	(0.037)
Other	-0.041
	(0.033)
MNE OECD	0.059
	(0.052)
MNE HKMTW	0.224***
	(0.047)
$logL$	-0.093***
	(0.012)
cons	17.647***
	(0.071)
Location dummies	YES
Year dummies	YES
Adj. R2	0.60
# obs.	2,559