(Learning to) Export Like China:
From Processing Trade to Ordinary Trade

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January 13, 2024

Abstract

In the past forty years, China has risen from a closed economy to the second largest trading economy in the world. What explain this unprecedented change? This study focuses on the role of processing trade in China. We find that Chinese firms first engage in processing trade and then start ordinary trade, in which they export their own products. Chinese firms learn from processing trade to overcome barriers to ordinary trade including information, technology, market knowledge, etc. This finding is obtained at firm, market, product, and firm-market-product levels. The finding survives several robustness checks.

Keywords: Processing Trade; Ordinary Trade; China

JEL Codes: F10, F13, F14, F23, F34

1 Introduction

China's international trade growth in the past 40 years has been unprecedented in the world's economic history; its share of global exports has risen from less than 1% in 1979 to 13.45% (the largest exporter) in 2018. What are the explanations for this miracle? What lessons can be drawn for other developing countries? Often-mentioned reasons are related to the open-door policy, domestic reform, export-promotion policy, China's accession to the WTO, cheap labor/resources, the role of foreign direct investment (FDI), and others. Providing a full and rigorous answer is highly challenging and important. This paper adds a building block to explanations of China's export success with a focus on processing trade.

Processing trade in China refers to business activities which import all or part of the raw and auxiliary materials, parts and components, accessories, and packaging materials from abroad in bond and re-export the finished products after processing or assembly by enterprises within China. This, together with ordinary trade, are the most important modes of trade in China. The share of processing trade in China's total trade has always been large, as high as 60% in the 1990s and 2000s, and still above 30% even in recent years. As shown by Brandt and Morrow (2017), processing exports represented 57.3% of China's total exports in 1999, 53% in 2006, and 34.8% in 2012. Existing studies have shown that processing trade has a higher unit value than other modes of trade (Schott, 2008), and facilitate other types of trade (Fernandes and Tang, 2015). However, processing trade has also been considered as being less efficient than ordinary trade. For example, it has been shown that processing trade has lower total factor productivity (TFP) and lower profitability than ordinary trade (Dai et al, 2016; Koopman et al, 2006; Manova and Yu, 2016). Moreover, it has been shown that ordinary trade is more prevailing in provinces which have better contract enforcement (Feenstra et al, 2013) and associated with firms which face fewer financial constraints (Manova and Yu, 2016).

Our paper has a different focus. We are motivated by a prominent feature of the development process of China's trade, that is, starting from processing trade and then maturing into ordinary trade, as indicated in the Table 1, Figure 1, and Figure 2 below, which we obtain based on our data.

<Table 1, Figure 1, and Figure 2 Here>

There are two observations. First, the figure shows the positive correlation between the log value of processing exports of each industry (HS 6-digit level) in 2000 (horizontal axis) and the log value of ordinary exports of corresponding industries in 2006 (vertical axis). Second, based on firms' export status, the table shows the likelihood of a firm starting ordinary exports (last column) is much higher if it has participated in processing exports before (last row). Therefore, rather than focusing on processing trade itself, we investigate the linkage between the two most important modes of trade. Specifically, we ask two questions. First, does China's ordinary trade learn from processing trade? Second, if the answer to the first question is 'yes', then how and by how much?

Although these two questions are important, they have not been systematically analyzed and satisfactorily answered. Our study is to address this issue. First, we set up a theoretical framework, which includes the decision of firms on the mode of export, i.e., processing and ordinary trade. The background of the model is that in the early years, when China just opened its doors, Chinese firms lacked the ability to compete in the international market in all dimensions, except for the fact that they had the advantage of low labor costs. In our theoretical analysis, we outline and understand the important mechanisms through which Chinese firms may first engage and learn from processing trade and then start ordinary trade. The possible channels include technology learning, product learning, market learning, and others.

We also conduct an empirical analysis based on the theoretical analysis and predictions. Our data come from many sources, such as detailed firm-level data from Chinese firms. We test the predictions of the theoretical model, examine the channels identified in the theoretical analysis, and obtain additional empirical results. We find evidence of *Chinese firms learning from processing exports before their ordinary exporting*. This finding is obtained at firm, market, product, and firm-market-product levels. The finding survives several robustness checks.

Our paper contributes to a small but growing literature.

The first is the literature on exploring the causes of ordinary and processing trade in China. Using provincial-level data, Feenstra et al. (2013) show that institution quality matters for processing trade. Manova and Yu (2016) check the role of financial frictions in deciding firms' choice between processing trade and ordinary trade. They show that credit constraints induce firms to conduct more processing trade and preclude them from pursuing higher value-added, more profitable ordinary trade. Thus, financial market imperfections impact the organization of production across firms and countries. Brandt and Morrow (2017) show that falling input tariffs explain around 80% of the observed average increase in the share of ordinary trade in exports at the industry-province level. The adjustment comes from both existing and new exporters. Our study complements these studies in that we explore how processing trade in China in the earlier years led to the growth of ordinary trade, resulting in an increased share of ordinary trade in China's total trade.

Another group of studies focus on comparing the characteristics and performance between processing and ordinary trade firms in China. For example, Koopman et al. (2012), Fernandes and Tang (2015), Yu (2015), Dai et al. (2016), and Kee and Tang (2016) all find that processing trade firms are less productive or domestic value-added than ordinary trade firms in China. Chen, et al. (2018) find that firms conducting both types of trade are superior to pure processing firms and pure ordinary trade firms. Different to these papers, our focus is not based on the comparison between different types of firms, but instead, the dynamic linkage of the two modes of trade by firms. While most of the existing studies focus on comparing the productivity levels of ordinary and processing firms, Brandt et al (2019) point out the problems associated with methodologies used in those studies, which include non-comparability of output prices between the two types of firms and input prices. Our study does not suffer from such a measurement problem because we are not to compare them.

A recent paper by Brandt et al. (2019) focuses on the welfare effects of China's discriminatory trade policies towards processing and ordinary trade. Our study is about the learning effects of processing trade on ordinary trade, and thus our analysis suggests that Brandt et al.'s (2019) analysis may understate the welfare effect of processing trade because it does not consider the learning effect of processing trade on ordinary trade.

Many studies exist that are based on China's trade, with reference to processing and ordinary trade, but their focuses are not about these two modes of trade (e.g., Schott, 2008; Liu and Qiu, 2016).

Our paper is also related to the literature on learning by exporting. Studies include De Loecker (2013) and Lileeva and Trefler (2010) on identifying the exporting effects. Bai et al. (2017) study the learning effects of Chinese exporters, depending on whether they directly export or do so via intermediates. Our paper deals with two new issues: (i) the learning effects through processing exports, and (2) the effects on the firms' subsequent trading mode, i.e., ordinary trade.

In summary, this study makes significant contributions to the literature on Chinese exports by providing the first theoretical analysis to help understand the channels through which processing trade in China affects ordinary trade; by using Chinese firm-level data to investigate the effects of processing trade; and by presenting important policy implications based on Chinese experiences.

2 Theoretical Model

This is the outline of the model. The model is intended to be simple but fits the reality of China in the early years of the country's opening up. It allows us to analyze firms' decisions on ordinary trade and processing trade. Existing models of China's processing and ordinary trade include Brandt and Morrow (2017) and Brandt et al. (2019). The model of Brandt et al. (2019) attempts to capture the feature of general equilibrium analysis of trade policy, and therefore has multi-country, multi-sector, and multi-factor components in the model. In contrast, Brandt and Morrow (2017) have a partial equilibrium model to analyze the effect of tariff reduction on firms' choice between processing and ordinary trade. We build our dynamic model based on the static model of Brandt and Morrow (2017).

There are two countries, China and Foreign, one industry (product), and one factor of production (in addition to labor). In this industry, if a firm chooses processing trade, it can import the intermediate input duty-free, but is prohibited from selling its product to the domestic market. On the contrary, if a firm chooses ordinary trade, it is allowed to sell its product to the domestic market (as well as foreign market) but at the cost of paying the tariffs of imported intermediate inputs.

Demand. Within the industry, there are horizontally differentiated varieties, each produced by a firm in a monopolistically competitive market. Assume that the elasticity of substitution is the same across all varieties within the industry and is equal to $\sigma > 1$.

Firms. In the industry, a firm i draws its productivity θ_i from a known distribution with a cumulative distribution Θ. If a firm chooses processing trade, it can only sell its product to the foreign market (F). If a firm chooses ordinary trade, it can sell its product to both the domestic (D) and foreign markets. Let Q^D and Q^F be the industry-level demand shifters for the domestic and foreign markets, respectively.

If a firm sells its product to the domestic market only, it is called a pure domestic firm (Z) and its revenue is $R^Z = Q^D[p^Z(\theta_i)]^{1-\sigma}$, where $p^Z(\theta_i)$ is the firm's price whose productivity is θ_i.

If a firm chooses processing trade (P), it can only sell to the foreign market and thus, its revenue is $R^P = Q^F[p^P(\theta_i)]^{1-\sigma}$, where $p^P(\theta_i)$ is the firm's price whose productivity is θ_i.

If a firm chooses ordinary trade (O), it can and will sell its product to both markets and thus, its revenue is $R^O = \left(Q^D + Q^F\right)[p^O(\theta_i)]^{1-\sigma}$, where $p^P(\theta_i)$ is the firm's price (same in both market) whose productivity is θ_i.

Exporting requires a firm to pay a fixed cost. Denote the export cost for ordinary trade firms by f_X^O and that for processing trade firms by f_X^P. We assume $f_X^O > f_X^P$ for two reasons. First, in the earlier years of opening up in China, Chinese firms did not have sales networks in the foreign market, their products were not known to foreign consumers, and their products were perceived to be low quality. All these require the firms to put in a lot of resources and efforts (such as advertising) in order to enter the foreign market. Second, most of the processing trade firms (especially those engaging in assembly) received help from foreign partners to sell products on the foreign market. Brandt and Morrow (2017) do not consider this export cost in their model, but it is very crucial in our model.

Production. We assume Cobb-Douglas production function with labor and a composite intermediate input M, where the cost share of labor is α and that of M is $(1-\alpha)$. Producing M requires domestic input as well as imported input via a CES technology with an elasticity of substitution γ. Assume exogenous wage rate for labor w, domestic input price p_D, imported price p_M, and ad valorem tariff rate on imported input τ. The fixed cost of entering the industry is f_E. Thus, the total costs associated with the three types of firms are, respectively,

$$TC^D(\theta_i) = c^D\left(\frac{q_i}{\theta_i}\right) + f_E,\ \ TC^O(\theta_i) = c^O\left(\frac{q_i}{\theta_i}\right) + f_E + f_X^O,\ \ TC^P(\theta_i) = c^P\left(\frac{q_i}{\theta_i}\right) + f_E + f_X^P,$$

where q_i is output and

$$c^D = c^O = w^\alpha\left[p_D^{1-\gamma} + (\tau p_M)^{1-\gamma}\right]^{\frac{1-\alpha}{1-\gamma}},\ \ c^P = w^\alpha\left(p_D^{1-\gamma} + {p_M}^{1-\gamma}\right)^{\frac{1-\alpha}{1-\gamma}}\ .$$

Institutional background. China began its economic reform and opening up in 1979. However, even by 1999, most of its trade was still carried out by state-owned foreign trade corporations and foreign invested enterprises, i.e., domestic producers were not allowed to directly export their products. These restrictions have gradually been removed since late 1990s. Hence, ordinary trade was new to almost all domestic private firms.

Dynamics. Brandt and Morrow (2017) analyze the sorting and effects of tariff cuts or domestic market expansion on the sorting to explain the increase of ordinary trade share in China's total exports. Our focus is different. Based on the aforementioned institutional background, we introduce a dynamic setting to investigate how a firm's choice of processing trade in the first period affects its decision on ordinary trade in the second period, which will eventually lead to an increase in ordinary trade share at an industry level.

Suppose that there are two periods, and the above-described environment is for the first period. In the second period, the external environment (demand, tariff and input prices) remains the same as in the first period, but the firms that have processing trade in the first period are different. When a firm chooses processing trade in the first period, its foreign partners provide good technology (such as production lines and product blueprints) to the firm. The firm learns the technology and applies in the second period. Accordingly, we assume that the firm's productivity in the second period becomes $s\theta_i$, where $s > 1$. We refer to this as the technology-learning effect. The firm's first period exporting experiences also allows it to lower its fixed cost of export in the second period should it choose ordinary trade. This is because the firm can overcome some of the problems associated with the fixed cost of ordinary export by Chinese firms such as becoming more familiar with the foreign market, getting its product known by foreign consumers, etc. Thus, we assume that having chosen processing trade in the first period, if the firm chooses ordinary trade in the second period, the fixed export cost it faces is reduced to vf_X^O, where $v < 1$. We call this market-learning effect. The learning effects of the first period processing trade could also take other forms. We will examine them in the extension of the model to generate more predictions for our empirical study.

Analysis and predictions.

We will conduct an analysis of the above model. *To be included.*

The analytical results help generate useful hypotheses regarding heterogeneous firms' decision on the mode of trade in the two periods, and the equilibrium changes resulting from changes in the environment such as demand, tariff, entry cost, contracting cost and financial constraints.

Extensions of the model. We extend the main model along several dimensions, one by one for clearness and tractability. The extensions will enable us to explore more mechanisms through which processing trade affects ordinary trade.

First, multiple products. While each firm produces only one variety in the first period, it can introduce a new variety in the second period. However, there is a fixed cost of introducing a new variety, denoted by f_n. Once the new variety is introduced, the firm can decide the mode of trade for this variety, independent of its existing variety. This extension will allow us to ask the following question: If a processing trade firm is going to adopt ordinary trade for one variety in the second period, is it more likely to be the existing (old) variety or the new variety? In the case of choosing the new variety for ordinary export, we refer to this as the product-learning effect.

Second, multiple markets. We assume that instead of having only one foreign market, there are two foreign markets with different fixed costs of exports, f^O_{X1} and f^O_{X2} for ordinary trade, and f^P_{X1} and f^P_{X2} for processing trade. Based on the analysis of the single-foreign-market model, we can generate the following equilibrium outcome in this extended model: In the first period, a firm chooses processing export on foreign market 1 but no export to foreign market 2. If technology-learning and market-learning effects are strong, the firm may start ordinary export on foreign market 2 in the second period. We refer to this as the new-market effect.

Third, spillovers. In the main model, some firms become pure domestic firms, i.e., no exporting, because their productivity levels are low and cannot jump over the high fixed cost of export. When neighboring firms are doing processing trade in the first period, a pure domestic firm may also learn the technology as well as the foreign market information. We refer to this as the spillover effect. Similar effects have been identified and confirmed using various countries' data although they are referring to more general spillovers from exporters to non-exporters, rather than the specific effect from processing exporters to non-exporters in our setting. In terms of modelling, we can assume that once a non-exporter (z) has a neighboring firm that does processing trade in the first period, its productivity in the second period becomes $s_0\theta_z$, where $s_0 > 1$, and the fixed cost of ordinary export it faces becomes $v_0 f^O_X$, where $v_0 < 1$. When the spillover effect is sufficiently strong (s_0 large and v_0 small), the firm will choose ordinary trade in the second period.

Our main model and all the extensions enable us to generate predictions about the increased ordinary trade in China, due to the positive effects of processing trade but through different channels. Our empirical study investigates the existence of the positive effects and identify the valid channels using Chinese data.

3 Empirical Analysis

3.1 Data

In this study we need detailed information of Chinese firms' export (the mode, product and destinations, etc.) and other characteristics. We obtain the information from two data sets. One is the

Chinese Customs Data, maintained by the China's General Administration of Customs. The other is the survey of Above Scale Industrial Firms (ASIF) for 1998-2007 (different English names have been adopted by various researchers), maintained by the National Bureau of Statistics of China (NBS).

First, the Customs data provides transaction-level information of import and export. In particular, it provides detailed information about the product (at HS 8-digit level), origin of import, destination of export, quantity, value, and trade types of exports. Trade types include ordinary trade, processing trade with assembly, and processing trade with imported inputs and assembly as the three main types (modes), which together account for most of the exports (e.g., they account for more than 95% of China's exports in terms of value during 2000-2006 (Brandt and Morrow (2017)). The data also records the name of each exporter. We will make particular use of the data on export of each product to each (foreign) market in each year by each firm (i.e., the firm-product-destination-year data). Moreover, we will identify whether the export is carried out in the form of ordinary or processing trade.

Second, the ASIF survey data covers all state-owned enterprises (SOEs) and large-scale (five million yuan Renminbi, or around US$600,000) non-SOE, in mining, manufacturing, and utilities industries. The number of firms in this data set varies from over 140,000 in the late 1990s to over 336,000 in 2007. The firms are from all 31 provinces and directly-controlled municipalities in China. They are from all manufacturing industries. The dataset provides detailed information of each firm, including official name, age, industry, location and ownership. It also contains most of the operation and performance items of each firm, based on the firm's accounting statements, such as employment, capital, intermediate inputs, research and development (R&D) expenditure, and new product sales. We will clean the ASIF data following the approach taken by Brandt et al. (2014), Yu (2015) and others.

Merging the above-mentioned data sets is not an easy task because there is no (or not available to us) common firm identifier for the two data sets. As such, our strategy is to design an algorithm to match them using the following information: firm name, zip code and telephone number. We can compare our matching results to those obtained by other researchers (e.g., Brandt et al., 2014; Yu, 2015; Manova and Yu, 2016; Liu and Qiu; 2016). As this study's emphasis is on the mode of trade in a dynamic setting, the data required is different from those used in the aforementioned studies. The data is sufficiently rich so that we can test our hypotheses. In particular, it contains import and export data by product, by destination, by trade mode (ordinary or processing trade). It also contains the firms' financial information, industry, and location. The data cover nine years.

We provide some descriptive statistics based on the merged dataset, in Table 2, paying special attention to firms' export mode and performance such as total factor productivity (TFP). Based on a small sample of the data, which we have now, we have found that before doing processing trade, processing trade firms are generally larger (in terms of employment, capital, and output) and more productive than other firms. We have also found some correlations between earlier years' processing trade and later years' ordinary trade, as described in Table 1, Figure 1, and Figure 2 before.

<Table 2 Here>

3.2 Empirical Model and Analysis

3.3 Baseline Model

We propose the following benchmark firm-level specification:

$$OExp_{ft} = \alpha + \beta PExp_{ft-1} + \mathbf{X}'_{ft}\gamma + \lambda_f + \lambda_t + \epsilon_{fit}, \tag{1}$$

where $OExp_{ft}$ is the ordinary export of firm f in year t and $PExp_{ft-1}$ is the processing export of firm f in year $t-1$. $OExp_{ft}$ is the ordinary trade indicator, which equals 1 if the firm has ordinary export in year t and 0 otherwise. $PExp_{ft-1}$ is the processing trade indicator, which equals 1 if the firm has any processing export in $t-1$ and 0 otherwise. $\mathbf{X}_{ft}$ is a series of time-varying control variables including firm age (in logarithm) for life-cycle consideration, firm size measured with labor employment (in logarithm), capital-labor ratio, and the share-holding by various stakeholders such as foreign investors, Hong Kong/Macao/Taiwan investors, and the government. We control for the firm (λ_f) and the year (λ_t) fixed effects. We cluster the standard errors at the firm level to deal with the potential heteroskedasticity and serial autocorrelation. We are interested in coefficient β, which captures the general impact of a firm's past processing export participation on its current ordinary export participation. We run linear probability (Probit) model or Logit model to estimate β.

Our firm-level regression results are reported in Table 3, which show that firms' ordinary exports benefit from their past participation in processing exports.

<Table 3 Here>

3.4 Robustness

Since in the data a firm may produce multiple products and export to multiple countries, the above estimation of model (1) only shows a general correlation between a firm's last year's processing export participation and this year's ordinary export participation. The result does not enable us to claim the validity of any prediction from the theoretical analysis section. We conduct a series of analyses to test those predictions, identify the channels, and check the robustness of the results.

We first consider whether the above finding is robust to other relevant factors that may affect Chinese firms' ordinary exporting, including tariffs (input tariff, output tariff, export tariff faced by Chinese firms), the presence of SOEs and FIEs in each industry, the degree of competition in each industry (HHI), and the degree of agglomeration in each industry (EG index). Second, in China, processing trade is classified into two types, that is, pure assembly processing trade (PTPA) and import-and-assembly processing trade (PTIA). We check whether different types of processing trade generates different impacts on ordinary trade.

The results are reported in Table 4, which show that our finding is robust to all these considerations.

<Table 4 Here>

3.5 Market-Learning Model

We can check the market-learning channel with the following firm-country level regression:

$$OExp_{fct} = \alpha + \beta PExp_{fct-1} + \mathbf{X}'_{ft}\gamma + \lambda_f + \lambda_t + \epsilon_{fit}, \tag{2}$$

where Exp_{fct} is firm f's ordinary exports to country c in year t and where $PExp_{fct-1}$ is firm f's processing exports to country c in year $t-1$. The analysis will enable us to see if processing export to a market will lead to ordinary export to the same market in the following year. We can also replace the dependent variable by Exp_{fc} which is firm f's ordinary exports to a country other than c in year t. This analysis enables us to see if there is cross-market learning effect.

The results are reported in columns (1)–(2) of Table 5. We find that *past processing export participation increases the ordinary exports of a firm to the same destination country of the processing export; decreases the exports to other countries.*

<Table 5 Here>

3.6 Product-Learning Model

We check the product specific technology-learning channel with the following firm-product level regression:

$$OExp_{fit} = \beta PExp_{fit-1} + \mathbf{X'}_{ft}\gamma + \lambda_f + \lambda_t + \varepsilon_{fit}, \tag{3}$$

where $OExp_{fit}$ is the ordinary exports of firm f with regard to product i (HS 6-digit level) in year t, $PExp_{fit-1}$ is the processing export indicator of firm f in product i (HS 6-digit level) in year $t-1$. Here we check the impact of $PExp_{fit-1}$ on the ordinary exporting behavior of firm f in three types of products: (1) on the same HS 6-digit product i; (2) on products related to i, called *related products*, i.e., products with different HS 6-digit code of i but with common HS 4-digit category; and (3) on other products unrelated to i, called *other unrelated products*, i.e., products belonging to different HS 4-digit category of product i.

The results are reported in columns (3)–(5) of Table 5. We find that *past processing export participation increases the ordinary exports of a firm in the same HS 6-digit product and the related products; decreases the exports of other unrelated products.*

3.7 Firm-Market-Product Model

Finally, we conduct the most disaggregated level analysis based on firm-country-product level data as below:

$$OExp_{fcit} = \beta PExp_{fcit-1} + \mathbf{X'}_{ft}\gamma + \lambda_f + \lambda_t + \varepsilon_{fit}, \tag{4}$$

where $PExp_{fcit-1}$ is the processing export indicator of firm f to destination country c in product i (HS 6-digit level) in year $t-1$. $OExp_{fcit}$ is the ordinary export performance of firm f, in product i in destination country c in year t. We consider six dimensions of ordinary exports, combining the market-linkage and the product-linkage channels: (1) exports of firm f in the same destination c of the same product i, denoted as *SameCSameP Exports*; (2) exports of firm f in product i in destinations other than c, denoted as *OtherCSameP Exports*; (3) exports of firm f in destination country c in related products, denoted as *SameCRelatedP Exports*; (4) exports of firm f in related products in destinations other than c, denoted as *OtherCRelatedP Exports*; (5) exports of firm f in destination country c in other unrelated products, denoted as *SameCOtherP Exports*; and (6) exports of firm f in other destinations in other products, called *OtherCOtherP Exports*.

The results are reported in Table 6. We find that *past processing export participation increases the ordinary exports of a firm in the same HS 6-digit product and the related products to all (the same and other) countries; decreases the exports of other unrelated products to all countries.*

<Table 6 Here>

3.8 Differentiated Impacts

Based on the firm-country-product specification, we further consider heterogeneities in the processing trade in country, product, and firm dimensions, respectively.

□ **Processing export destinations.** In the country dimension, we check the role of the processing export destination, that is, whether the processing export destination is an OECD country or not. Generally, OECD countries are developed countries with better technology, therefore there may be more technology or knowledge transfer to the Chinese processing firms. On the other hand, however, OECD countries generally have stringent intellectual property rights (IPRs) protection and thus may deter Chinese firms from learning the technology and conducting ordinary trade. To check these possibilities, we run regression (4) by further including an interaction term between processing export indicator and OECD dummy indicating whether the processing export destination is an OECD country or not. We also run regression (4) for two subsamples: processing export to OECD countries, and processing export to non-OECD countries. The results are reported in Table 7. We find that *relative to with non-OECD countries, processing trade with OECD countries decreases ordinary export to other countries, increases ordinary export to the same country, whatever the product is.*

<Table 7 Here>

□ **Product heterogeneities.** Chinese firms process different products for foreign firms and thus may benefit from the processing activities differently. We consider two types of product heterogeneities. The first is whether the product is a consumption good, an intermediate good, or a capital good, according to the classification of the Broad Economic Categories (BEC) published by the United

Nations Statistics Division. We run regression (4) for these three subsamples of processing products. The second is whether a product is a differentiated product or a homogenous good, following the classification of Rauch (1999), and we similarly run regressions for these two subsamples. We report the results in Tables 8 and 9, respectively.

Not very clear for BEC classification. (Relative to consumption goods, processing trade in intermediate and capital goods decreases ordinary export to the same country in related products, increases ordinary export to other countries in unrelated products.)

Relative to homogenous goods, processing differentiated goods brings even more benefits for the same and related products ordinary exports, but further worsen the ordinary export of other unrelated products.

<Tables 8 and 9 Here>

□ **Firm ownership.** One prominent feature of Chinese firms is that they are classified into different categories according to their ownership structures, that is, state-owned enterprises (SOEs), private firms, and foreign-invested enterprises (FIEs). These firms have very different governance and thus incentive of learning. We run regression (4) for these three subsamples of firms and report the results in Table 10.

Compared with SOEs, processing trade by FIEs has no impact on ordinary exports, processing trade by private firms has positive impact on ordinary exports to the same country.

<Table 10 Here>

3.9 Summary

In sum, the basic empirical findings are: learn to produce the same and related products, whatever the destination is (seems that firms focus on the same and related products after learning from processing trade, but move away from other products (maybe due to capacity constraints)); there are some heterogeneities.

<Table 11>

3.10 Causality: IV Estimation

We check two potential IVs for processing export. One is the export processing zones (EPZs) policy in China. The other is the spillover effect of processing exports.

□ **Export Processing Zones (EPZs)**. During 2000-2005 the Chinese government set up export processing zones (EPZs) in some cities to promote processing export. Each EPZ focuses on several specific industries. We codify this policy and define an indicator EPZ_{rit} which equals one for city r industry i if the city is designated as an EPZ covering industry i in any year before t, otherwise EPZ_{rit} equals zero. This policy is likely to affect processing export but not ordinary export directly. We then use EPZ_{rit} as an IV for processing exports in the 2SLS firm-country-product regressions. We do find that EPZs promote processing exports in the first stage results. The instrumented estimation results in the second stage confirm that processing exports promote ordinary exports (but insignificant), as shown in Table 12.

<Table 12 Here>

□ **Spillover effect of processing exports.** We find that firms benefit in their processing exports, but not in ordinary exports, from the presence of other firms' processing exports in the same city-industry cluster. That is, there is spillover effect of processing exports on processing exports, but not on ordinary exports. Thus we can try the presence of processing exports in a city-industry as an IV for processing exports. We construct the presence of processing exports $PTInd_{rit}$ for city r industry i year t following the method in the FDI spillover literature, with labor size as the weight, as below :

$$PTInd_{rit} = \frac{\sum_{f\in\Omega} \frac{PExp_{frit}}{Sales_{frit}} \cdot Labor_{frit}}{\sum_{f\in\Omega} Labor_{frit}}.$$

We get similar results when we use total assets of firms as the weight, as shown in Table 10.

3.11 Mechanisms and Alternative Explanations

Why does processing export participation bring such impact on ordinary exports? Any direct evidence for the mechanisms? We test some possibilities here.

□ **Productivity**. We find that processing export participation improves firms' productivity.

□ **Export price.** We find that processing export participation improves product price of ordinary exports.

$$OPrice_{fcit} = \beta PExp_{fcit-1} + \mathbf{X}'_{ft}\boldsymbol{\gamma} + \lambda_f + \lambda_t + \varepsilon_{fit}$$

where $OPrice_{fcit}$ is the price of ordinary exporting of firm f in product i in destination country c in year t.

<Table 13 Here>

□ **Industrial heterogeneities.** We consider industrial capital-intensity, R&D intensity, and industrial competition degrees (HHI) with the following regressions:

$$OExp_{fcit} = \beta PExp_{fcit-1} + \beta PExp_{fcit-1} \cdot Ind_i + \mathbf{X}'_{ft}\boldsymbol{\gamma} + \lambda_f + \lambda_t + \varepsilon_{fit}$$

where Ind_i is an industrial index. We are interested in the interaction term.

Processing trade in capital-intensive industries, R&D intensive industries, and concentrated industries (high HHI) decreases ordinary exports to the same country, but increases ordinary exports to other countries, whatever the product is.

<Table 14 Here>

□ **Financial constraints.**

Does Chinese firms just earn money from processing trade and then break the financial constraints to conduct ordinary trade, thus stronger impact in the financially constrained industries? Or on the contrary, financial constraints just dampen the learning effect, thus weaker impact in the financially constrained industries?

We use several indices to measure industrial financial constraints: asset tangibility, liquidity, and leverage ratio. No clear pattern emerges from the results.

<Table 15 Here>

4 Conclusions

To be included.

5 References

To be included.

Figure 1. Shares of processing and ordinary export in China's total export

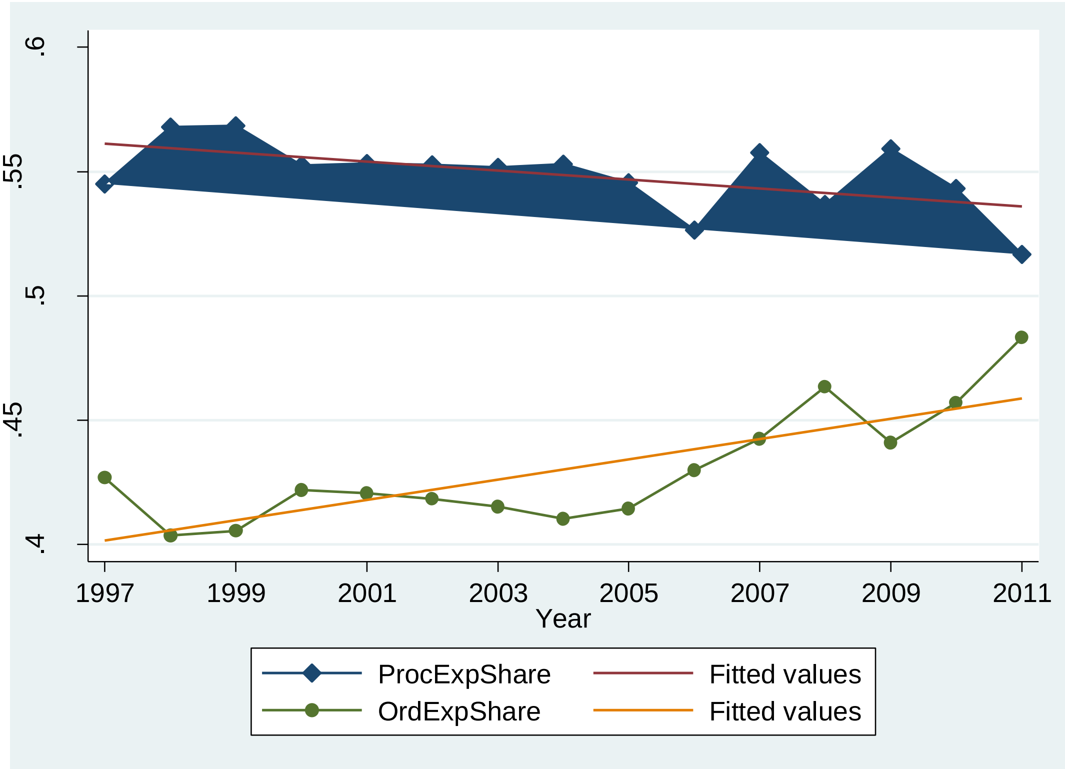

Figure 2. HS 6-digit product export: Correlation between processing export in 2000 and ordinary export in 2006

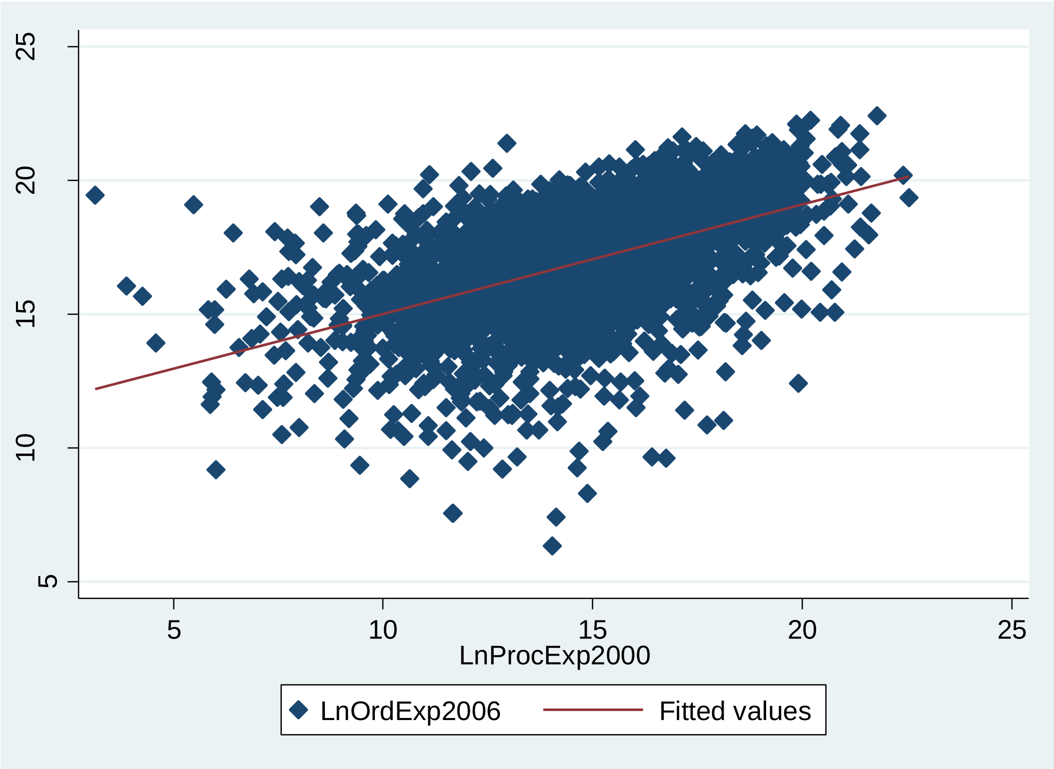

Table 1. Likelihood of processing exporting (PT) and ordinary exporting (OT).

	Exporting status at t					
	PT=0&OT=0	PT=1&OT=0	PT=0&OT=1	PT=1&OT=1	OT=1	PT=1
Exporting status at t-1	(1)	(2)	(3)	(4)	(5)=(3)+(4)	(6)=(2)+(4)
PT=0&OT=0	95.50%	0.39%	3.27%	0.84%	4.11%	1.23%
PT=1&OT=0	12.09%	73.80%	0.90%	13.20%	14.10%	87.01%
PT=0&OT=1	18.25%	0.15%	75.60%	6.01%	81.60%	6.15%
PT=1&OT=1	9.70%	3.96%	9.48%	76.86%	86.34%	80.82%

Table 2. Descriptive Statistics

EXP	Freq.	Percent	Cum.
PT=0&OT=0	1,127,590	83.19%	83.19
PT=1&OT=0	33,755	2.49%	94.50
PT=0&OT=1	119,502	8.82%	92.01
PT=1&OT=1	74,595	5.50%	100
Total	1,355,442	100.00%	

Table 3. Basic results

VARIABLES	(1) ln(Ordinary exports)	(2) ln(Ordinary exports)	(3) ln(Ordinary exports)	(4) ln(Ordinary exports)	(5) Ordinary export dummy	(6) Ordinary export dummy
Processing export dummy = L,	0.6357***	0.6162***			0.0479***	
	(0.0552)	(0.0551)			(0.0042)	
ln(Processing exports) = L,			0.0461***	0.0443***		0.0034***
			(0.0041)	(0.0041)		(0.0003)
lnAge		0.1230***		0.1227***	0.0087***	0.0087***
		(0.0175)		(0.0175)	(0.0013)	(0.0013)
lnLabor		0.5198***		0.5187***	0.0366***	0.0365***
		(0.0185)		(0.0185)	(0.0014)	(0.0014)
CapitalIntensity		0.0960***		0.0959***	0.0074***	0.0074***
		(0.0086)		(0.0086)	(0.0006)	(0.0006)
Foreign share		0.4518***		0.4511***	0.0330***	0.0330***
		(0.0623)		(0.0623)	(0.0049)	(0.0049)
State Share		0.1623***		0.1622***	0.0125***	0.0125***
		(0.0414)		(0.0414)	(0.0031)	(0.0031)
Constant	2.3882***	-0.8186***	2.3867***	-0.8135***	-0.0484***	-0.0480***
	(0.0104)	(0.1129)	(0.0105)	(0.1129)	(0.0086)	(0.0085)
Observations	884,669	877,720	884,669	877,720	877,720	877,720
R-squared	0.8056	0.8075	0.8056	0.8075	0.8018	0.8018

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Robustness checks

VARIABLES	(1) ln(Ordinary exports)	(2) ln(Ordinary exports)	(3) ln(Ordinary exports)	(4) ln(Ordinary exports)	(5) ln(Ordinary exports)	(6) ln(Ordinary exports)
Processing export dummy = L,	0.6053***	0.6007***	0.6004***	0.6005***	0.6005***	
	(0.0582)	(0.0588)	(0.0588)	(0.0588)	(0.0588)	
PTPA = L,						0.2154**
						(0.0910)
PTIA = L,						0.5737***
						(0.0604)
lnAge	0.1152***	0.1181***	0.1130***	0.1125***	0.1125***	0.1125***
	(0.0184)	(0.0186)	(0.0186)	(0.0186)	(0.0186)	(0.0186)
lnLabor	0.5142***	0.5180***	0.5157***	0.5153***	0.5153***	0.5153***
	(0.0194)	(0.0197)	(0.0197)	(0.0197)	(0.0197)	(0.0197)
CapitalIntensity	0.0958***	0.0962***	0.0963***	0.0963***	0.0963***	0.0962***
	(0.0090)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
Foreign share	0.4369***	0.4413***	0.4406***	0.4407***	0.4407***	0.4396***
	(0.0656)	(0.0665)	(0.0665)	(0.0665)	(0.0665)	(0.0665)
State Share	0.1734***	0.1747***	0.1615***	0.1609***	0.1608***	0.1609***
	(0.0427)	(0.0432)	(0.0432)	(0.0432)	(0.0432)	(0.0432)
Input Tariff	1.4465**	1.4620**	0.8025	0.7299	0.7220	0.7139
	(0.5796)	(0.5835)	(0.5973)	(0.5985)	(0.5989)	(0.5991)
Output Tariff	-0.3962*	-0.4562**	-0.3262	-0.3326	-0.3252	-0.3257
	(0.2170)	(0.2231)	(0.2235)	(0.2236)	(0.2247)	(0.2247)
Export Tariff		0.0748	-0.0145	-0.0773	-0.0749	-0.0823
		(0.5364)	(0.5424)	(0.5427)	(0.5428)	(0.5431)
SOE share			1.0194***	1.0306***	1.0209***	1.0284***
			(0.1625)	(0.1629)	(0.1631)	(0.1631)
FIE share			0.4102**	0.4325**	0.4406**	0.4413**
			(0.1732)	(0.1741)	(0.1755)	(0.1756)
HHI				-0.0256*	-0.0250*	-0.0251*
				(0.0144)	(0.0144)	(0.0144)
EG					-0.1154	-0.1192
					(0.2781)	(0.2782)
Constant	-0.8420***	-0.9436*	-0.9189	-0.9875*	-0.9807*	-0.9686*
	(0.1264)	(0.5605)	(0.5623)	(0.5646)	(0.5645)	(0.5648)
Observations	795,515	784,486	784,486	784,486	784,486	784,486
R-squared	0.8112	0.8119	0.8119	0.8119	0.8119	0.8119

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Market linkage or product linkage

VARIABLES	(1) ln(SameC exports)	(2) ln(OtherC exports)	(3) ln(SameP exports)	(4) ln(RelatedP exports)	(5) ln(OtherP exports)
LPT	0.6767***	-0.0978***	0.6755***	0.5266***	-0.2910***
	(0.0106)	(0.0100)	(0.0138)	(0.0174)	(0.0112)
lnAge	0.0572***	0.1319***	0.0488***	0.0390***	0.1025***
	(0.0090)	(0.0152)	(0.0078)	(0.0091)	(0.0125)
lnLabor	0.1731***	0.4260***	0.1510***	0.1274***	0.3776***
	(0.0089)	(0.0132)	(0.0081)	(0.0092)	(0.0149)
CapitalIntensity	0.0381***	0.0651***	0.0371***	0.0190***	0.0586***
	(0.0047)	(0.0067)	(0.0043)	(0.0048)	(0.0066)
Foreign share	0.0812***	0.1136***	0.0660***	0.0378*	0.0574*
	(0.0189)	(0.0320)	(0.0189)	(0.0216)	(0.0347)
State Share	0.0628**	0.1142***	0.0217	-0.0140	0.0375
	(0.0286)	(0.0404)	(0.0240)	(0.0277)	(0.0374)
Input Tariff	0.8760***	1.8651***	0.4054	-0.3417	1.5263***
	(0.3258)	(0.4754)	(0.2682)	(0.2714)	(0.4555)
Output Tariff	0.1152	-0.2264	0.0097	-0.1182	-0.4976***
	(0.1218)	(0.1888)	(0.1039)	(0.1077)	(0.1748)
Export Tariff	-0.1241	-0.0625	-0.2075	-0.3935	-0.1598
	(0.2516)	(0.3612)	(0.2126)	(0.2422)	(0.3623)
SOE share	0.2592***	0.5094***	0.2849***	0.4626***	0.6177***
	(0.0822)	(0.1267)	(0.0714)	(0.0758)	(0.1264)
FIE share	-0.0877	-0.0158	0.1310**	0.1777**	0.3262***
	(0.0757)	(0.1164)	(0.0662)	(0.0735)	(0.1221)
HHI	-0.0126*	-0.0097	-0.0255***	-0.0298***	-0.0193*
	(0.0071)	(0.0099)	(0.0067)	(0.0079)	(0.0112)
EG	0.0138	-0.1144	0.0372	-0.0221	-0.1845
	(0.1099)	(0.1574)	(0.0980)	(0.1070)	(0.2007)
Constant	1.5138***	2.2192***	1.2480***	0.9262***	1.9214***
	(0.2643)	(0.3811)	(0.2195)	(0.2489)	(0.3719)
Observations	2,562,412	2,562,412	2,297,116	2,297,116	2,297,116
R-squared	0.7315	0.9198	0.6532	0.4546	0.9085

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Market and product linkage: firm-country-product level analyses

VARIABLES	(1) ln(SameCSameP Exports)	(2) ln(OtherCSameP Exports)	(3) ln(SameCRelatedP Exports)	(4) ln(OtherCRelatedP Exports)	(5) ln(SameCOtherP Exports)	(6) ln(OtherCOtherP Exports)
LPT	0.3052***	0.5141***	0.2893***	0.1809***	-0.1873***	-0.3776***
	(0.0134)	(0.0199)	(0.0138)	(0.0214)	(0.0156)	(0.0124)
lnAge	-0.0089	0.0643**	-0.0108	0.0771**	0.0957***	0.2322***
	(0.0159)	(0.0275)	(0.0157)	(0.0300)	(0.0281)	(0.0400)
lnLabor	0.0330***	0.2218***	0.0957***	0.2353***	0.2676***	0.4759***
	(0.0112)	(0.0224)	(0.0136)	(0.0255)	(0.0219)	(0.0318)
CapitalIntensity	-0.0065	0.0123	0.0062	0.0268*	0.0470***	0.0654***
	(0.0073)	(0.0129)	(0.0083)	(0.0154)	(0.0126)	(0.0181)
Foreign share	0.0218	0.0102	0.0275	-0.0086	0.0281	0.0027
	(0.0171)	(0.0324)	(0.0173)	(0.0320)	(0.0287)	(0.0426)
State Share	0.0051	-0.0479	-0.0183	-0.0796	-0.0117	0.0014
	(0.0500)	(0.0772)	(0.0548)	(0.0862)	(0.0773)	(0.0948)
Input Tariff	0.8736**	0.4641	0.5884	-0.2984	1.7426**	-0.1148
	(0.4364)	(0.7698)	(0.4645)	(0.9018)	(0.7805)	(1.0503)
Output Tariff	0.1292	0.1693	0.0748	-0.2420	-0.0797	0.0733
	(0.1627)	(0.3042)	(0.1669)	(0.3419)	(0.2789)	(0.4123)
Export Tariff	-0.2311	-0.4192	-0.1042	0.5003	-0.5402	-0.5468
	(0.2700)	(0.4561)	(0.2724)	(0.5248)	(0.4843)	(0.6260)
SOE share	0.1459	-0.1531	0.2208**	0.4755**	0.0553	0.4569*
	(0.1083)	(0.1980)	(0.1079)	(0.2240)	(0.1779)	(0.2605)
FIE share	-0.2064***	0.1008	-0.0420	0.1020	0.0502	0.2205
	(0.0799)	(0.1413)	(0.0763)	(0.1542)	(0.1453)	(0.1888)
HHI	-0.0257***	-0.0356**	-0.0126	-0.0131	-0.0032	-0.0258
	(0.0089)	(0.0147)	(0.0090)	(0.0177)	(0.0155)	(0.0213)
EG	0.0342	-0.0039	0.1974	0.4125	0.2436	0.1058
	(0.1109)	(0.2270)	(0.1302)	(0.2544)	(0.2329)	(0.3237)
Constant	3.4708***	3.7219***	0.9381***	1.0829*	2.4627***	3.9724***
	(0.2870)	(0.5067)	(0.3057)	(0.5677)	(0.5137)	(0.6611)
Observations	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638
R-squared	0.5085	0.5414	0.2965	0.5044	0.5449	0.8633

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Processing export destination: OECD or not

	OECD Destinations					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3941***	0.6323***	0.3465***	0.2442***	-0.2745***	-0.3940***
	(0.0148)	(0.0209)	(0.0166)	(0.0207)	(0.0172)	(0.0139)
Observations	2,330,641	2,330,641	2,330,641	2,330,641	2,330,641	2,330,641
R-squared	0.4999	0.5342	0.3183	0.4932	0.5989	0.8638

	non-OECD Destinations					
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.1569***	0.4465***	0.1288***	0.1435***	-0.2051***	-0.2894***
	(0.0159)	(0.0247)	(0.0141)	(0.0284)	(0.0181)	(0.0143)
Observations	1,748,992	1,748,992	1,748,992	1,748,992	1,748,992	1,748,992
R-squared	0.5617	0.5919	0.3237	0.5435	0.5688	0.8792

				Interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.1209***	0.5684***	0.1149***	0.1918***	-0.3939***	-0.3333***
	(0.0148)	(0.0235)	(0.0128)	(0.0264)	(0.0215)	(0.0142)
LPTOECD	0.2995***	-0.0882***	0.2834***	-0.0178	0.3356***	-0.0719***
	(0.0133)	(0.0140)	(0.0142)	(0.0150)	(0.0225)	(0.0114)
Observations	4,079,633	4,079,633	4,079,633	4,079,633	4,079,633	4,079,633
R-squared	0.5089	0.5414	0.2969	0.5044	0.5451	0.8633

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Product heterogeneity: BEC

	Consumption goods					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3525***	0.1807***	0.4260***	-0.0200	0.1812***	-0.3604***
	(0.0154)	(0.0207)	(0.0191)	(0.0216)	(0.0160)	(0.0142)
Observations	1,653,258	1,653,258	1,653,258	1,653,258	1,653,258	1,653,258
R-squared	0.5683	0.6278	0.3499	0.5816	0.6255	0.8778
	Intermediate goods					
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3864***	0.6160***	0.1132***	0.0698***	-0.1800***	-0.3243***
	(0.0200)	(0.0270)	(0.0140)	(0.0226)	(0.0191)	(0.0155)
Observations	1,899,600	1,899,600	1,899,600	1,899,600	1,899,600	1,899,600
R-squared	0.4983	0.5523	0.2926	0.5480	0.5382	0.8630
	Capital goods					
	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.1598***	0.2203***	0.2305***	0.1304***	-0.0261	-0.1880***
	(0.0297)	(0.0416)	(0.0287)	(0.0448)	(0.0329)	(0.0345)
Observations	539,446	539,446	539,446	539,446	539,446	539,446
R-squared	0.5931	0.6909	0.3520	0.6293	0.5853	0.9058

VARIABLES	(1) ln(SameCSameP Exports)	(2) ln(OtherCSameP Exports)	(3) ln(SameCRelatedP Exports)	(4) ln(OtherCRelatedP Exports)	(5) ln(SameCOtherP Exports)	(6) ln(OtherCOtherP Exports)
LPT	0.3237***	0.4344***	0.4509***	0.2410***	-0.1200***	-0.4316***
	(0.0177)	(0.0277)	(0.0221)	(0.0349)	(0.0211)	(0.0147)
LPTINTCAP	-0.0360	0.1556***	-0.3156***	-0.1174***	-0.1316***	0.1054***
	(0.0231)	(0.0353)	(0.0250)	(0.0428)	(0.0279)	(0.0201)
Constant	3.4717***	3.7179***	0.9461***	1.0858*	2.4660***	3.9697***
	(0.2869)	(0.5069)	(0.3048)	(0.5676)	(0.5133)	(0.6611)
Observations	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638
R-squared	0.5085	0.5415	0.2969	0.5045	0.5449	0.8633

VARIABLES	(7) ln(SameCSameP Exports)	(8) ln(OtherCSameP Exports)	(9) ln(SameCRelatedP Exports)	(10) ln(OtherCRelatedP Exports)	(11) ln(SameCOtherP Exports)	(12) ln(OtherCOtherP Exports)
LPT	0.3248***	0.4353***	0.4491***	0.2363***	-0.1182***	-0.4294***
	(0.0177)	(0.0277)	(0.0222)	(0.0350)	(0.0212)	(0.0148)
LPTINT	0.0382	0.1808***	-0.3454***	-0.2365***	-0.0256	0.0874***
	(0.0246)	(0.0367)	(0.0250)	(0.0425)	(0.0274)	(0.0193)
LPTCAP	-0.2154***	0.0904	-0.2171***	0.2116***	-0.3967***	0.1284***
	(0.0348)	(0.0606)	(0.0361)	(0.0716)	(0.0454)	(0.0368)
Constant	3.4515***	3.7012***	0.9452***	1.0889*	2.4468***	3.9503***
	(0.2875)	(0.5064)	(0.3048)	(0.5665)	(0.5145)	(0.6611)
Observations	4,075,461	4,075,461	4,075,461	4,075,461	4,075,461	4,075,461
R-squared	0.5082	0.5415	0.2968	0.5048	0.5447	0.8633

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Product heterogeneity: Differentiated or homogenous

	Differentiated goods					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3102***	0.4437***	0.3078***	0.1682***	-0.1314***	-0.3539***
	(0.0137)	(0.0202)	(0.0148)	(0.0226)	(0.0162)	(0.0130)
Observations	3,444,666	3,444,666	3,444,666	3,444,666	3,444,666	3,444,666
R-squared	0.5174	0.5670	0.3126	0.5255	0.5695	0.8726
	Homogenous goods					
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3066***	0.2924***	0.1083***	-0.1788***	0.1540***	-0.3294***
	(0.0489)	(0.0564)	(0.0387)	(0.0519)	(0.0375)	(0.0317)
Observations	456,490	456,490	456,490	456,490	456,490	456,490
R-squared	0.4996	0.6003	0.3092	0.6149	0.5237	0.8483

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.2078***	0.4015***	0.0831**	-0.2213***	-0.0060	-0.3802***
	(0.0489)	(0.0629)	(0.0391)	(0.0632)	(0.0399)	(0.0322)
LPTDIFF	0.1041**	0.1010	0.2337***	0.4352***	-0.1764***	0.0071
	(0.0497)	(0.0650)	(0.0417)	(0.0678)	(0.0419)	(0.0335)
Observations	3,901,156	3,901,156	3,901,156	3,901,156	3,901,156	3,901,156
R-squared	0.5119	0.5480	0.3002	0.5128	0.5484	0.8649

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10. Firm ownership

			SOE			
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	-0.0291	0.6533*	0.1729	0.1918	-0.1278	-0.3210***
	(0.2097)	(0.3638)	(0.1533)	(0.2207)	(0.1414)	(0.0949)
Observations	108,920	108,920	108,920	108,920	108,920	108,920
R-squared	0.2868	0.3930	0.2130	0.4298	0.4625	0.8627
			PRIVATE			
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.5587***	0.8412***	0.4886***	0.2323***	-0.0614	-0.4335***
	(0.0526)	(0.0566)	(0.0613)	(0.0629)	(0.0491)	(0.0284)
Observations	1,259,013	1,259,013	1,259,013	1,259,013	1,259,013	1,259,013
R-squared	0.2776	0.3882	0.2497	0.4609	0.5049	0.8549
			FIE			
	(13)	(14)	(15)	(16)	(17)	(18)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.2835***	0.4785***	0.2715***	0.1778***	-0.2013***	-0.3750***
	(0.0133)	(0.0207)	(0.0136)	(0.0228)	(0.0165)	(0.0135)
Observations	2,711,705	2,711,705	2,711,705	2,711,705	2,711,705	2,711,705
R-squared	0.5368	0.5737	0.3222	0.5105	0.5622	0.8563

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.0158	0.7652**	0.2048	0.2728	-0.1168	-0.2205*
	(0.2040)	(0.3437)	(0.1490)	(0.2235)	(0.1482)	(0.1138)
LPTFIE	0.2694	-0.2892	0.0649	-0.0988	-0.0852	-0.1547
	(0.2044)	(0.3442)	(0.1496)	(0.2248)	(0.1491)	(0.1152)
LPTPrivate	0.5153**	0.0651	0.2766*	-0.0411	0.0554	-0.2013*
	(0.2088)	(0.3439)	(0.1572)	(0.2294)	(0.1529)	(0.1163)
Observations	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638	4,079,638
R-squared	0.5086	0.5415	0.2966	0.5044	0.5449	0.8633

Table 11. Summary of results

Destination	Product			
	Same	Related	Other	Overall
Same	+	+	−	+
Other	+	+	−	−
Overall	+	+	−	+

Table 12. Causality: EPZ and industrial processing export presence as IV

VARIABLES	(1) 2nd ln(Ordinary exports)	(2) 2nd ln(Ordinary exports)	(3) 2nd ln(Ordinary exports)	(4) 2nd ln(Ordinary exports)
LPT	0.8088	0.6007***	0.6665***	0.6772***
	(0.6068)	(0.1067)	(0.1173)	(0.1123)
Observations	978,866	978,866	978,866	978,866
R-squared	0.0184	0.0188	0.0187	0.0187
Number of firmid	272,376	272,376	272,376	272,376

VARIABLES	(1) 1st LPT	(2) 1st LPT	(3) 1st LPT	(4) 1st LPT
LEPZ	0.0340***			
	(0.0013)			
LPTlaborind		1.7788***		
		(0.0114)		
LPTtotal_assetind			1.5149***	
			(0.0107)	
LPTsaleind				1.7923***
				(0.0121)
Observations	978,866	978,866	978,866	978,866
Number of firmid	272,376	272,376	272,376	272,376

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13. Firm productivity and product price

VARIABLES	(1) VA PC	(2) TFP_LP	(3) lnOrdPrice
Processing export dummy = L,	0.0475***	0.0395***	0.1055***
	(0.0081)	(0.0083)	(0.0183)
Observations	772,236	733,947	3,090,816
R-squared	0.8266	0.8502	0.5479

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14. Industrial capital-intensity, R&D intensity, and industrial competition degrees

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.8705***	0.3070**	1.0005***	-0.1657	0.7507***	-0.5658***
	(0.0838)	(0.1196)	(0.0734)	(0.1054)	(0.0918)	(0.0793)
LPT*K/L	-0.1504***	0.0551*	-0.1892***	0.0922***	-0.2496***	0.0501**
	(0.0227)	(0.0328)	(0.0190)	(0.0295)	(0.0250)	(0.0216)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5086	0.5414	0.2967	0.5045	0.5450	0.8633
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3165***	0.4758***	0.3072***	0.1193***	-0.1212***	-0.3863***
	(0.0157)	(0.0217)	(0.0174)	(0.0232)	(0.0167)	(0.0135)
LPT*R&D	-13.0834	44.4051***	-20.8241	71.5164***	-76.7891***	10.1887
	(13.6709)	(16.0381)	(12.8408)	(15.5129)	(10.1249)	(8.5402)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5085	0.5414	0.2965	0.5045	0.5450	0.8633
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(SameCSameP Exports)	ln(OtherCSameP Exports)	ln(SameCRelatedP Exports)	ln(OtherCRelatedP Exports)	ln(SameCOtherP Exports)	ln(OtherCOtherP Exports)
LPT	0.3292***	0.5015***	0.3212***	0.1507***	-0.1435***	-0.3974***
	(0.0140)	(0.0204)	(0.0150)	(0.0223)	(0.0165)	(0.0135)
LPT*HHI	-0.8971***	0.4705	-1.1969***	1.1335***	-1.6437***	0.7431***
	(0.2650)	(0.3530)	(0.1972)	(0.4134)	(0.2410)	(0.2465)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5085	0.5414	0.2966	0.5045	0.5449	0.8633

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15. Industrial financial constraints

VARIABLES	(1) ln(SameCSameP Exports)	(2) ln(OtherCSameP Exports)	(3) ln(SameCRelatedP Exports)	(4) ln(OtherCRelatedP Exports)	(5) ln(SameCOtherP Exports)	(6) ln(OtherCOtherP Exports)
LPT	0.0724	0.3549***	0.4105***	0.4862***	-0.4738***	-0.2178***
	(0.0599)	(0.1028)	(0.0735)	(0.1287)	(0.0833)	(0.0684)
LPT*Tangibility	0.5145***	0.3517*	-0.2679*	-0.6747***	0.6329***	-0.3531**
	(0.1270)	(0.2136)	(0.1498)	(0.2580)	(0.1682)	(0.1411)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5086	0.5414	0.2965	0.5045	0.5449	0.8633

VARIABLES	(1) ln(SameCSameP Exports)	(2) ln(OtherCSameP Exports)	(3) ln(SameCRelatedP Exports)	(4) ln(OtherCRelatedP Exports)	(5) ln(SameCOtherP Exports)	(6) ln(OtherCOtherP Exports)
LPT	0.3493***	0.5356***	0.3071***	0.1527***	-0.1204***	-0.4131***
	(0.0170)	(0.0243)	(0.0172)	(0.0242)	(0.0177)	(0.0145)
LPT*Liquidity	-0.7788***	-0.3815	-0.3151*	0.4990**	-1.1836***	0.6278***
	(0.1900)	(0.3043)	(0.1742)	(0.2535)	(0.2362)	(0.2077)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5086	0.5414	0.2965	0.5044	0.5449	0.8633

VARIABLES	(1) ln(SameCSameP Exports)	(2) ln(OtherCSameP Exports)	(3) ln(SameCRelatedP Exports)	(4) ln(OtherCRelatedP Exports)	(5) ln(SameCOtherP Exports)	(6) ln(OtherCOtherP Exports)
LPT	-0.0057	0.2733*	0.2807***	0.5120***	-0.6972***	-0.1035
	(0.1060)	(0.1621)	(0.0992)	(0.1426)	(0.1225)	(0.1087)
LPT*Leverage	0.3415***	0.2644	0.0095	-0.3636**	0.5600***	-0.3010***
	(0.1152)	(0.1736)	(0.1076)	(0.1509)	(0.1294)	(0.1153)
Observations	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639	4,079,639
R-squared	0.5085	0.5414	0.2965	0.5044	0.5449	0.8633

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1