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What has China learned from processing trade?

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Abstract
Processing trade in China has been prevalent, despite rapid economic growth and consequent structural changes. This study examines the role of the processing trade, especially as it relates to exports productivity and export variety. Our model predicts that high productivity of processing exports, which can be characterized by leverage and coverage, may enhance the productivity of the sector. An empirical analysis gives firm support to the model. It also shows a learning effect of processing exports to the productivity of ordinary exports.

Keywords: Processing trade, Foreign enterprise, Chinese economy

1 Introduction

Chinese exports in early 1990s were specialized in labor-intensive products (Lardy 1994), as classical theory would predict. From the 1990s, the utilization of processing trade and special economic zones attracted a vast amount of foreign direct investment (FDI) and reformed export structures. ICT products, such as smartphone or laptop computer, are their representative export products now. This can be explained in the realm of new trade theory, which emphasizes the importance of product differentiation, economies of scale, and firm heterogeneity (Dixit and Norman 1980; Melitz 2003). Factor mobility and economies of scale allow China to produce almost any kind of product in the world. The biggest obstacle to China, faced with the reality of being a leading manufacturing center, is a lack of accumulated technology. FDI and consequent production activity captured by processing trade may enhance overall productivity through technology transfer and knowledge spillover. If there were no experience in the manufacturing of smartphones under provision of foreign companies, for example, China would not be able to have the original brands it has now.

Rodrik (2006) claims that China has achieved a significantly higher level of sophistication compared to other developing economies. This is due to foreign enterprises and processed exports (Xu and Lu 2009). Schott (2008) finds a higher unit value of processing trade than others.

Despite the facilitative effect and the contribution to trade stability (Fernandes and Tang 2015), there is another strand of the literature insisting on the inefficiency of processing trade compared with ordinary trade. Joining firm balance sheet data and trade data, Dai et al. (2016) argue for relatively low total factor productivity (TFP) of processing trade. Manova and Yu (2016) also point out the low profitability of processing trade measured by value added. Koopman et al. (2008) develop a calculating method for foreign shares in exports of China in support of the low profitability of processing trade.

There has been less interest in the external effects of processing trade. The literature emphasizing the low profitability of processing trade often ignores knowledge transfer from foreign enterprises and the positive externalities of processing trade. There has been less attention to the factors of processing export productivity. We will fill these gaps by investigating productivities reflected in the export basket and its interactions.

Before the investigation, we first check the stylized facts about processing trade. And we adopt the model developed by Hausmann et al. (2007), which relies on cost discovery externality. Hausman and Rodrik (2003) claim discovering costs of domestic production activities has great social externality in developing countries.

In our modified setting, entrepreneurs can achieve higher level of productivity on average by using processing trade. As in Hausmann et al. (2007), an entrepreneur can choose between imitation and self-discovery. However, individual productivity accounts into the final output even if he did an imitation. Imitation outputs are varying over individual. Also, individuals can choose another option of processing trade which guarantees a fixed outcome but also entails some uncertainty. The model predicts that overall productivity can be enhanced with processing trade in terms of average. Also, processing trade can affect the future by shifting frontier entrepreneurs' productivity in some cases. The model implies that the high productivity of processing exports may have effects on the productivity of ordinary exports.

This research relates to the literature of processing trade in China since it shares a similar dataset (Schott 2008; Fernandes and Tang 2015; Manova and Yu 2016). Our approach is unique in emphasizing the role of the productivity gap in productivity catch-up. Also, there is another related strand of the literature on export sophistication and economic growth. Though our scope does not include economic growth, the base philosophy that "what a country exports matters (Hausmann et al. 2007)" is the same. In contrast to the majority of this literature, we refine manufacturing down to hundreds of subsectors to analyze the interaction of enterprises.

The remainder of this paper will be organized as follows. Section 2 provides background with a theoretic framework. In Sect. 3, we present the empirical analysis. Concluding remarks may be found in Sect. 4.

2 Background

In this section, we will briefly see the characteristics of processing trade in China and will introduce a theoretic framework for examining the overall effect of processing trade on overall productivity.

2.1 Stylized facts about processing trade

2.1.1 Processing trade and foreign enterprises in China

First, we define "processing trade" by regime of trade. China Customs classifies each type of trade into 19 regimes (or modes) by its nature. There are two important regimes of processing trade: *processing and assembling trade with customer-supplied materials* and *processing trade with imported materials*. In the first case, most processing firms in China hardly manage their profit levels because their only added value, processing fees, is determined by ordering organizations outside of China. As for a firm in the second case, a processing firm can handle their profits by choosing trading partners. Ordinary trade is the opposite concept to processing trade. Table 1 shows a distribution of trade of China by trade regimes and type of enterprises. As shown in Table 1, the three regimes account for about 87% of total trade in 2014. Other regimes will be omitted as we cannot access detailed information about the processing. China Customs also compiles the trade statistics by 8 types of enterprise. In this paper, "foreign enterprise" is defined as all types of enterprise with foreign capital.[1]

Not surprisingly, foreign enterprises conducted about 80% of processing trade in 2014. Wholly owned foreign enterprises are more likely to concentrate on processing trade with imported materials. Privately owned enterprises contribute only 11.1% of processing trade, while their contribution to ordinary trade is 43%. Also, the three regimes mentioned before account for 86.5% of total trade.

Inward foreign direct investment in China is believed to promote manufacturing export performance (Zhang and Felmingham 2001; Long 2005; Zhang 2015). Figure 1 shows a positive relationship between FDI stock and processing export performance.

2.1.2 Role in trade balance, structural characteristics

The share of processing trade in total trade is gradually decreasing due to the emergence of ordinary trade. However, its importance in the balance of trade has been maintained. Figure 2 shows that trade surplus from processing trade overtook the total trade surplus in most of the time. The demand-driven nature of processing trade allows processing firms to take less risk than other firms.

Structurally, processing trade is concentrated on a few products and is different from ordinary trade as depicted in Fig. 3. Over 65% of processing trade falls into the category of "Machinery and transport equipment (SITC 7)," which requires more technology than the others. Also, 19 out of 5200 Harmonized System 6-digit products account for half of total trade, while 171 products take the same share in ordinary trade.

To summarize, most processing trade is related to foreign enterprises and their home countries. The role of processing trade in the balance of trade is substantial, though its composition is highly concentrated on specific sectors and commodities.

2.2 A simple model: Hausmann et al. (2007) revisited

In this section, we bring a simple model modified from Hausmann et al. (2007) in order to see the effects of processing trade on the productivity of the Chinese economy. Following the original model, all production activities can be divided into two sectors: the traditional and the modern sector. In the traditional sector, there is no uncertainty to entrepreneurs, while the entrepreneurs in the modern sector face cost uncertainty. In other words, in the traditional sector, outcomes are homogeneous and individual productivity does not affect to the output. But, in the modern sector, individual productivity

[1] China–foreign contractual joint ventures, China–foreign equity joint ventures, and foreign wholly owned enterprises.

Table 1 Composition of China's trade by trade mode and type of enterprise (2014). ***Source*****: China Customs**

	State owned enterprises	Foreign enterprises		Privately owned enterprises	Other	Total
		China–foreign joint ventures	Wholly owned foreign enterprises			
Ordinary trade	12.5	6.2	9.2	23.1	2.8	53.8
Processing and assembling trade with customer-supplied materials	1.0	0.7	2.0	0.5	0.2	4.4
Processing trade with imported materials	1.1	5.8	17.4	3.2	0.8	28.4
Inbound/outbound goods in bonded warehouses	1.3	0.7	0.3	1.3	0.1	3.6
Storage of transit goods in bonded warehouses	0.9	0.6	2.7	2.7	0.0	6.9
Others	0.6	0.2	0.2	1.9	0.0	3.0
Total	17.4	14.3	31.9	32.6	3.9	100.0

Unit: percent

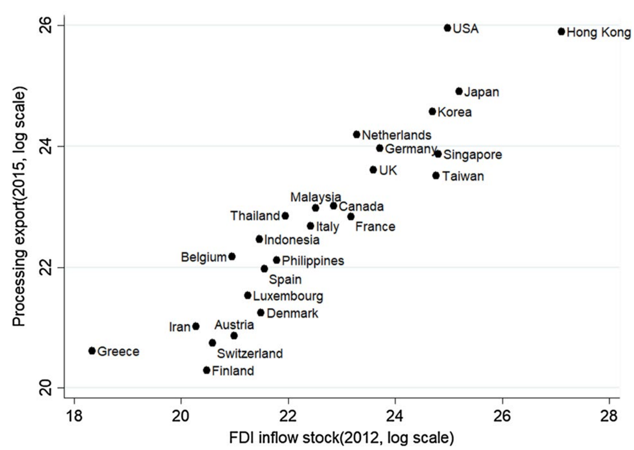

Fig. 1 Relationship between FDI inflow stock and processing exports in log scale. Each dot represents a country. *Source*: UNCTAD, China Customs

matters since there should be some discovery procedure to produce a new good. The traditional sector only work for clearing wage level. Thus, we concentrate on the modern sector.

Let $N = \{1, 2, 3, \ldots\}$ be a (finite or infinite) universe of all potential varieties that a country can produce in the modern sector. Unit price of all goods is same, and each good only can be distinguished by its required productivity of production. A function θ maps each good in N into the closed nonnegative interval $[0, h]$ which called "the

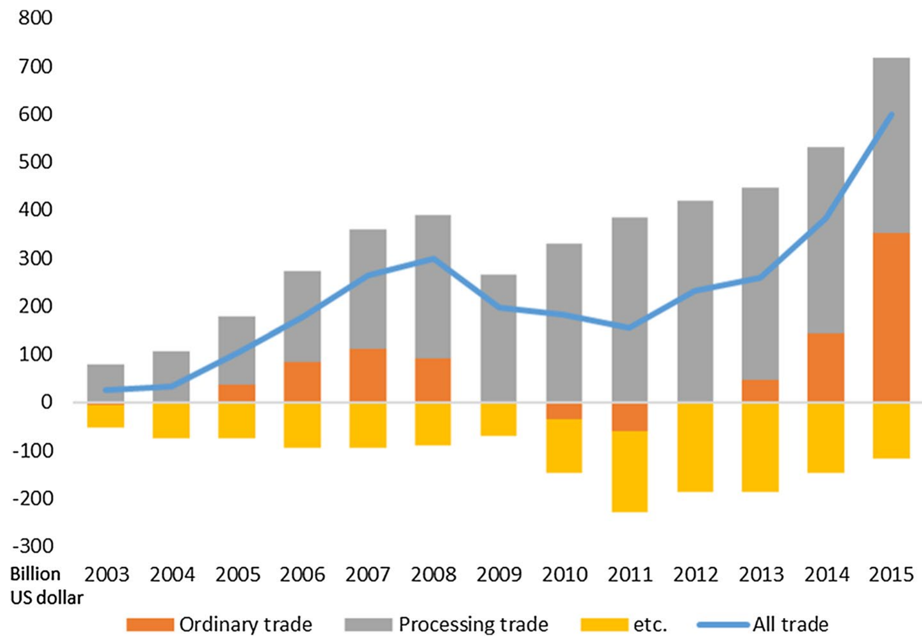

Fig. 2 Trade balance by trade regimes from 2003 to 2015. Orange, gray, and yellow bar represent ordinary, processing, and other trade, respectively. Blue line represents aggregated trade. *Source*: China Customs

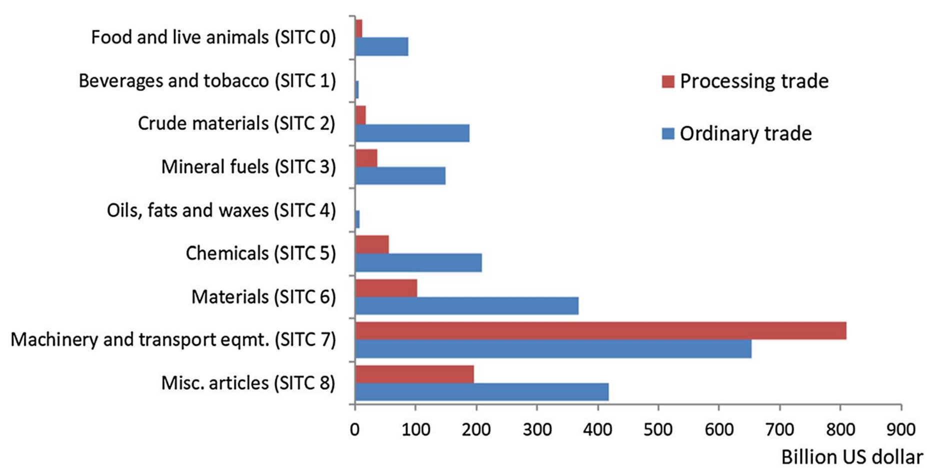

Fig. 3 Composition of processing and ordinary trade by industries in 2015. Blue and red bar represent ordinary and processing trade, respectively. *Source*: China Customs

production space" in Hausmann et al. (2007). h means the upper bound of productivity. The required productivity level for i, denoted by θ_i, can identify good inversely. Thus, θ is injective but not surjective.

Let assume marginal cost for production of good i is given as follows:

$$c_i = \frac{b}{\theta_i} w \tag{1}$$

where $\frac{b}{\theta_i}$ is the number of labor force and w is the wage. Even if there exist two goods, let us say good 1 and good 2, identical to every consumer, they are heterogeneously identified in our model as $\theta_1 \neq \theta_2$. A good only can be produced by entrepreneurs with appropriate productivity. Each entrepreneur (investor) has intrinsic level of productivity but never know before it discovered. Let $M = \{1, 2, \ldots, m\}$ be the finite set of entrepreneurs in a country. They are potential exporters who can be characterized by their productivity. Different from the map θ given as a state-of-nature, a productivity of investor is given by probability distribution. Suppose investor j decided to enter the market. His own (potential) productivity θ_j is revealed soon after his fixed cost sunk. For convenience, we assume the distribution of productivity is uniform in $[0, h]$.

Let assume m_t numbers of entrepreneurs invest to the modern sector at time t. At the time t, their fixed cost sunk and they do not know their available outcomes because they do not know their productivity. At the beginning of time $t + 1$, individual j knows his productivity θ_j. Naturally he will stick with the best project (product) that he can afford. Thus, his output is also identified with his productivity. Without loss of generality, exit cases of investors are ruled out in our model.

We will distinguish $\hat{\theta}_j$, productivity of "realized" outcome of j, and θ_j since we allow imitation. In the early version of the model (Hausman and Rodrik 2003) assumes that it is possible to imitate all products perfectly. Hausmann et al. (2007) adopt imperfect imitation which depends on the maximum level of revealed productivity in an economy. Both allow that any follower can imitate former product regardless of his original productivity. However, intrinsic productivity matters even for simple imitation in the real world. We assume each investor who engaged at time t will face two choices at the beginning of time $t + 1$. And his outcome depends on his own productivity. Then, the revealed productivity of j can be expressed as follows.

$$\hat{\theta}_j = \max\{\alpha\theta_j + \beta, \theta_j\} \tag{2}$$

In (2), we assume a discount parameter of imitation α lays in $[0, 1)$ and every imitation gives a constant level of outcome represented by β. Naturally, $\beta \in (0, h)$. Figure 4 shows

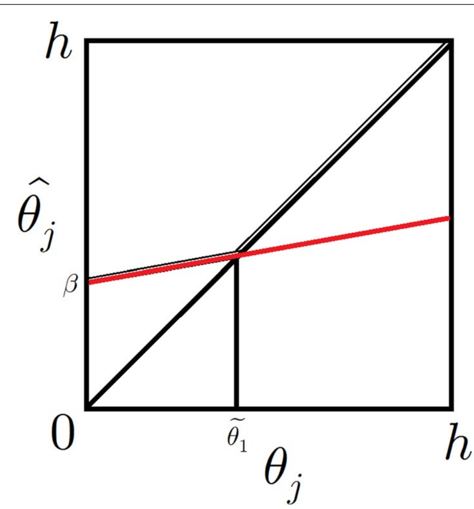

Fig. 4 Horizontal axis represents potential productivity of individuals, and vertical axis represents realized productivity. Entrepreneurs with higher productivity than $\tilde{\theta}_1$ will realize their productivity along with 45° line. But the others will follow the red line. Kinked double line will be the frontier for individuals

how production frontier changes by imitation. One can think α and β are positively associated with maximum level of revealed productivity, $\widehat{\theta_{\max}}$ of the economy. Hausmann et al. (2007) assume $\alpha = 0$ and β is strictly increasing in $\widehat{\theta_{\max}}$. We simply assume β is non-decreasing in $\widehat{\theta_{\max}}$.

Overall revealed productivity level of an economy is as follows:

$$E\left(\hat{\theta}\right) = \text{Prob}\left(\theta_j \geq \tilde{\theta}_1\right)E\left(\hat{\theta}|\theta_j \geq \tilde{\theta}_1\right) + \text{Prob}\left(\theta_j < \tilde{\theta}_1\right)E\left(\hat{\theta}|\theta_j < \tilde{\theta}_1\right) \tag{3}$$

$$E\left(\hat{\theta}\right) = \frac{\tilde{\theta}_1}{h}\frac{\beta + \tilde{\theta}_1}{2} + \frac{h - \tilde{\theta}_1}{h}\frac{\tilde{\theta}_1 + h}{2} = \frac{h}{2} + \underbrace{\frac{\beta^2}{2h(1-\alpha)}}_{\text{additional productivity acquired by imitation}} \tag{4}$$

where $\tilde{\theta}_1 = \frac{\beta}{1-\alpha}$.

Note that additional productivity from imitation does not affect the maximum productivity $\widehat{\theta_{\max}}$ directly. Now we introduce another imitation "processing trade." Every processing trade has a relationship with foreign affiliates. It is risky business compared with local imitations. Similar to the case for local imitation, we assume investor j who engaged in processing trade will get his outcome $\alpha'\theta_j + \beta'$ and the fixed outcome β' is smaller than β. We can expect that α' and β' are much related to outside of the country, so those are set exogenously in the model. In Fig. 5, the production frontier changed compared to Fig. 4.

Hypothesis 1 The productivity level of processing firms reflected in the export basket will be higher than the local imitators but lower than local frontiers. In formula, $\beta' < \beta$ and $\alpha' < 1$.

Set $\tilde{\theta}_2 = \frac{\beta'}{1-\alpha'}$ and $\tilde{\theta}_3 = \frac{\beta'-\beta}{\alpha-\alpha'}$; then, we can get expected productivity of an economy as follows:

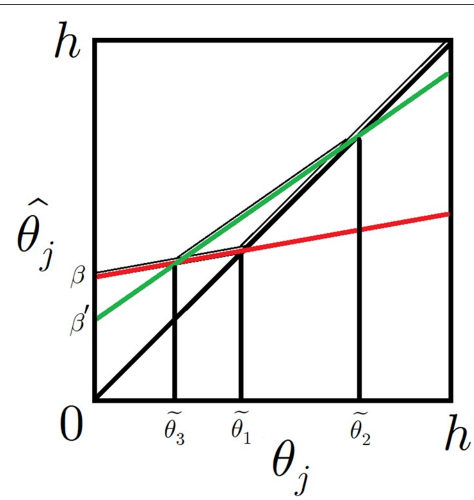

Fig. 5 Same as in Fig. 4. The only addition is the green line. Processing trade entails a little bit risk but guarantees better outcome than domestic imitation. That is why the slope is stiffer and the intercept is smaller than the red line

$$E\left(\hat{\theta}\right) = \text{Prob}\left(\theta_j \geq \tilde{\theta}_2\right)E\left(\hat{\theta}|\theta_j \geq \tilde{\theta}_2\right) + \text{Prob}\left(\theta_j \in \left[\tilde{\theta}_3, \tilde{\theta}_2\right)\right)E\left(\hat{\theta}|\theta_j \in \left[\tilde{\theta}_3, \tilde{\theta}_2\right)\right) + Prob\left(\theta_j < \tilde{\theta}_3\right)E\left(\hat{\theta}|\theta_j < \tilde{\theta}_3\right) \tag{5}$$

$$E\left(\hat{\theta}\right) = \frac{\tilde{\theta}_3}{h}\frac{\beta + \left(\beta + \alpha\tilde{\theta}_3\right)}{2} + \frac{\tilde{\theta}_2 - \tilde{\theta}_3}{h}\frac{\alpha'\left(\tilde{\theta}_3 + \tilde{\theta}_2\right) + 2\beta'}{2} + \frac{h - \tilde{\theta}_2}{h}\frac{\tilde{\theta}_2 + h}{2}. \tag{6}$$

Subtracting (4) from (6) gives the additional productivity from processing trade as follows:

$$\frac{1}{2}\underbrace{\left((1-\alpha')\tilde{\theta}_3 - \beta'\right)}_{\text{I}}\underbrace{\left(\tilde{\theta}_1 - \tilde{\theta}_2\right)}_{\text{II}} \tag{7}$$

Notice term I and II are always negative by definitions. Thus, the model states that the additional (average) productivity gain from conducting processing trade depends on its size of leverage (I) and coverage (II).

Hypothesis 2 The share of processing trade decided leverage and coverage of processing trade. In other words, share of processing trade will be large if the level of productivity achievable by processing trade is relatively high or the productivity coverage of processing trade is wide.

Does processing trade not affect to the productivity of local firms? No, it is also possible by shifting β. Let $F\left(\hat{\theta}\right)$ and $F'\left(\hat{\theta}\right)$ be the cumulative distribution of $\hat{\theta}$ without/with processing trade, respectively. Then $F'\left(\hat{\theta}\right)$ first-order stochastically dominates $F\left(\hat{\theta}\right)$ as the additional term (7) is nonzero. Thanks to the theorem of maximum of independent and identically distributed random variables, the cumulative distribution function of $\widehat{\theta_{\max}}$ is a permutation of individual cumulative distributions. It suffices to state that expected maximum productivity $\widehat{\theta_{\max}}$ with processing trade always dominates the opposite case. Thus, productivity of local firms will be affected by processing trade especially in terms of catch-up.

Hypothesis 3 Experience of processing exports will facilitate the productivity catch-up of ordinary exports.

3 Empirics

3.1 Definitions, data, and methods

3.1.1 Definition of PRODY and EXPY

We adopt an index called EXPY (Hausmann et al. 2007) as a proxy variable for measuring average $\hat{\theta}$, a revealed productivity of a country. The underlying idea and construction of the index are as follows. We assume that rich countries export more sophisticated (productive) products than others. Each product can be ranked by average wealth of exporting countries. First, we construct a product-wise index by calculating average per capita GDP of exporting countries. For a given commodity, a value share of a country divided by the sum of value share of all countries can represent a revealed comparative advantage[2] of the country in the commodity market. Weighted according to comparative advantage, we can calculate the average per capita GDP by product, called PRODY. In a formula, it can be expressed as:

$$\mathrm{PRODY}_i = \sum_{\mathrm{c}} \left(\frac{x_{i\mathrm{c}}/X_{\mathrm{c}}}{\sum_{\mathrm{c}} \left(\frac{x_{i\mathrm{c}}}{X_c} \right)} \mathrm{GDP}_{\mathrm{c}} \right) \tag{8}$$

where $x_{i\mathrm{c}}$: export of good i of country c, X_{c}: total export of country c.

Now we define productivity level associated with the export variety of a country as:

$$\mathrm{EXPY}_{\mathrm{c}} = \sum_{i} \left(\frac{x_{i\mathrm{c}}}{X_i} \mathrm{PRODY}_i \right). \tag{9}$$

Typically, firms with high productivity export. In Hausmann et al. (2007), EXPY is used as a proxy of $\widehat{\theta_{\max}}$. We use as the proxy of $\hat{\theta}$, because in our setting, every investor is exporter. Also productivity varies over firms and sectors.

We apply EXPY by trade regimes and subsectors. Since there is no discrimination of consumers' preference for the trade regime, we assume that each commodity has unique PRODY at the same time. By confining the range of EXPY, we can calculate an average productivity of processing or non-processing firms in a given sector.

3.1.2 Data and methods

In this study, all trade data are based on the Harmonized System 6-digit level and a time span of 9 years between 2007 and 2015. The Harmonized System has been revised every 4 or 5 years by the World Customs Organization, and each revision follows different nomenclature systems. We combined data under the 3rd revision (2007–2011) and the 4th revision (2012–2015). Data with invalid nomenclature are eliminated to maintain the consistency of product codes across countries. The trade data for this study come from various sources. The first is UN COMTRADE. Trade data from China with trade regimes and types of enterprise are from China Customs. Since UN COMTRADE data are missing for Taiwan and Korea, we fill the gaps with data from Trade Map and Korea Customs. And data from Macau are deleted in the full set since it distorts PRODY and EXPY.

In using trade statistics, any trade flow is measured by the import and the export country. Choosing import statistics is more common for analyses because of the relation with tariffs. However, we will use some export statistics together with import statistics to utilize the China trade statistics with extra information about trade regime and type of enterprise. To calculate PRODY and *EXPY*, along with trade data, real GDP per capita data from Penn World Table 9.0 database was used. All values of trade data were measured in current US dollars and GDP is PPP-adjusted at 2011 US dollars (Table 1).

[2] This is a bit different from the Revealed Comparative Advantage index proposed by Balassa (1965).

Classifications of trade statistics divide broadly into two categories: product- and industry-based. They have different origins and most trade statistics are product-based. Industry-based classifications are advantageous in analyzing interactions within industries. However, industry classifications such as the International Standard Industry Classification do not have a direct concordance to the Harmonized System. The Central Product Classification can bridge these two, but with many $n : n$ correlations. Therefore, we divide the modern sector into subsectors by using a product-based classification. Specifically, the first three digit codes of the Standard International Trade Classification revision 3 are considered as a subsector since they have roots in the Harmonized System, but are time-consistent over our time span. There are 262 subsectors in total, and each subsector comprises 20 Harmonized System 6-digit products on average.

3.2 Static analysis

Table 2 shows some descriptive statistics of EXPY. China's productivity level has been gradually increased, similar to the world mean.[3] When it comes to the relative position, the famous argument of Rodrik (2006), "China is special," still looks valid. Figure 6 shows China's high EXPY conditional on the income level. However, as in Xu and Lu (2009), the consideration of trade regimes alleviates deviation of China's EXPY from the conditional mean. We observe persistent gaps between processing and ordinary exports. China exports more sophisticated products by processing exports. Also, between processing and ordinary exports, there is not a significant difference of shares in total exports.

Strikingly, share of processing trade in Fig. 7 varies over industries and its distribution over EXPY is inversed U-shaped. In other words, share of processing trade is low in the top- and the bottom-level goods. This supports our first hypothesis and Fig. 5 which guesses processing trade will work for entrepreneurs with intermediate level of productivity.

The competitiveness of a sector relates to productivity and capabilities. If non-processing firms in a sector are competitive, processing firms are likely to attain high productivity since they might access production factors more easily: skilled workers, quality intermediate goods, infrastructure, institutional supports, etc. But our second hypothesis claims a slightly different side.

The model predicts a low productivity of ordinary exports, far from the processing exports, will generate a leverage (or an incentive) of processing trade. Leverage and coverage are divided mathematically in the formula (7). But there is a positive correlation between two if we consider α' as a constant. Since a coverage is hard to measure, only EXPY ratio ($\text{EXPY}^{\text{processing}}/\text{EXPY}^{\text{ordinary}}$) is accounted to verify the second hypothesis. To control the overall productivity and related environments, sectoral EXPY and RCA of ordinary exports were included in regressions.

Table 3 shows regressions in which the share of and processing exports is regressed on the ratio and other regressors. We show both OLS and FE results since Hausman tests

[3] The years between 2007 and 2012 have fewer observations due to data availability. In those years, a revision of the Harmonized System was newly enforced in the relevant countries. Adopting a new system entails a lack of time occasionally since each country should change its own tariff lines conforming to the new Harmonized System. Thus, there is a systematic bias caused by omission of low-income countries for those years. Since there is a correlation between ranges of reporting countries and observed one, level-based interpretation should be excluded.

Table 2 Descriptive statistics of EXPY. *Source*: Author's calculation

World					China					
Year	Mean EXPY	Min EXPY	Max EXPY	Obs	EXPY: total export	EXPY: ordinary export (*A*)	EXPY: processing export (*B*)	Gap (*B* − *A*)	Share of processing export (%)
2007	25,360	6530	44,858	78	27,671	25,485	29,505	4020	53.4
2008	20,355	4924	42,196	111	25,187	23,415	27,097	3682	50.5
2009	18,860	4180	38,299	133	23,121	20,987	25,052	4065	52.6
2010	17,899	2150	39,345	139	23,815	21,727	25,808	4081	50.7
2011	19,856	2331	65,192	139	24,844	22,807	27,017	4210	47.7
2012	25,239	11,431	46,066	96	27,696	26,020	29,226	3206	46.6
2013	25,662	8827	67,212	112	27,092	25,250	28,634	3384	44.1
2014	24,203	6674	72,871	122	27,276	25,869	28,631	2762	42.4
2015	25,684	7068	84,839	97	28,519	26,708	30,770	4062	39.5

Simple mathematics can prove the equivalence of Mean EXPY and MEAN GDP

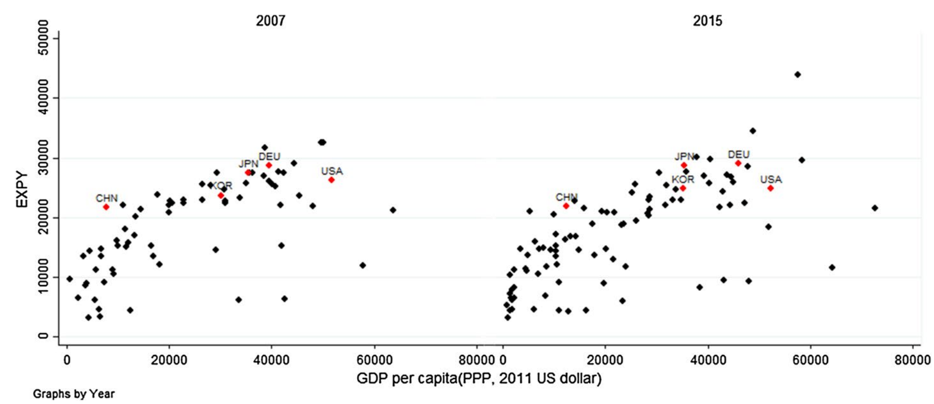

Fig. 6 Position of countries in GDP-EXPY distribution. Each dot represents productivity level and GDP of country. Some interested countries are depicted as red color. *Source*: Penn World Table, Author's calculation

point out a systematic difference in coefficients in all the regressions. Ratio enters with a positive coefficient that is statistically significant in all FE specifications. The estimated coefficient is distributed between 0.034 and 0.054. This result implies that there is a positive relationship between relative productivity of processing export and share of processing exports.

Productivity of ordinary export is a significant factor only in OLS classifications. A high RCA of ordinary export was a negative factor in all specifications. Those observations imply that when China has a large export market for their ordinary exports, share of processing export will be relatively low.

It is interesting to see that EXPY turned out not to be that significant. Intuitively, a frontier ordinary exporter may shift the overall level of productivity. But in case of China, regional difference may hamper dispersion of cost discoveries.

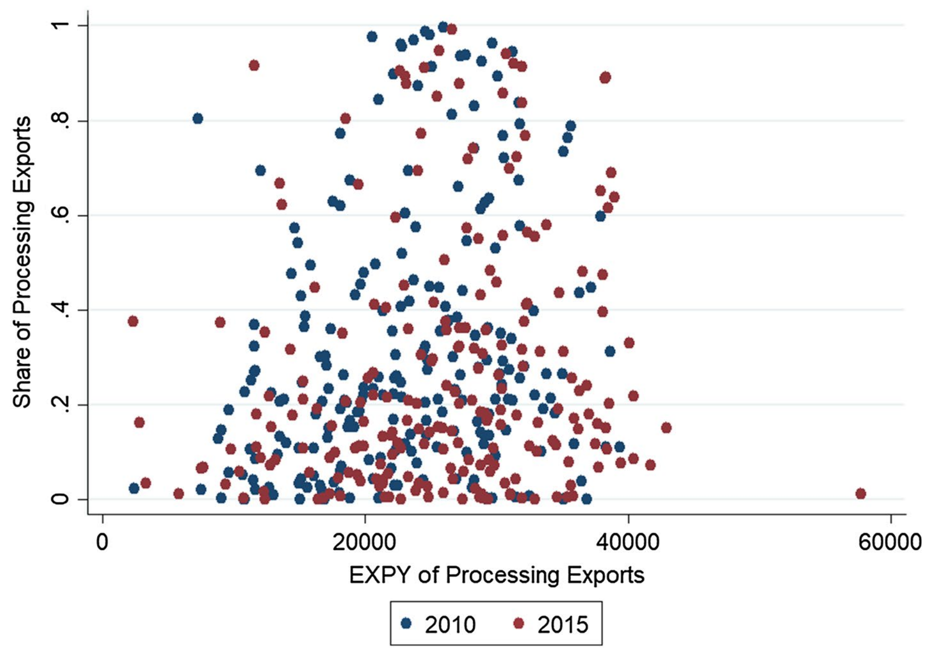

Fig. 7 Share of processing exports sorted by EXPY of processing exports. Inversed U-shaped implies that varieties exported by processing trade is not that innovative but quite sophisticated product to China. *Source*: Author's calculation

3.3 What has China learned from processing trade?

By proving Hypotheses 1 and 2, we show that the productivity of processing exports is systematically higher than that of ordinary exports. The gap is large when the productivity of ordinary exports is lower than the world average.

Hypothesis 3 addresses the learning effect from processing exports on ordinary exports. To test the hypothesis, we set $\mathrm{EXPY}_t^{\mathrm{ordinary}}$ as our dependent variable. All regressions in Table 4 include the lagged difference $\mathrm{EXPY}_t^{\mathrm{processing}} - \mathrm{EXPY}_t^{\mathrm{ordinary}}$ as a covariate. This

Table 3 Share of processing exports in total exports—OLS and FE estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: share of processing exports in total exports					
	OLS	**OLS**	**OLS**	**FE**	**FE**	**FE**
Ratio	−0.021	−0.080	−0.025	0.034	0.052	0.045
	(0.66)	(2.59)**	(0.81)	(2.11)*	(3.52)**	(2.91)**
EXPY	0.152		0.140	−0.015		−0.018
	(8.60)**		(7.92)**	(1.19)		(1.48)
RCA		−0.012	−0.010		−0.062	−0.062
		(7.30)**	(6.49)**		(11.18)**	(11.21)**
Constant	−1.214	0.400	−1.065	0.413	0.344	0.529
	(6.45)**	(12.31)**	(5.67)**	(3.16)**	(19.88)**	(4.18)**
R^2	0.04	0.03	0.06	0.00	0.07	0.08
N	1868	1868	1868	1868	1868	1868

* $p < 0.05$; ** $p < 0.01$

Table 4 China's productivity of ordinary export—OLS, FE, and GMM estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: China's EXPY of ordinary export					
	OLS	OLS	FE	FE	GMM	GMM
L(agged). dependent var.	0.890	0.887	0.087	0.085	0.257	0.252
	(72.31)**	(71.49)**	(3.28)**	(3.19)**	(2.22)*	(2.14)*
L. productivity gap	0.095	0.099	0.015	0.015	0.307	0.305
	(4.72)**	(4.88)**	(0.53)	(0.56)	(3.08)**	(3.06)**
L. processing export	66.793	126.091	233.496	226.898	309.905	305.111
	(2.15)*	(2.97)**	(2.16)*	(2.10)*	(0.89)	(0.88)
L. ordinary export		−119.104		−198.345		22.301
		(2.05)*		(1.17)		(0.05)
Constant	1516.113	2460.343	22,579.408	25,556.789		
	(3.03)**	(3.62)**	(14.55)**	(8.56)**		
R^2	0.79	0.79	0.46	0.46	0.38	0.25
N	1663	1663	1663	1663	1435	1435

* $p < 0.05$; ** $p < 0.01$

difference can be interpreted a quality gap. If this quality gap positively affects the productivity of ordinary exports in dynamics, the higher productivity of processing firms transfers to other firms in the sector. Regressions selectively include lagged value of processing or ordinary exports, or both. These variables can be understood as measures of quantitative experience. We expect positive signs for all regressors. As our variables have an intrinsic autoregressive data generating process, we use GMM (Arellano Bond estimator) for panel regression. For a robustness check, we also conducted OLS and FE.

As expected, the productivity gap becomes significant in all regressions. Especially in the GMM setting, the size of coefficients is bigger than in the other regressions, suggesting that the higher productivity of processing exports is pulling the productivity of ordinary exports with a time lag. The quantitative variables of export experience are not consistently significant. The lagged value of processing exports is significant in OLS and fixed-effect setting, but not in GMM.

4 Concluding remarks

Our model reconciles contrary arguments about processing trade. Firms engaged in processing trade are not a pioneer. Since we cannot consider allocation of profit, their "real" productivity measured by value added may be lower. However, their productivity measured by sophistication level of their exporting product is systemically higher than the others. If doing a processing trade is better to the entrepreneurs in terms of productivity, processing trade can enhance overall productivity of the economy simultaneously. Also, processing trade entails a learning effect by changing the maximum productivity of a sector.

Although many papers point out the profitability of processing trade, processing firms indeed contribute productivity enhancement in the industry by knowledge spillover. Despite the rapid growth of labor costs, processing trade in China has maintained its volume. More than its volume, "what exports by which regime" is now important for making appropriate trade policies.

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Competing interests
The authors declare that they have no competing interests.

Availability of data and materials
Trade data from UN COMTRADE are publicly available at https://comtrade.un.org/or http://wits.worldbank.org. Chinese trade data are not open to the public. You may purchase the data from authorized dealers from China Customs. For further information, contact directly to the author.

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