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China's Firm-Level Processing Trade: Trends, Characteristics, and Productivity[1]

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Abstract

This paper provides a comprehensive overview of China's processing trade using highly disaggregated 2010 transaction-level data. By highlighting the key role of processing trade in China's foreign trade, we argue that various free-trade zones have served as important instruments in boosting processing trade. We then explore various characteristics of processing imports from both industry-level and firm-level perspectives: origin countries of imports, main products, transport modes, entry ports, consumption destinations, quality of commodities, and scope of processing trade. A careful estimation of firm-level total factor productivity using the Olley–Pakes approach suggests that processing firms are less productive than non-processing firms. We also contribute to the literature by offering an efficient way of matching firm-level production data with transaction-level trade data, a rather challenging task due to data format restrictions.

Keywords: Processing Trade, Export Processing Zones, Quality of Products, Firm Scope, Total Factor Productivity, Transaction-Level Trade Data, Firm-Level Evidence

JEL Code: F1, L1, O1

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1. **Introduction**

Popular in China, processing trade involves domestic firms obtaining raw materials or intermediate inputs from abroad, processing them locally, and exporting the value-added goods. Governments usually offer tariff reduction or tariff exemption to encourage the development of processing trade. The current paper aims to provide a comprehensive review of various trends, characteristics, and productivity levels of processing trade as opposed to ordinary trade in China.

We begin with an overview of processing trade, focusing on its size and main types. Thereafter, we analyze why processing trade has developed rapidly in China in the last three decades. China’s open-door policy, particularly the establishment of special export zones, has played a significant role in the rapid growth of processing trade. We use transaction-level trade data (2000–2006) from China to investigate various factors affecting processing trade, such as origin and destination countries, leading import and export commodities, transport modes, firm ownership, leading ports and their trade volume, and top cities and provinces where producers and consumers are located.

Our transaction-level trade data set includes firm-level information. Each trade transaction is attributable to a particular firm. We investigate the number of products (i.e., scope) imported and exported by firms, as well as their number of trading destinations. More importantly, because firm productivity is key to understanding trade performance (Melitz, 2003), we investigate the productivity growth of firms by matching transaction-level trade data with firm-level production data, and using the Olley–Pakes (1996) semi-parametric approach for estimating firm productivity. Furthermore, in carefully scrutinizing processing trade in China, the present paper contributes to the literature by providing a novel and orderly way of matching two powerful data sets (transaction-level trade data and firm-level production data), given the complexity involved and restrictions in data format.

We find that processing firms mostly come from Korea, Hong Kong, and Japan. The electrical machinery and transport equipment industry has the largest volume of processing imports. The majority of processing imports are shipped to China by sea and air. Shanghai, Shenzhen, and Nanjing are the top three busiest customs ports for processing imports, whereas Shenzhen, Pudong, and Suzhou are the districts or areas with the highest volume of processing imports. The industry with the highest per-unit value of commodities is the aircraft and spacecraft industry. The top five countries in terms of quality of goods shipped to China for processing are all located in Europe: Norway, France, Finland, Germany, and Netherlands. With regard to importer ownership, foreign-owned enterprises are the major importers of processing goods. Approximately 20% of all processing firms import a single variety, whereas approximately 50% import less than 10 varieties. The number of imported varieties has also declined over the years. Moreover, processing firms are considered less productive than ordinary firms.

The rest of the paper is organized as follows. Section 2 discusses the policy setting that supports processing trade in China. Section 3 explores various characteristics of China's processing trade. Section 4 offers a careful scrutiny of correlated data from firm-level production and transaction-level trade, followed by a precise measure of the total factor productivity of firms using a semi-parametric approach. Section 5 concludes.

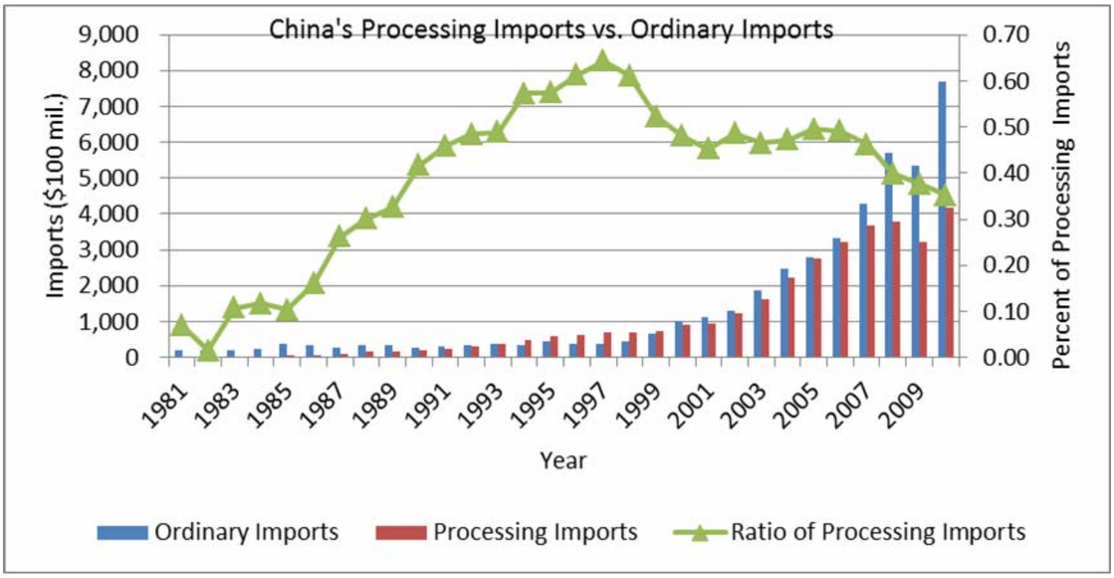
2. Policy Setting to Promote Processing Trade

Similar to its GDP growth, China's foreign trade has grown rapidly in the last three decades. Despite having a low openness ratio or sum of exports and imports over GDP in the early 1980s, China has improved its openness ratio to around 70% in 2006; the country's exports account for 39% of its GDP, whereas imports account for 31% of its GDP. Although China's exports declined by 16% in 2009 due to the financial crisis, it still surpassed Germany's and became the world's largest exporter of commodities. Today, China's foreign trade volume (i.e., the sum of exports and imports) accounts for over 10% of the world's trade volume.

Source: China Statistical Yearbook (2011).

Figure 1: China's Exports and Imports as percent of GDP (1978-2010)

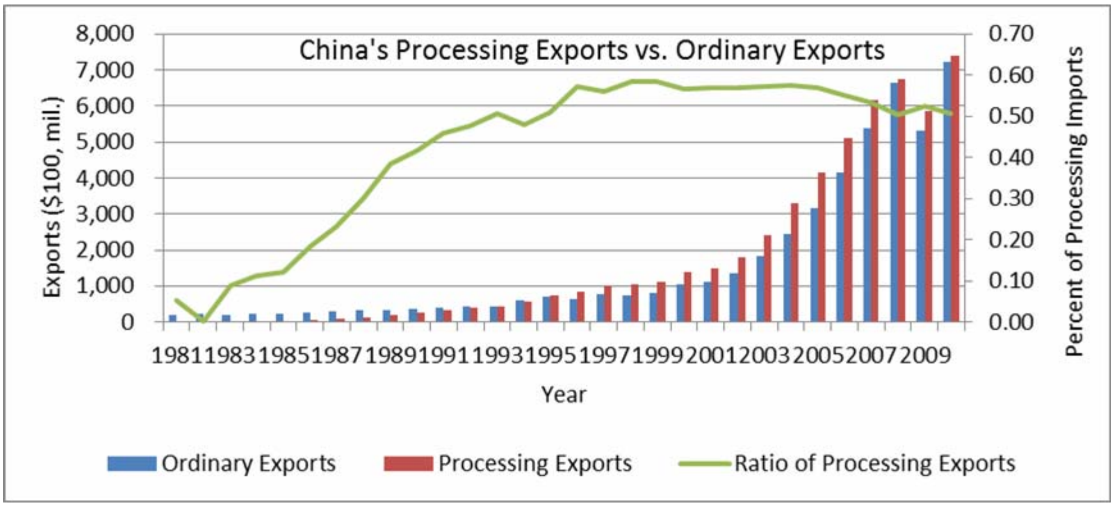
Processing trade constitutes a very large proportion, usually half, of China's total trade. This trade began in China in the late 1970s. In the early 1980s, processing imports only accounted for a small proportion of total imports. However, China's processing imports dramatically increased in the early 1990s, and began surpassing ordinary imports in 1994 (Figure 2A). Processing trade peaked at 64% in 1997 and reached a plateau at 50% for a decade. Processing trade declined to around 37% during the most recent financial crisis.



Sources: China’ Statistical Yearbook (2011)

Figure 2A: China’s Processing Imports and Ordinary Imports (1981-2010)

China’s processing exports exhibit a similar evolution. After local assembly and processing, China exports the final value-added goods to the rest of the world. China’s processing exports surpassed ordinary exports in 1998, a year after processing imports peaked in volume (Figure 2B). This suggests that processing and assembly usually takes a considerable amount of time in China, usually lasting one year. In the new century, China’s processing exports have steadily accounted for more than half of its total exports. Even with the financial crisis in 2008, the proportion of China’s processing exports remained higher than 50%, whereas processing imports declined to around 35%, indicating a gradual increase in value-adding activities associated with processing trade.



Sources: China’ Statistical Yearbook (2011)

Figure 2B: China’s Processing Exports and Ordinary Exports (1981-2010)

A classification by China’s customs bureau shows 19 types of trade regimes: ordinary trade (code: 10), aid or donation from government or from international organizations (11), donations from Chinese overseas or Chinese with foreign citizenship (12), compensation (13), processing with assembly (14), processing using imported inputs (15), goods on consignment (16), border trade (19), contracting projects (20), equipment imported for processing and assembly (22), goods on lease (23), equipment invested by foreign-invested enterprises (25), outward processing (27), barter trade (30), duty-free commodities (31), customs warehousing trade (33), entrepôt trade by bonded area (34), imported equipment by export processing zone (35), and others (39). Table 1 shows the percentage of trade value for each customs regime in 2010.

Table 1: Proportion for Customs Regime by Trade Value in 2010

Codes	Trade Type by Customs Regime	Imports (%)	Exports (%)
10	Ordinary trade	55.096	45.673
11	International aid	0.002	0.019
12	Donation by Overseas Chinese	0.013	0.000
13	Compensation trade	0.000	0.000
14	Process with assembling	7.117	7.118
15	Process with imported materials	22.783	39.802
16	Goods on consignment	0.000	0.000
19	Border trade	0.690	1.040
20	Equipment for processing trade	0.087	0.000
22	Goods for foreign contracted project	0.000	0.800
23	Goods on lease	0.404	0.009
25	Equipment/Materials investment by foreign-invested enterprise	1.168	0.000
27	Outward processing	0.009	0.012
30	Barter trade	0.000	0.000
31	Duty-free commodity	0.001	0.000
33	Warehousing trade	4.377	2.242
34	Entrepôt trade by bonded area	7.826	2.313
35	Equipment imported into Export Process Zone	0.286	0.000
39	Other trade	0.141	0.972

Sources: China Trade and External Economic Statistical Yearbook (2011)

Table 1 shows that processing imports account for approximately 45% of total imports, whereas processing exports account for approximately 55% of total exports in 2010. Processing imports are supposedly transformed into processing exports after local assembly and process. However, some firms consider their imported intermediate inputs as “processing imports” upon arrival on the ports but sell their final value-added products in the domestic market.[4] Such behavior reinforces the idea that the high share of processing exports is due to the addition of value involved in processing trade. Nevertheless, throughout this paper, we rely on processing *imports* rather than on processing *exports* in measuring processing trade.

Of the 19 types of trade regimes, processing with assembly and processing with

[4] Such imported intermediate inputs are not eligible for customs duty rebate.

intermediate inputs are the most important in China. As shown in Table 1, processing imports (exports) with assembly account for roughly 7.12% of China's total imports (exports). In contrast, processing imports with imported materials account for over 22% of total imports and 39.8% of total exports. Processing with assembly was prevalent in the 1980s, and processing with imported inputs became popular after 1990.

There are two key differences between processing with assembly and processing with intermediate inputs. First, processing with assembly does not require firms to pay for the raw materials. Chinese firms, in fact, import raw materials for free, and then send the value-added products to the same firm in the country of origin. Chinese firms do not need to pay for intermediate costs but earn payment for their service (i.e., assembly). In contrast, firms engaged in processing with imported materials are required to pay for the imported intermediate inputs. Firms import raw materials or intermediate inputs from abroad, and then sell their valued-added products to the rest of the world. Here, the source and destination countries can be different.

Second, processing assembly is one hundred percent duty free. Meanwhile, firms engaged in processing using imported inputs must pay import duties for these inputs first. After exporting their processed or final goods, they can obtain full duty rebate, indicating that firms engaged in processing using imported inputs face more credit constraints because they need to have sufficient cash flow to cover import duties (Feenstra-Li-Yu, 2011). Table 1 clearly shows that processing with imported inputs currently exceeds processing with assembly and other types of processing trade in terms of trade volume. It is worthwhile to explore the rapid growth in China's processing trade over the last three decades.

The prevalence of processing trade in China can be directly attributed to the establishment of various free-trade zones, such as special economic zones (SEZs), economic and technological development zones (ETDA), hi-technology industrial development zones (HTIDA), and export processing zones (EPZs), which underwent three phases. In the first phase, shortly before SEZs were established, several cities were allowed to contract with Hong Kong-based firms for processing with assembly. Small-scale trade was initially established.

In the spring of 1980, four coastal cities in Guangdong and Fujian Provinces, namely, Shenzhen, Zhuhai, and Shantou in Guangdong and Xiamen in Fujian, were selected as SEZs, mainly for their strong social connections with Southeast Asia. People in Shantou and Xiamen, for instance, have enjoyed a long trading tradition and history with the region. Foreign firms found this social network favorable for investment in mainland China. In SEZs, imports are completely duty free. Foreign investors likewise enjoy additional benefits, such as reduced income taxes. The Chinese government grants foreign-invested firms (FIEs) located in the zones tax exemption in the first two years and tax reduction in the subsequent three years. In addition, firms located in SEZs enjoy greater administrative flexibility and easier access to foreign markets. These policies have proven to be highly effective. Shenzhen, formerly a small and poor village, is now one of two regional financial centers in China.

In 1984, China's government allowed 14 eastern coastal cities to become "open cities" in the sense that they would have similar privileges as those enjoyed by the four SEZs. This marked the second phase of trade liberalization. Shortly thereafter, China established two more SEZs, namely, Pudong SEZ and Hainan Island SEZ. Furthermore, China designated the Pearl River Delta and the Yangzi River Delta as economic development areas, and opened four northern ports to trade with Mongolia, Russia, and North Korea in 1991.

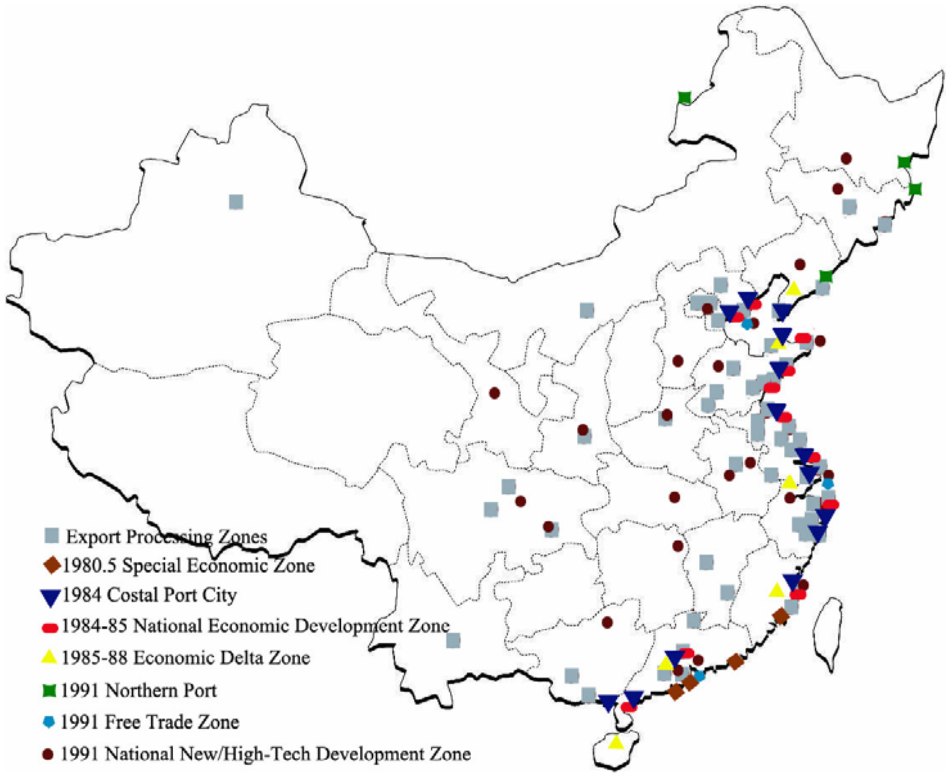


Figure 3: China's Free-Trade Zones

As shown in Figure 3, the third phase of China's trade liberalization occurred in early 1992. China extended its open-door policy from the eastern coast to Central China and Western China. Industrial cities in Central and Western China established various economic development zones and high-tech development zones. Table 2 shows that there were at least 8 SEZs, 55 EPZs, 33 ETDZs, 49 HTIDZ, and 5 bonded zones or export-oriented units (EOUs) by the end of 2010. Total processing imports in these free-trade zones accounted for over 22% of China's processing imports.

Table 2: Number of Special Economic Areas in China (till 2010)

Types of Special Economics Areas	Number	Proportion of Processing imports
Special Economic Zones (SEZs)	8	3%
Export Processing Zones (EPZs)	55	11.2%
Economic & Technological Development Zones (ETDZs)	33	12.8%
High-technology Industrial Development Zone (HTIDZs)	49	4%
Bonded Zones/ Export-Oriented Units (EOUs)	5	1%

Sources: Tian and Yu (2012) and updated using China's Customs Data (2010).

Perhaps the most direct and relevant policy in promoting processing trade is the establishment of EPZs beginning year 2000. Barely a year before China's accession to WTO, China built EPZs in several eastern coastal cities. Only processing firms were allowed in the zones and granted various privileges, such as free duties and minimal administrative restrictions. By 2010, China had established 55 EPZs. Table 3 ranks these EPZs and their proportion of imports over total country-wide processing imports. In 2010, all processing imports in the EPZs accounted for 11.5% of China's total processing trade. Jiangsu has the largest number of EPZs, with 12 out of 55 EPZs. Kunshan EPZ in Jiangsu Province is the largest among all EPZs, contributing 2.62% of China's total processing imports.

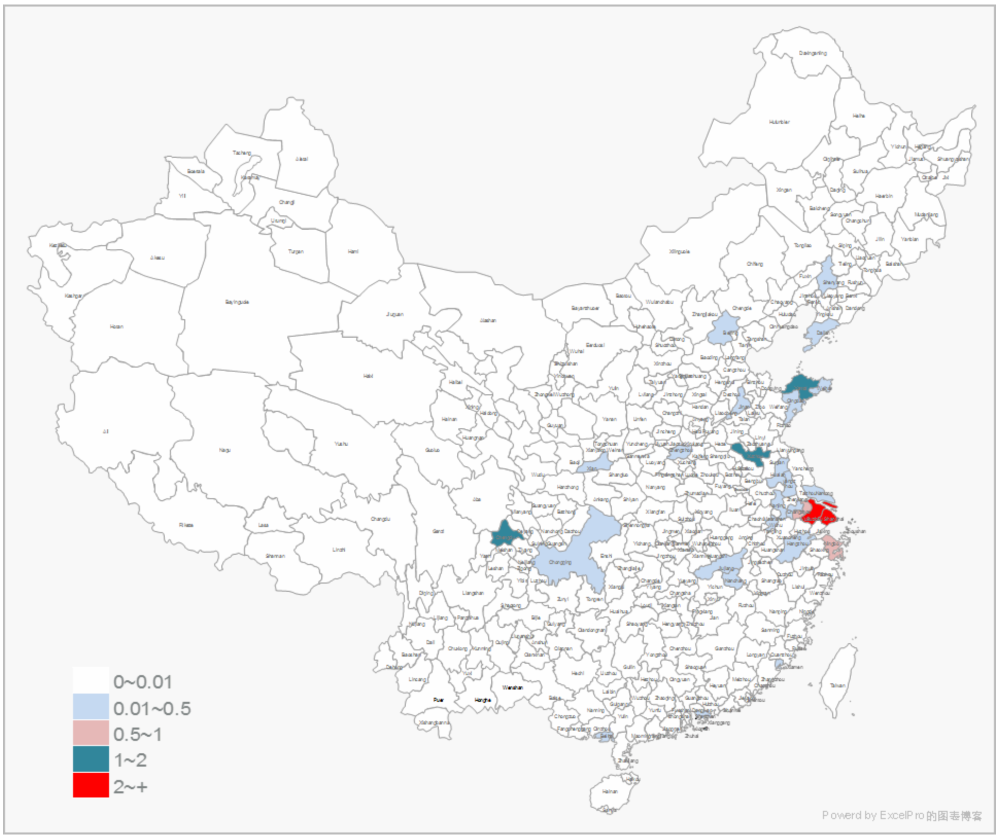
Table 3: Ranking of Export Processing Zones by Processing Import in 2010

Ranking	Name	Percent (%)	Ranking	Name	Percent (%)
1	Kunshan, JS	2.6213	29	Jinan, SD	0.0165
2	Songjiang, SH	1.8914	30	Nantong, JS	0.0157
3	Yantai, SD	1.3422	31	Yubei, CQ	0.0146
4	Xuzhou, JS	1.0562	32	Nanchang, JX	0.0144
5	Chengdu, SC	1.0019	33	Jiading, SH	0.0128
6	Wuxi, JS	0.6701	34	Shenyang, LN	0.0113
7	Ningbo, ZJ	0.5542	35	Changshu, JS	0.0109
8	Minhang, SH	0.4190	36	Jiaxing, ZJ	0.0099
9	Xi'an, SX	0.2945	37	Fuzhou, FJ	0.0097
10	Shenzhen, GD	0.1725	38	Zhuhai, GD	0.0081
11	Hanzhou, ZJ	0.1618	39	Zhenjiang, JS	0.0073
12	Fengxian, SH	0.1127	40	Wuhan, HB	0.0065
13	Weihai, SD	0.0971	41	Guangzhou, GD	0.0064
14	Nanjing, JS	0.0834	42	Shijiazhuang, HB	0.0062
15	Changzhou, JS	0.0538	43	Hohhot, IM	0.0057
16	Dalian, JN	0.0531	44	Tanggu, TJ	0.0057
17	Shunli, BJ	0.0437	45	Cixi, ZJ	0.0054
18	Xiamen, FJ	0.0411	46	Binzhou, HN	0.0048
19	Yanzhou, JS	0.0395	47	Lianyungang, JS	0.0040
20	Qingpu, SH	0.0374	48	Kunming, YN	0.0034
21	Beihai, GD	0.0349	49	Hunchun, JL	0.0031
22	Qingdao, SD	0.0339	50	Quanzhou, FJ	0.0028
23	Haiyin, JS	0.0303	51	Weifang, SD	0.0022
24	Zhengzhou, HN	0.0285	52	Mianyan, SC	0.0021
25	Wujiang, JS	0.0227	53	Qinhuangdiao, HB	0.0011

26	Wuhu, AH	0.0198	54	Ganzhou, JX	0.0004
27	Pudong, SH	0.0187	55	Urumqi, XJ	0.0002
28	Jiujiang, JX	0.0169			

Source: China's Customs Data (2010), Authors own compilation.

Figure 4 presents a geographic distribution of EPZs in China. Processing imports are concentrated in three areas: Suzhou in Jiangsu Province, Shanghai, and Yantai in Shandong Province. The cities of Xuzhou in Jiangsu Province, Chengdu in Sichuan Province, Wuxi in Jiangsu Province, and Ningbo in Zhejiang Province yield processing imports that comprise over 1% of country-wide processing imports. Most EPZs are located in eastern coastal cities, as expected. A notable and interesting finding is that all EPZs are located in the north of Yangzi River. This suggests, to some degree, the Chinese government's intention to promote processing trade in Northern China.



Notes: numbers shown in the figure represent the percentage of the export processing zone over the total processing import in China.

Figure 4: Geographic Distribution and Proportion of Export Processing Zones in China (2010)

Aside from EPZs, other free-trade zones have contributed to the surge of processing trade in China. Although China has only eight SEZs, processing imports in these SEZs comprise over 3% of the country's total processing trade, as illustrated in Table 4.

Table 4: Ranking of Special Economic Zones by Processing Imports in 2010

Ranking	Name	Percent (%)	Ranking	Name	Percent (%)
1	Shenzhen, GD	1.7464	5	Shantou, GD	0.0777
2	Zhuhai, GD	0.6235	6	Yunfu, GD	0.0538
3	Xiamen, FJ	0.5908	7	Other, HN	0.0152
4	Haikou, HN	0.1334	8	Sanya, HN	0.0029

Source: China's Customs Data (2010), Authors own compilation.

Total processing imports from bonded areas is relatively small. There were five bonded areas in China in 2010, namely, Tanggu, Pudong, Ningbo, Qingdao, and Zhanjiagang. Only the bonded area of Tanggu, located in Tianjin Province, yielded a relatively large share of processing imports (0.81%). Contributions from other bonded areas are relatively economically insignificant. By way of comparison, hi-technology industrial development areas (HTIDA) yield approximately 4% of China's total processing imports. As shown in Table 5, there are 49 HTIDA in China today, the largest of which is Suzhou HTIDA in Jiangsu Province, which accounts for 1.38% of China's total processing imports, as exhibited in Table 5.

Table 5: Ranking of HTIDA by Processing Imports in 2010

Ranking	Name	Percent (%)	Ranking	Name	Percent (%)
1	Suzhou, JS	1.3834	26	Minhang,SH	0.0043
2	Wuxi, JS	1.0092	27	Fengtai,BJ	0.0037
3	Guangzhou, GD	1.0063	28	Xianyang,SX	0.003
4	Huizhou, GD	0.228	29	Mianyang,SC	0.0029
5	Wuhan, HB	0.2104	30	Changping,BJ	0.0028
6	Xuhui, SH	0.1231	31	Jilin,JL	0.0024
7	Shenzhen, GD	0.085	32	Anshan,LN	0.0015
8	Baoding, HB	0.0838	33	Zhongshan,GD	0.0015
9	Xiamen, FJ	0.0819	34	Guilin,GX	0.001
10	Weihai, SD	0.0551	35	Jiulongpo,CQ	0.001
11	Haidion, BJ	0.0534	36	Xiangfan,HB	0.001
12	Nankai, TJ	0.0495	37	Nanjing,JS	0.0009

13	Shenyang, LN	0.0344	38	Chaoyang,BJ	0.0008
14	Chengdu, SC	0.0321	39	Weifang,SD	0.0006
15	Nanchang, JX	0.0311	40	Changsha,HN	0.0003
16	Xi'an, SX	0.0301	41	Zhengzhou,HN	0.0002
17	Dalian, LN	0.021	42	Lanzhou,GS	0.0001
18	Kunming,YN	0.0207	43	Zhuzhou,HN	0.0000
19	Hefei,AH	0.0147	44	Urumqi.XJ	0.0000
20	Changzhou,JS	0.0138	45	Shijiazhuang,HB	0.0000
21	Nanjing,JS	0.012	46	Jinan,SD	0.0000
22	Hangzhou,ZJ	0.0109	47	Nanning,GX	0.0000
23	Zibo,SD	0.0052	48	Guiyang,GZ	0.0000
24	Zhuhai,GD	0.0052	49	Taiyuan,SX	0.0000
25	Changchun,JL	0.0045			

Source: China's Customs Data (2010). Authors own compilation.

Economic and technological development areas (ETDA) are the leading zones for processing imports. As shown in Table 6, Suzhou ETDA in Jiangsu Province accounts for 4.83% of China's total processing imports, which is significantly higher than that accounted for by the largest EPZ, Kunshan EPZ in Jiangsu. Combined processing imports from the 33 ETDAs (12.8%) are higher than that from the 55 EPZs (11.5%). One possible reason is that EPZs were established much later than ETDAs were. This implies that the absorption of processing imports takes time to materialize. Jiangsu Province has outperformed other provinces in welcoming processing imports.

Table 6: Ranking of ETDA by Processing Imports in 2010

Ranking	Name	Percent (%)	Ranking	Name	Percent (%)
1	Suzhou,JS	4.8365	18	Shenyang,LN	0.034
2	Pudong,SH	2.1234	19	Taiyuan,SX	0.0277
3	Tanggu,TJ	1.4245	20	Hefei,AH	0.0277
4	Daxing,BJ	0.8821	21	Nanhui,SH	0.0258
5	Dalian,LN	0.8012	22	Lianyungang,JS	0.0252
6	Guangzhou,GD	0.7714	23	Wuhu,AH	0.0189
7	Yantai,SD	0.3768	24	Zhanjiang,GD	0.0117
8	Ningbo,ZJ	0.296	25	Changchun,JL	0.0047
9	Qingdao,SD	0.2247	26	Harbin,HLJ	0.0042
10	Other,HN	0.1621	27	Wenzhou,ZJ	0.0032
11	Fuzhou,FJ	0.1609	28	Nanan,CQ	0.001

12	Nantong,JS	0.1293	29	Chengdu,SC	0.0008
13	Hangzhou,ZJ	0.123	30	Xining,QH	0.0000
14	Wuhan,HB	0.0766	31	Yinchuan, NX	0.0000
15	Urumqi,XJ	0.0618	32	Shihezi, XJ	0.0000
16	Qinhuangdao, HB	0.0575	33	Changning, SH	0.0000
17	Minhang, SH	0.0469			

Source: China’s Customs Data (2010). Authors own compilation.

In brief, the rapid growth of China’s processing trade is largely due to the establishment of various free-trade zones, such as SEZs, ETDAs, HTIDAs, and EPZs, in the last three decades. ETDAs and EPZs lead in terms of promoting processing imports.

3. The Characteristics of Processing Trade

In this section, we discuss various characteristics of processing trade: the top 10 countries with which China imports processing intermediate inputs, top 10 industries of processing imports, percent distribution of processing import by transport mode, percent distribution of share of imports by ownership of firms, the scope of processing firms, and the quality of processing imports. Processing imports, ordinary imports, and total imports are compared. To realize comparison, we rely on transaction-level trade data provided by China’s customs, which recorded around 3.3 million import transactions in 2010. The data set includes information on customs district, location of China’s importers, customs regime, countries of departure/origin, location of China’s consumers, transport modes, HS 8-digit codes, quantity, and monthly values (measured in US$). However, this data set does not include firm-level information. Considering that firm-level analysis is critical to understanding China’s processing trade from the micro-perspective, we resort to using transaction-level trade data (2000–2006), which include firm-level information.

3.1 The Origin of Processing Imports

Our initial inquiry rests on the origin of processing imports. We compile customs data for the year 2010 to determine the top 10 countries in terms of total imports, processing imports, and ordinary imports. As shown in the last two columns of Table

7, China primarily imports from Japan, Korea, and Taiwan Province. China also imports much from its entrepôt, Hong Kong and Macao. Although the United States ranks only fifth in terms of total imports, it ranks next to Japan in terms of ordinary imports. In terms of processing imports, Korea ranks first, followed by Hong Kong, Japan, and Taiwan Province. This partly suggests that China imports core intermediate inputs from Korea and Japan, and then exports final value-added products to the United States and Europe.

Table 7: Ranking of Imports by Region by Customs Regime in 2010

Ranking	Country	Processing Imports (%)	Country	Ordinary Imports (%)	Country	Total Imports (%)
1	Korea	14.97	Japan	11.77	Japan	12.80
2	China	14.43	United States	8.34	Korea	10.02
3	Japan	14.06	Germany	7.66	Taiwan	8.40
4	Taiwan	13.93	Australia	7.37	China	7.76
5	United States	6.17	Korea	5.95	United States	7.36
6	Malaysia	5.43	Brazil	4.58	Germany	5.40
7	Thailand	3.43	Taiwan	3.87	Australia	4.38
8	Germany	2.65	Saudi Arabia	3.41	Malaysia	3.66
9	Singapore	2.43	Angola	2.78	Brazil	2.77
10	Philippines	1.85	China	2.28	Thailand	2.41
Total		79.34		58.02		64.96

Source: China's Customs Data (2010), Authors own compilation. Here proportions denote the ratio of processing (ordinary, or both) imports by country over China's total processing (ordinary, or both) imports in 2010. "China" here refers to imports from Hong Kong and Macao special administrative regions.

In terms of total import volume, the top 10 regions comprise two-thirds of China's total imports and 80% of China's processing imports. The remaining 20% of processing imports is produced by 200 trading partners in the rest of the world. The next section discusses the kinds of products that China imports as intermediate inputs.

3.2 Top Products of Processing Imports

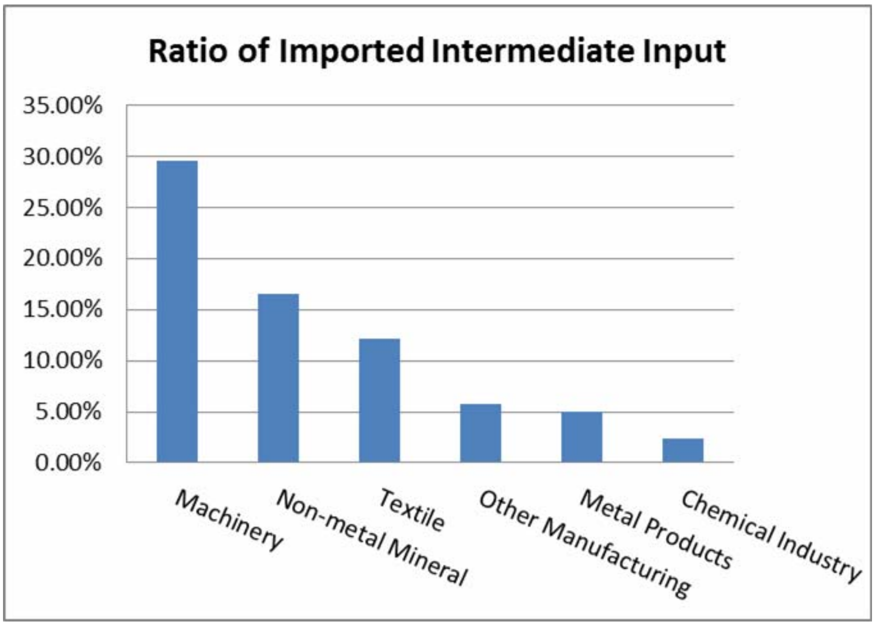
As shown in Table 8, the electrical machinery and transport equipment industry yields the largest volume of processing imports, accounting for approximately 40% of China's total. Along with this industry, four other industries, namely, machinery and mechanical appliance, optical and photographic instrument, mineral fuel and oil, and plastic, account for approximately 70% of China's total processing imports. These five industries import a huge volume of intermediate inputs. However, it is still worthwhile to investigate whether these industries adopt a large volume of domestic inputs.

Table 8: Ranking of Imports by Industry in 2010

Ranking	HS 2-Digit	Proportion of Imports	HS 2-Digit	Proportion of Imports
1	Electrical machinery & equipment	38.97	Electrical machinery & equipment	22.83
2	Machinery & Mechanical appliance	13.99	Mineral fuels, mineral oils	13.71
3	Optical, photographic instrument	10.25	Machinery & Mechanical appliance	12.51
4	Mineral fuels, mineral oils	5.98	Ores, slag, & ask	7.90
5	Plastics & articles thereof	5.44	Optical, photographic instrument	6.54
6	Copper & articles thereof	3.10	Plastics & articles thereof	4.63
7	Organic chemicals	2.35	Vehicles other than railway	3.60
8	Iron & steel	1.74	Organic chemicals	3.50
9	Rubber & articles thereof	1.59	Copper & articles thereof	3.35
10	Aircraft, spacecraft, and part	1.10	Oil seeds, industrial plants	1.97

Source: China's Customs Data (2010), Authors own compilation. Here proportions denote the ratio of processing (or total) imports by HS 2-digit industry over China's total processing (total) imports in 2010.

We calculate the ratio of *imported* intermediate inputs against total intermediate inputs for several industries. Industrial intermediate inputs combine both imported and domestic intermediate inputs. We utilize data on intermediate inputs maintained by China's customs bureau and China's input-output data for year 2005 to calculate the ratio of imported intermediate inputs. As shown in Figure 5, the five aforementioned industries use a large amount of imported intermediate inputs (e.g., the ratio for machinery is 30%, whereas the ratio for non-metal minerals is 17%).



Source: cited from Yu (2011, ADB project)

Figure 5: Ratio of Imported Intermediate Inputs (2006)

3.3 Transportation Modes

There is ample evidence showing electrical machinery and transport equipment commodities to be the most dominant among processing imports in China. How these products reach China's ports is another interesting question. Do these imports arrive in China by sea, land, or air? We classify these imports by transport mode used in 2010. Six types of transport mode are identified in this paper: sea (or river if applicable), railway, truck, air, post, and others. The last column of Table 9 shows that 62.52% of processing imports (in terms of value) reached China by sea in 2010, suggesting sea shipment to be the prevailing mode of transportation. This observation is consistent with the fact that most of China's free-trade zones are located in its eastern Pacific coast. The second most common transport mode is by air (19.63%) and then by truck (15.72%).

Table 9: Proportion of Imports by Transport Mode in 2010

Transport Mode	Processing	Ordinary	Total
By Sea	41.47	79.81	62.52
By Railway	1.09	1.58	1.36
By Truck	27.42	6.12	15.72
By Air	29.56	11.47	19.63

By Post	0.01	0.04	0.03
Other	0.45	0.99	0.75

Source: China's Customs Data (2010), Authors own compilation. Here proportions denote the ratio of processing (ordinary, or both) imports by transport mode over China's total processing (ordinary, or both) imports in 2010.

The leading transport modes for all processing imports are the same as above. Sea shipment accounts for 41%, whereas air shipment and truck shipment account for 29.56% and 27.42%, respectively. It is surprising to note that the percentage of air shipment is higher than that of truck shipment because, intuitively, there should be more commodities shipped by truck. However, the value of imports was used as measurement, not the quantity of goods. The average per-unit price of commodities sent by air shipment is usually higher than that of commodities sent by truck.

3.4 The Most Important Ports

We switch our interest to customs ports in China having the largest volume of total imports, processing imports, and ordinary imports. The top 10 ports in terms of the volume of processing imports in 2010 are Shanghai, Shenzhen, Nanjing, Qingdao, Huangpu of Guangzhou, Guangzhou, Tianjin, Gongbei of Shanghai, Dalian, and Beijing (Table 10). Except for Beijing, these ports are sea ports or river ports (e.g., Nanjing) located in the eastern Pacific coast. Shanghai port is the largest port not only for processing imports but also for ordinary imports. Moreover, Shanghai port is the largest port for total imports, followed by Shenzhen, a special economic zone located in Guangdong Province.

Table 10: The Top 10 Ports with Largest Imports (2010)

Ranking	Ports	Processing	Ports	Ordinary	Ports	Total Imports
1	Shanghai	22.57	Shanghai	15.99	Shanghai	18.97
2	Shenzhen	17.77	Qingdao	10.46	Shenzhen	12.64
3	Nanjing	15.23	Tianjin	8.57	Nanjing	11.38
4	Qingdao	9.19	Shenzhen	8.42	Qingdao	9.15
5	Huangpu	7.57	Nanjing	8.23	Huangpu	6.46
6	Guangzhou	3.40	Ningbo	6.10	Tianjin	6.14
7	Tianjin	3.19	Dalian	4.62	Ningbo	4.42
8	Gongbei	3.02	Huangpu	4.23	Dalian	3.80
9	Dalian	2.80	Hangzhou	4.05	Guangzhou	3.69

10	Beijing	2.78	Guangzhou	3.92	Beijing	3.38

Source: China's Customs Data (2010). Authors own compilation

The top three ports with the largest share of processing imports are Shanghai, Shenzhen, and Nanjing, comprising over 55% of China's total processing imports. This confirms that most processing imports are located in Shanghai, Guangdong, and Jiangsu. In contrast, the top three ports with the most ordinary imports, namely, Shanghai, Qingdao, and Tianjin, account for only 35% of China's total ordinary imports. This suggests that China's processing imports are more concentrated than its ordinary imports.

3.5 The Top Strongly-Demanded Location

We examine the destination of processing imports in China. Most processing goods are imported through Shanghai, Shenzhen, and Nanjing, so a natural conjecture is that processing importers are concentrated in these areas. Processing firms would choose their closest ports to reduce transport costs. To verify this conjecture, we determine the top 10 strongly-demanded cities/districts using China's transaction-level trade data in 2010.

Table 11: The Top 10 Strongly-Demanded Cities (2010)

Ranking	City	Processing	City	Ordinary	City	Total Imports
1	Shenzhen, GD	7.40	Chaoyang, BJ	10.05	Chaoyang, BJ	6.41
2	Pudong, SH	6.11	Xicheng, BJ	5.71	Shenzhen, GD	3.58
3	Suzhou, JS	4.56	Haidian,BJ	3.06	Pudong, SH	3.27
4	Dongguan, GD	3.64	Chaoyang, BJ	2.87	Mentougou, BJ	3.22
5	Shenzhen, GD	2.38	Pudong, SH	1.76	Suzhou, JS	2.38
6	Chaoyang, BJ	1.98	Shenzhen, GD	1.47	Dongguan, GD	1.89
7	Songjiang, SH	1.74	Guangzhou, GD	1.13	Haidian, BJ	1.71
8	Dongguan, GD	1.74	Pudong, SH	1.06	Chanyang, BJ	1.58
9	Kunshan, JS	1.24	Shenzhen, GD	0.95	Pudong, BJ	1.33
10	Dongguan, GD	1.09	Pudong, SH	0.93	Shenzhen, GD	1.08

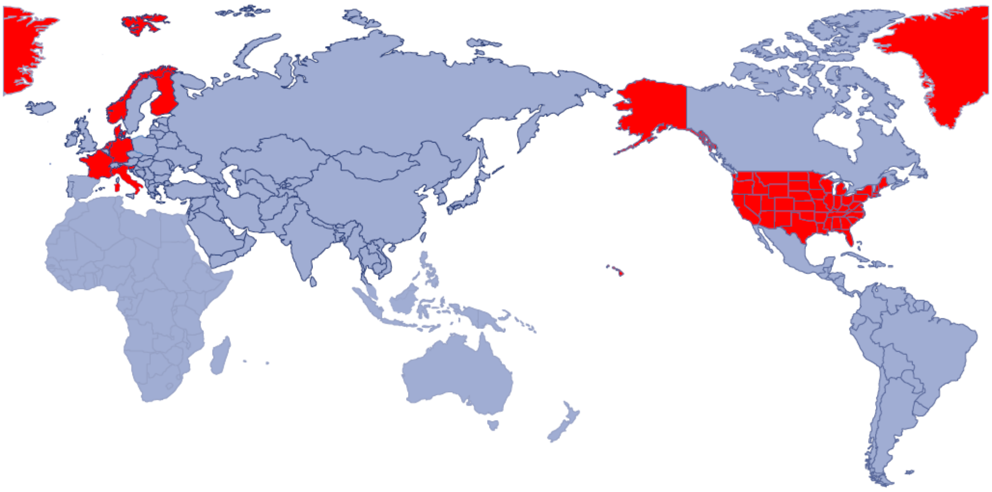
Source: China's Customs Data (2010). Authors own compilation. Sometimes a city is displaced more than once since it could contain firms in different zones such as EPZ, ETDA, and HTIDA.

Shenzhen, Pudong, and Suzhou prove to be the top three districts or areas with the most processing imports. However, they account for only 18% of total processing imports. The leading destinations of processing imports are different from the leading destinations of ordinary imports (i.e., Chaoyang, Xicheng, and Haidian, which are all in Beijing). One possible explanation is that ordinary imports include more final consumption goods, whereas processing imports include mostly intermediate goods. Combining processing imports and ordinary imports, Chaoyang of Beijing replaces Shenzhen and Pudong as the top import destination in 2010, receiving 6.41% of total imports in China.

3.6 Quality of Processing Imports

Another interesting issue is the quality of processing imports. China imports raw materials from many trading partners, so which countries ship products with the highest quality? Which goods have higher quality? Answering these questions requires coming up with an appropriate measure of the quality of goods, which is a challenging task (Khandelwal, 2010). A common gauge is the per-unit value of products (Hallak, 2006), which is obtained by dividing a good's value by its quantity.

Figure 6 shows the top 10 countries that ship goods with the highest quality to China. Interestingly, nine out of these ten countries (regimes) are located in Europe. The top five countries are as follows: Norway, France, Finland, Germany, and Netherlands. The United States ranks sixth. Meanwhile, the top five countries (regimes) with the highest quality of *ordinary* imports are Cayman Island, Finland, Germany, Panama, and Austria. Cayman Island is capable of exporting high-quality products due to its "tax-haven" privileges. Certain countries can export their products to Cayman Island, which serves as an entrepôt, for eventual shipment to China.



Notes: The color areas denotes the top 10 countries (regimes) that with highest product quality for processing goods shipped to China in 2010: Norway, France, Finland, Germany, Netherlands, the United States, Austria, Switzerland, Italy, and Denmark.

Figure 6: The Top 10 Countries with Highest Quality for Processing Goods Shipped to China

Table 12 lists industries that lead in terms of importing high-quality raw materials for processing. Imports from the aircraft and spacecraft industry have the largest per-unit value at approximately $2.39 million, followed by ships and boats, and machinery and mechanical appliances. The table likewise shows very high differences in the per-unit value of products imported by the top three importing industries.

Table 12: Top 10 industries with Highest Quality for Processing Imports (2010)

Code	Descriptions of HS 2-Digit Codes	Unit Value
88	Aircraft, spacecraft, and parts thereof	2,398,441
89	Ships, boats and floating structures	482,843
84	Nuclear reactors, boilers, machinery and mechanical appliances	42,994
90	Optical, photographic, medical or surgical instruments	17,576
87	Vehicles other than railway or tramway rolling-stock	13,083
86	Railway or tramway locomotives, rolling-stock and parts	3,493
85	Electrical machinery & equipment and parts thereof	2,890
30	Pharmaceutical Products	1,064
92	Musical Instruments, parts and accessories	878
81	Other base metals, cermet, articles thereof	727

Sources: China's Customs Data (2010). Authors' own compilation.

3.7 Ownership of Processing Importing Firms

Thus far, we have gained some understanding of China's processing imports from the industrial perspective, specifically the origin countries, main products, transport mode, entry ports, consumption destinations, and even quality of commodities. Now, we take a step forward to understand the micro-mechanism. In particular, we explore what types of firms frequently engage in processing trade. In terms of ownership, what types of firms account for the largest proportion of China's processing imports? We use China's customs transaction-level data in 2010 to answer this question.

Table 13: Proportion of Imports by Ownership of Firms in 2010

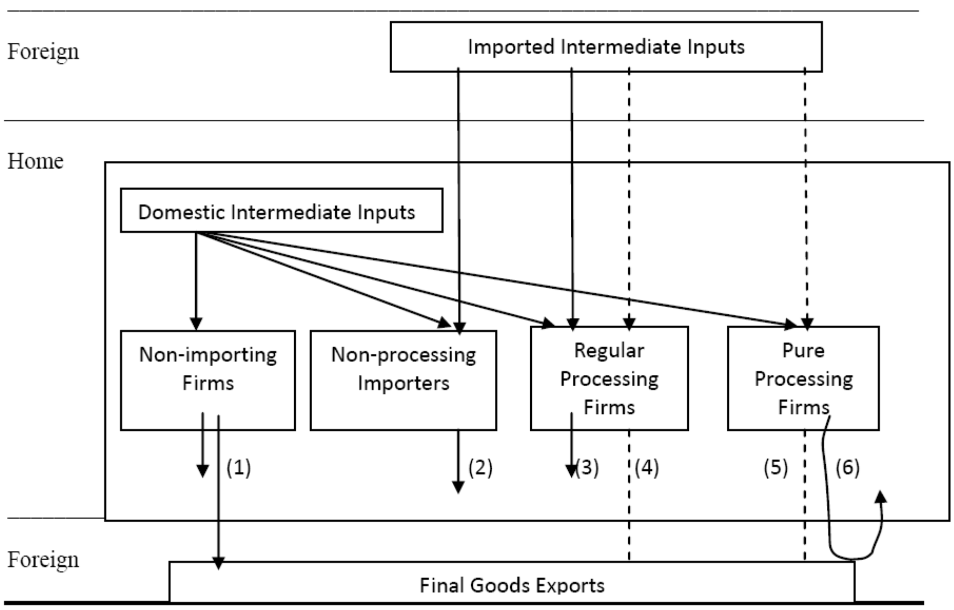
Firm Types	Processing	Ordinary	Total
State-owned enterprise	12.24	41.23	28.16
Sino-foreign contractual joint venture	0.66	0.44	0.54
Sino-foreign equity joint venture	16.53	14.14	15.22
Foreign-invested enterprise	58.76	20.70	37.86
Collective enterprise	1.42	3.45	2.54
Private enterprise	10.17	20.00	15.57
Other, including foreign company's office in China	0.01	0.01	0.01

Source: China's Customs Data (2010), Authors own compilation. Here proportions denote the ratio of processing (ordinary, or both) imports by ownership of firms over China's total processing (ordinary, or both) imports in 2010.

As shown in Table 13, over half of processing imports are attributable to foreign-invested enterprises. Another 17% of processing imports are attributable to Sino-foreign joint ventures (either contractual or equity joint ventures). State-owned and private enterprises only account for a relatively small proportion (12.2% and 10.2%, respectively). Meanwhile, state-owned enterprises are the most important type of firms involved in ordinary imports (second column of Table 12). Combining both processing and ordinary imports (last column of Table 10), foreign-invested enterprises are the most important type of importers (37.86%), followed by state-owned enterprises (28.16%).

3.8 Scopes for Processing Importing Firms

How many varieties do processing firms import? Compared to ordinary importing firms, do processing firms import more varieties? Answering these questions requires a data set containing firm-level information. China's 2010 customs data set (the most recently released version) does not include such information. As a compromise, we have to rely on previous data sets. We therefore adopt China's transaction-level trade data in 2000–2006, which include firm-level information, such as firm name, address, zip code, and telephone numbers.



Sources: The figure is cited from Yu (2011). Dotted lines represent firms' processing imports (exports) whereas real lines denote firms' non-processing (i.e., ordinary) imports (exports).

Figure 7: Four Types of Firms in China

Before investigating the importation scope of processing firms, we also need to provide a formal definition of such firms. Yu (2011) classified firms in China into four types as shown in Figure 7: (1) non-importing firms that do not use any foreign intermediate inputs; (2) non-processing importing firms that could use some foreign intermediate inputs but do not sell their final products abroad; (3) hybrid (or regular) processing firms that could engage in both processing and ordinary imports; and (4) pure processing firms that only engage in processing imports and exports, and do not sell their products in the domestic market. In the present paper, we define both hybrid and pure processing firms as processing importers. In other words, a firm engaging in some processing imports is labeled as a processing firm.

Table 14A: The Scope of Importing Firms by Year (2000-2006)

Scope	2000	2001	2002	2003	2004	2005	2006
1	19.04	18.9	19.76	20.32	21.65	22.66	23.6

2	10.27	10.14	10.55	10.77	11.43	11.97	12.19
3	6.67	7.15	7.23	7.34	7.66	7.93	8.1
4	5.26	5.39	5.42	5.76	5.64	5.78	5.96
5	4.38	4.41	4.5	4.62	4.63	4.65	4.62
6	3.61	3.87	3.9	3.79	3.8	3.69	3.76
7	3.29	3.26	3.34	3.34	3.2	3.17	3.2
8	2.98	2.89	2.89	2.81	2.79	2.7	2.73
9	2.44	2.66	2.54	2.53	2.49	2.38	2.34
10	2.33	2.35	2.36	2.26	2.12	2.13	2.11
11-50	31.21	30.68	28.23	28.24	26.71	25.74	24.51
51-100	5.05	4.23	4.9	4.97	4.78	4.43	4.34
101-1000	3.24	3.1	2.94	2.99	2.86	2.58	2.34
>1000	0.23	0.97	1.34	0.26	0.24	0.19	0.2
maximum	3497	3404	3321	3211	3070	3023	2839

Sources: China's Customs Data (2000-2006). Authors' own calculation.

Table 14A reports the scope of processing trade by year. In 2000–2006, around 20% of firms imported only a single variety, and around 10% imported two varieties. In 2000, around 45% imported less than 5 varieties, whereas around 50% imported less than 10 varieties. Another 31% imported more than 10 but less than 50 varieties. The other 3.24% imported more than 50 but less than 1,000 varieties. Only 0.23% of the firms imported more than 1,000 varieties, with 3,497 as the highest number of varieties imported.

Table 14A also shows the dynamic pattern for each cohort. In the same period, the proportion of firms importing less than 5 varieties increased from 45% to 54%. Similarly, the proportion of firms importing less than 10 varieties increased from 60% to 68%. In contrast, the proportion of firms importing more than 10 varieties but less than 50 varieties declined from 31.2% to 24.5%. The highest number of varieties imported also declined to 2,839 in 2006.

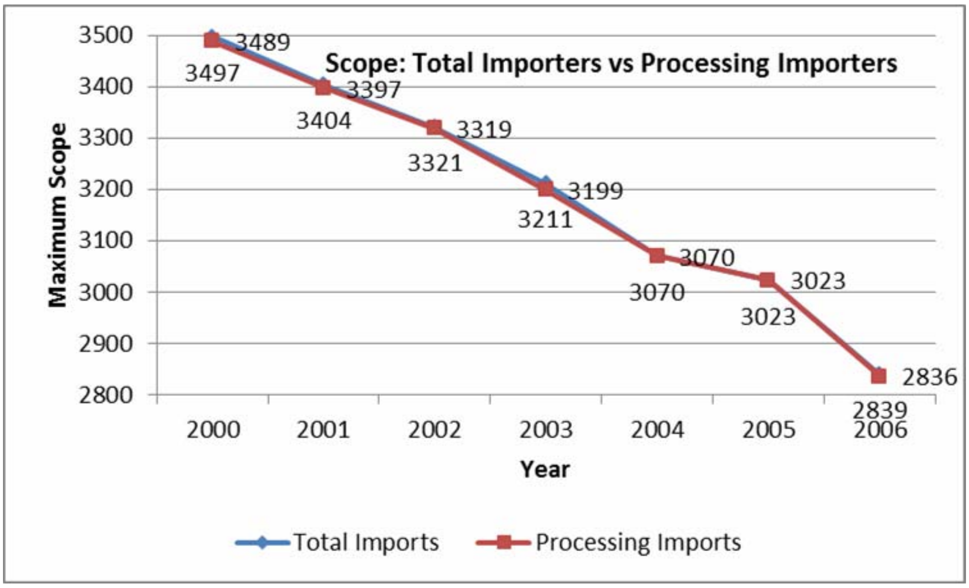
Table 14B: The Scope of Processing Importing Firms by Year (2000-2006)

Scope	2000	2001	2002	2003	2004	2005	2006
1	20.6	20.34	21.6	22.37	23.41	24.4	25.42
2	10.69	10.56	11.09	11.45	11.71	11.97	12.32
3	6.82	7.21	7.39	7.66	7.7	7.98	8.07
4	5.42	5.7	5.55	5.78	5.77	5.86	6.07
5	4.53	4.57	4.67	4.83	4.72	4.69	4.69
6	3.69	4.06	3.9	3.95	3.87	3.88	3.81

7	3.38	3.32	3.47	3.35	3.46	3.25	3.33
8	2.9	2.95	2.86	2.99	2.98	2.79	2.75
9	2.63	2.72	2.68	2.5	2.54	2.5	2.45
10	2.32	2.44	2.44	2.34	2.29	2.21	2.16
11-50	31.04	30.62	29.37	27.93	26.73	25.96	24.51
51-100	3.96	3.73	3.45	3.36	3.37	3.09	3.1
101-1000	1.83	1.58	1.34	1.3	1.3	1.27	1.18
>1000	0.19	0.2	0.19	0.19	0.15	0.15	0.14
maximum	3489	3397	3319	3199	3070	3023	2836

Sources: China's Customs Data (2000-2006). Authors' own calculation.

Processing and non-processing firms share a similar importation scope pattern. However, more processing firms import a single variety than non-processing firms. In 2006, the proportion of single-variety processing importers (25.4%) was higher than that of single-variety non-processing importers (23.6%). In the same year, the proportion of processing firms (4.42%) importing more than 50 varieties was lower that of non-processing firms (6.88%), as shown in Table 13A.



Sources: China's Customs Data (2000-2006). Authors' own compilation.

Figure 8: The Maximum of Scope for Importing Firms and Processing Importing Firms

Figure 8 shows that the number of varieties that firms import declines over time. Such a pattern is true for both processing and ordinary importers. For most years in the sample, processing firms have imported fewer varieties than ordinary firms. Thus, the highest number of varieties for all importers is higher than that for processing importers only.

Thus far, we have understood that processing firms mostly come from Korea, Hong Kong, and Japan. The industry with the largest processing imports is electrical machinery and transport equipment. Most of the processing imports are shipped to China by sea and air. The top three busiest customs ports for processing imports are Shanghai, Shenzhen, and Nanjing, whereas the top three districts/areas that have the most processing imports are Shenzhen, Pudong, and Suzhou. The industry with the highest per-unit value of commodities is the aircraft and spacecraft industry. The top five countries with the highest quality of goods shipped to China for processing are all located in Europe: Norway, France, Finland, Germany, and Netherlands. In terms of types of importer ownership, foreign-invested enterprises are the top importers of processing goods. Around 20% of processing firms only import a single variety, and around 50% import less than 10 varieties. Furthermore, the number of imported varieties declines over time. However, an important question is still unanswered: do processing firms have higher (or lower) productivity than non-processing firms? We now seek to answer this question.

4. Matching Transaction-Level Trade Data and Firm-Level Production Data

To explore processing firms' productivities, we need data on processing firm's output level and labor. If productivity is measured as total factor productivity, we also need data on capital and intermediate inputs. Transaction-level trade data offer rich information but do not contain information on production factors, such as output and input factors. Hence, we have to appeal to firm-level production data and use a merged data set. Below, we begin by describing two data sets, and we present a detailed technique for their merging. Thereafter, we discuss the performance of the matched data set. Indeed, the two data sets are widely accepted in the study of China's foreign trade and firm heterogeneity. Yet, as far as we know, very few papers offer a detailed and reliable means to discuss the matching of these two data sets. Thus, our paper aims to fill a research gap on the heterogeneity of Chinese firms.

4.1 Transaction-level Trade Data Set

Extremely disaggregated transaction-level monthly trade data for 2000–2006 are obtained from China's General Administration of Customs. Each transaction is described at the HS 8-digit level. The number of monthly observations increased from around 78,000 in January 2000 to more than 230,000 in December 2006. As shown in Column (1) of Table 15, the annual number of observations is over 10 million in 2000 and 16 million in 2006, ending with a huge number of observations (118,333,831 in total) for seven years. Column (2) of Table 14 shows that 286,819 firms engaged in international trade during this period.

For each transaction, the data set compiles three types of information: (1) five variables on basic trade information, including value (measured in US current dollar), trade status (export or import), quantity, trade unit, and value per unit (value divided by quantity); (2) six variables on trade mode and pattern, including country of destination for exports, country of origin for imports, routing (whether the product is shipped through an intermediate country/regime), customs regime (processing trade or ordinary trade), trade mode (by sea, truck, air, or post), and customs port (where the product departs or arrives); and (3) seven variables on firm information associated with each transaction, including firm name, identification number set by customs, Chinese city where the firm is located, telephone number, zip code, name of the manager/CEO, and ownership type of firm (foreign affiliate, private, or state-owned).

4.2 Firm-level Production Data Set

The sample used in this paper comes from a rich firm-level panel data set covering around 230,000 manufacturing firms per year for the years 2000–2006. The number of firms doubled from 162,885 in 2000 to 301,961 in 2006. The data, including full information on three accounting sheets (i.e., balance, loss and benefit, and cash flow sheets) are collected through an annual survey of manufacturing enterprises and maintained by China's National Bureau of Statistics. On average, the annual entire value of industrial production covered by such a data set accounts for around 95% of China's total annual industrial production. Aggregated data on the industrial sector in China's Statistical Yearbook from the Natural Bureau of Statistics (NBS) are compiled from this data set. The data set includes over 100 financial variables listed in the main accounting sheets of all covered firms. Briefly, two types of manufacturing firms are covered: all SOEs and all non-SOEs with annual sales more than five million RMB. The number of firms increased from over 160,000 in 2000 to 301,000 in 2006. As shown in Column (3) of Table 15, the number of firms that were included in the data set at any time in 2000–2006 is 615,951 in total.

However, the raw production data set still has quite some noise given that many unqualified firms are included, largely due to misreporting by some firms. For example, information on some family-based firms, which usually have no formal accounting system in place, is based on a unit of one RMB, whereas the official requirement is a unit of 1,000 RMB. Following Cai-Liu (2009) and Feenstra-Li-Yu (2011), we delete observations according to generally accepted accounting principles if any of the following are true: (1) liquid assets are higher than total assets; (2) total fixed assets are larger than total assets; (3) the net value of fixed assets is larger than total assets; (4) the firm's identification number is missing; or (5) an invalid established time exists (e.g., the opening month is later than December or earlier than January). Accordingly, the total number of firms covered in the data set is reduced to 438,165, and around one-thirds of firms are dropped from the sample after such a filtering process. As shown in Column (4) of Table 15, the filter ratio is even higher in the initial years: around one-half of firms in 2000 are dropped.

4.3 Matching Method

Although the two available data sets have rich information on production and trade, matching them is challenging. Both data sets contain firm identification numbers. However, the coding systems in these data sets are completely different. For example, the length of firm IDs in the transaction-level data set is 10 digits, whereas that in the firm-level data set is only 9 digits. China's customs administration has a coding system that is completely different from that adopted by the National Bureau of Statistics.

We go through two stages to match transaction-level trade data with firm-level production data. In the first stage, we match the two data sets by firm name and year. If a firm has an exact Chinese name in both data sets in a particular year, they should be the same firm. The year variable is necessary as an auxiliary identification variable because some firms could have different names across years, and newcomers could possibly take their original names. Using the raw production data set, we come up with 83,679 matching firms; this number is further reduced to 69,623 with the more accurate filtered production data set.

In the second stage, we use another matching technique as supplement. Here, we rely on two other common variables to identify firms, namely, zip code and the last seven digits of a firm's phone number. The rationale is that firms should have different and unique phone numbers within a postal district. Although this method seems straightforward, subtle technical and practical difficulties still exist. For example, the production-level trade data set includes both area phone codes and a hyphen in phone numbers, whereas the firm-level production data set does not. Therefore, we use the last seven digits of the phone number to serve as proxy for firm identification for two reasons. First, in 2000–2006, some large Chinese cities added one more digit at the start of their seven-digit phone numbers. Therefore, sticking to the last seven digits of the number will not confuse firm identification. Second, in the original data set, phone number is defined as a string of characters with the phone zip code. However, it is inappropriate to de-string such characters to numerals because a hyphen is used to connect the zip code and phone number. Using the last seven-digit substring neatly solves this problem.

A firm could miss its name information in either trade or production data set. Similarly, a firm could lose its phone and/or zip code information. To assure that our matched data set can cover as many common firms as possible, we then include observations in the matched data set if a firm occurs in *either* the name-adopted matched data set *or* the phone-and-post-adopted matched data set. The number of matched firms increases to 90,558 when the raw production data set is used, as shown in Column (7) of Table 15. Our matching performance is comparable to (or even better than) that of other similar studies. For example, Ge et al. (2011) used the same data sets and similar matching techniques, but ended up with 86,336 matching firms. Meanwhile, if we match the more rigorously filtered production data set with the firm-level data set, we end up with 76,823 firms in total, as shown in the last column of Table 15.

Table 15: Matched Statistics--Number of Firms

Year	Trade Data		Production Data		Matched Data			
Number	Transactions	Firms	Raw Firms	Filtered Firms	w/ Raw Firms	w/ Filtered Firms	w/ Raw Firms	w/ Filtered Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	10,586,696	80,232	162,883	83,628	18,580	12,842	21,665	15,748
2001	12,667,685	87,404	169,031	100,100	21,583	15,645	25,282	19,091
2002	14,032,675	95,579	181,557	110,530	24,696	18,140	29,144	22,291
2003	18,069,404	113,147	196,222	129,508	28,898	21,837	34,386	26.930
2004	21,402,355	134,895	277,004	199,927	44,338	35,007	50,798	40,711
2005	24,889,639	136,604	271,835	198,302	44,387	34,958	50,426	40,387
2006	16,685,377	197,806	301,960	224,854	53,748	42,833	59,133	47,591
All Year	118,333,831	286,819	615,951	438,165	83,679	69,623	90,558	76,823

Notes: Column (1) reports number of observations of HS eight-digit monthly transaction-level trade data from China's General Administration of Customs by year. Column (2) reports number of firms covered in the transaction-level trade data by year. Column (3) reports number of firms covered in the firm-level production dataset compiled by China's National Bureau of Statistics without any filter and cleaning. By contrast, Column (4) presents number of firms covered in the firm-level production dataset with careful filter according to the requirement of GAAP. Accordingly, Column (5) reports number of matched firms using exactly identical company's names in both trade dataset and raw production dataset. By contrast, Column (6) reports number of matched firms using exactly identical company's names in both trade dataset and filtered production dataset. Finally, Column (7) reports number of matched firms using exactly identical company's names and exactly identical zip code and phone numbers in both trade dataset and raw production dataset. By contrast, Column (8) reports number of matched firms using exactly identical company's names and exactly identical zip code and phone numbers in both trade dataset and filtered production data set.

How is the performance of our matched data set? Table 16 compares several key firm-level variables between the matched data set and the full-sample production data set. The matched sample clearly has higher means of sales, exports, number of employees, log of capital-labor ratio, and even log of labor productivity compared with the full sample, suggesting that the merged sample is skewed toward large firms. By construction, the full-sample firm-level production data set contains only large firms (i.e., with annual sales larger than $770,000), and our matched data set contains around 70% of total exports. Thus, our matched data set is sufficiently representative of large Chinese exporting firms.

Table 16: Comparison of the Merged Dataset and the Full-sample Production Dataset

Variables	Matched Data set			Full-sample Production Data set		
	Mean	Min.	Max.	Mean	Min.	Max.
Sales	156,348	5000	1.57e+08	85,065	5000	1.57e+08
Exports	51,751	0	1.52e+08	16,544	0	1.52e+08
Number of Employees	479	10	157,213	274	10	165,878
Log of Capital-Labor Ratio	3.62	-5.71	9.87	3.53	-6.22	11.14
Log of Labor Productivity	3.86	-7.75	10.78	3.84	-8.96	10.79

Sources: Cited from Qiu and Yu (2012).

5. Productivity for Processing Firms

With a matched trade and firm-level production data set, we are now ready to explore the productivity of processing firms. Labor productivity is a simple and straightforward measure of productivity. However, labor productivity cannot measure the contribution of input factors other than labor. As such, total factor productivity (TFP) is a better measure because it captures contributions from all input factors.

The TFP literature usually suggests using the Cobb–Douglas production function to introduce technology improvement:

$$Y_{it} = \pi_{it} M_{it}^{\beta_m} K_{it}^{\beta_k} L_{it}^{\beta_l}, \qquad (1)$$

Where Y_{it}, M_{it}, K_{it}, L_{it} is firm i's output, materials, capital, and labor at year t , respectively. To measure firm's TFP, π_{it}, one needs to estimate (1) by taking a log function first:

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_k \ln K_{it} + \beta_l \ln L_{it} + \epsilon_{it}, \qquad (2)$$

Traditionally, TFP is measured by the estimated Solow residual between the true data on output and its fitted value, $\ln \hat{Y}_{it}$. That is:

$$TFP_{it} = \ln Y_{it} - \ln \hat{Y}_{it}. \qquad (3)$$

However, this approach suffers from two problems: simultaneity bias and selection bias. As first suggested by Marschak and Andrews (1944), at least some parts of TFP changes could be observed by firms early enough for them to change their input decisions and maximize profit. Thus, TFP could have reverse endogeneity in its input factors. The lack of such a consideration would make the maximized choice of firms biased. In addition, the dynamic behavior of firms also introduces selection bias. With international competition, firms with low productivity would die and exit the market, whereas those with high productivity would remain (Melitz, 2003). In a panel data set, the firms observed are those that have already survived. Meanwhile, firms with low productivity, which collapsed and exited the market, are excluded from the data set. This means that the firms included in the regression are not randomly selected, resulting in estimation bias.

Econometricians have strived to address the empirical challenge of measuring TFP but have been unsuccessful until the pioneering work of Olley and Pakes (1996). In the beginning, researchers used two-way (firm-specific and year-specific) fixed effects estimations to mitigate simultaneity bias. Although the fixed-effect approach controls for several unobserved productivity shocks, it does not offer much help in dealing with reverse endogeneity and thus remains unsatisfactory. Similarly, to mitigate selection bias, one might estimate a balanced panel by dropping observations that have disappeared during the investigation. The problem is that a substantial part of the information contained in the data set is wasted, and the dynamic behavior of firms is completely unknown.

Fortunately, the Olley–Pakes methodology contributes significantly in addressing the challenge of TFP measurement. Assuming that the expectation of the future realization of the unobserved productivity shock, υ_{it}, relies on its contemporaneous value, a firm i's investment is modeled as an increasing function of both unobserved productivity and log capital, $k_{it} \equiv \ln K_{it}$. Following previous studies, such as van Biesebroeck (2005) and Amiti and Konings (2007), we revise the Olley–Pakes approach by adding the export decisions of firms as an extra argument in the investment function because most export decisions are determined in the previous period (Tybout, 2003):

$$I_{it} = \tilde{I}(\ln K_{it}, \upsilon_{it}, EF_{it}, IF_{it}), \qquad (4)$$

where EF_{it} (IF_{it}) is a dummy variable measuring whether firm i exports (imports) at year t. Therefore, the inverse function of investment is $\upsilon_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it}, IF_{it})$.[5] Unobserved productivity also depends on log capital and firm i's export decisions. Accordingly, Estimation Specification (1) can now be written as

$$\ln Y_{it} = \beta_0 + \beta_m \ln M_{it} + \beta_l \ln L_{it} + g(\ln K_{it}, I_{it}, EF_{it}, IF_{it}) + \varepsilon_{it}, \qquad (6)$$

Wwhere $g(\ln K_{it}, I_{it}, EF_{it})$ is defined as $\beta_k \ln K_{it} + \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it})$. Following Olley and Pakes (1996) and Amiti and Konings (2007), fourth order polynomials are used in log-capital, log-investment, export dummy, and import dummy to approximate $g(\cdot)$.[6] In addition, our firm data set covers the period 2000–2006, so we include a WTO dummy (i.e., one for a year after 2001 and zero for before) to characterize the function $g(\cdot)$ as follows:

$$g(k_{it}, I_{it}, EF_{it}, IF_{it}, WTO_t) = (1 + WTO_t + EF_{it} + IF_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} k_{it}^h I_{it}^q. \qquad (7)$$

After finding the estimated coefficients $\hat{\beta}_m$ and $\hat{\beta}_l$, we calculate the residual R_{it} which is defined as $R_{it} \equiv \ln Y_{it} - \hat{\beta}_m \ln M_{it} - \hat{\beta}_l \ln L_{it}$.

The next step is to obtain an unbiased estimated coefficient of β_k. Amiti and Konings (2007) suggested estimating the probability of a survival indicator on a high-order polynomial in log-capital and log-investment to correct selection bias as mentioned above. We can then

[5] Olley and Pakes (1996) showed that the investment demand function is monotonically increasing in the productivity shock υ_{ik}, by making some mild assumptions on the production technology of firms.

[6] Using higher-order polynomials to approximate $g(\cdot)$ does not change the estimation results.

accurately estimate the following specification:

$$R_{it} = \beta_k \ln K_{it} + \tilde{I}^{-1}(g_{i,t-1} - \beta_k \ln K_{i,t-1}, \hat{p}r_{i,t-1}) + \varepsilon_{it}, \qquad (8)$$

where $\hat{p}r_i$ is the fitted value of the probability of firm i's exit in the next year. The specific "true" functional form of the inverse function $\tilde{I}^{-1}(\cdot)$ is unknown, making it appropriate to use fourth order polynomials in $g_{i,t-1}$ and $\ln K_{i,t-1}$ as approximation. In addition, Equation (8) requires the estimated coefficients of the log-capital in the first and second terms to be identical. Therefore, non-linear least squares seem to be the most desirable econometric technique (Pavcnik, 2002; Arnold, 2005). Finally, the Olley–Pakes type of TFP for each firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

$$TFP_{ijt}^{OP} = \ln Y_{it} - \hat{\beta}_m \ln M_{it} - \hat{\beta}_k \ln K_{it} - \hat{\beta}_l \ln L_{it}. \qquad (9)$$

As discussed above, the revised Olley–Pakes approach assumes that capital responds to unobserved productivity shock with a Markov process, whereas other input factors do so without any dynamic effects. However, labor may be correlated with unobserved productivity shocks as well (Ackerberg et al., 2006). This consideration may fit with China's case very closely, given that China is a country with abundant labor. When facing unobserved productivity shocks, firms might prefer adjusting their labor rather than their capital to re-optimize their production behavior. We then use the Blundell–Bond (1998) system GMM approach to capture the dynamic effects of other input factors. Assuming that the unobserved productivity shock depends on firm i's previous period realizations, the system GMM approach models TFP to be affected by all types of firm i's inputs in both current and past realizations.[7] In particular, this model has a dynamic representation

[7] Note that the first-difference GMM introduced by Arellano and Bond (1991) also allows a firm's output to depend on its past realization. However, such an approach would lose instruments for the factor inputs because the lag of output and factor inputs are correlated with past error shocks and the autoregressive error term. In contrast, by assuming that the first difference of instrumented variables is uncorrelated with the fixed effects, the system GMM approach can introduce more instruments and thereby dramatically improve efficiency.

as follows:

$$\ln y_{it} = \gamma_1 \ln L_{it} + \gamma_2 \ln L_{i,t-1} + \gamma_3 \ln K_{it} + \gamma_4 \ln K_{i,t-1} + \gamma_5 \ln M_{it} + \gamma_6 \ln M_{i,t-1} + \gamma_7 \ln y_{i,t-1} + \varsigma_i + \zeta_t + \omega_{it}, \quad (10)$$

where ς_i is firm i's fixed effect and ζ_t is the year-specific fixed effect. The idiosyncratic term ω_{it} is serially uncorrelated if no measurement error exists.[8] We can obtain consistent estimates of the coefficients in (12) using a system GMM approach. The idea is that labor and material inputs are not taken as exogenously given. Instead, they are allowed to change over time as capital grows. Although the system GMM approach still faces a technical challenge to control for selection bias when a firm exits, using this approach to estimate a firm's TFP as a robustness check is still worthwhile.

Table 17 summarizes the estimates of the Olley–Pakes input elasticity of Chinese firms at the HS two-digit level. We first cluster the 97 HS two-digit industries into 15 categories and calculate their estimated probability and input elasticity. The estimated survival probability of a firm in the next year varies from 0.977 to 0.996, with a mean of 0.994, suggesting that firm exits are less severe in the sample and in the given period.[9]

Table 17 presents differences in the estimated coefficients for labor, materials, and capital using both the Olley–Pakes methodology and the system GMM approach. The last row of Table 17 suggests that, on average, the Olley–Pakes approach yields a higher elasticity of capital ($\alpha_k^{OP} = .117, \alpha_k^{GMM} = .001$), whereas the system GMM approach yields a higher elasticity of labor ($\alpha_l^{OP} = .052, \alpha_l^{GMM} = .240$). Summarizing all the estimated elasticity, the implied scale elasticity is

8 As discussed by Blundell and Bond (1998), even if there is a transient measurement error in some of the series (*i.e.*, $\omega_{it} \sim MA(1)$), the system GMM approach can still reach consistent estimates of the coefficients in (6).

9 Note that here, firm exit means a firm either stops trading and exits the market, or simply has an annual sales figure lower than the "large scale" amount (five million RMB in sales per year) and dropped from the data set. Owing to data set restrictions, we cannot distinguish the difference between the two.

0.989 using the Olley–Pakes approach,[10] which is close to the constant returns-to-scale elasticity.[11] Turning to the comparison between the OLS and Olley–Pakes approaches, the estimates suggest that the usual OLS approach has a downward bias ($TFP^{OLS} = .958; TFP^{OP} = 1.188$) largely because of the lack of control for simultaneity bias and selection bias.

Finally, for a cross-country comparison of the Olley–Pakes estimates, the estimation results suggest that intermediate inputs are more important for Chinese firms than for American firms (Keller and Yeaple, 2009) or for Indonesian firms (Amiti and Konings, 2007). However, the elasticity of capital input is less important for Chinese firms than for American or Indonesian firms. This implies that processing trade does play a significant role in China's productivity growth.

Table 17: Estimates of Olley-Pakes Input Elasticity of Chinese Firms

HS 2-digit	Labor		Materials		Capital	
	OP	GMM	OP	GMM	OP	GMM
Animal Products (01-05)	.056**	.053	.888**	.970**	.048**	-.022
	(3.32)	(.87)	(55.36)	(17.71)	(1.80)	(-.43)
Vegetable Products (06-15)	.007	.031**	.891**	.571**	.052**	.019
	(.49)	(8.55)	(68.05)	(9.82)	(5.49)	(.46)
Foodstuffs (16-24)	.036**	-.020	.874**	.595**	.044	.027
	(2.23)	(-.25)	(68.48)	(10.73)	(1.07)	(.46)
Mineral Products (25-27)	.035*	.241**	.872**	.671**	.099**	.089
	(1.70)	(3.78)	(51.00)	(15.51)	(2.69)	(1.57)
Chemicals & Allied	.014**	.127**	.831**	.488**	.103**	.071
Industries (28-38)	(1.98)	(1.95)	(121.70)	(10.99)	(7.79)	(1.48)
Plastics / Rubbers (39-40)	.064**	.321**	.796**	.298**	.103**	-.003

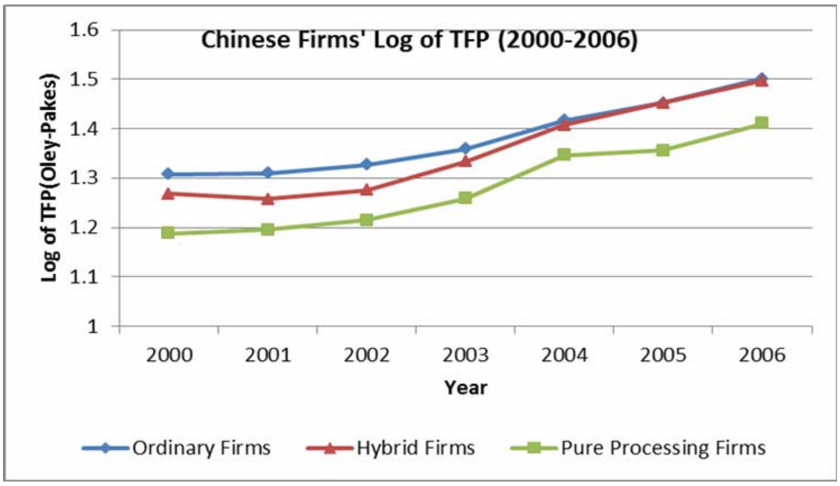
[10] This is calculated as $.052 + .820 + .117 = .989$ using the Olley–Pakes approach.

[11] Note that here, we use the industrial deflator as proxy of a firm's price. Indeed, it is even possible that Chinese firms exhibit the increasing returns-to-scale property in the new century when the actual prices of firms are used to calculate "physical" productivity. This is a possible future research topic provided that relevant data are available.

	(8.49)	(6.98)	(107.17)	(4.54)	(5.59)	(-.08)
Raw Hides, Skins, Leather	.102**	.125*	.810**	.738**	.090**	.043
& Furs (41-43)	(7.76)	(1.85)	(65.53)	(11.55)	(3.36)	(.66)
Wood Products	.039**	.041	.855**	.266**	.012	.118**
(44-49)	(4.29)	(.46)	(97.11)	(6.83)	(.47)	(2.99)
Textiles (50-63)	.085**	.157**	.810**	.653**	.066**	.043*
	(19.50)	(4.81)	(192.59)	(22.96)	(10.38)	(1.95)
Footwear / Headgear (64-67)	.072**	.138	.864**	.703**	.033**	.108**
	(5.93)	(1.62)	(73.17)	(10.77)	(5.43)	(2.38)
Stone / Glass (68-71)	.104**	.233**	.785**	.448**	.103**	.063
	(9.14)	(3.56)	(67.02)	(11.58)	(8.19)	(1.16)
Metals (72-83)	.045**	.191**	.832**	.400**	.109**	.084**
	(6.30)	(4.22)	(131.73)	(11.67)	(16.23)	(2.72)
Machinery/Electrical (84-85)	.065**	.056	.825**	.548**	.150**	.175**
	(13.36)	(1.15)	(206.22)	(13.43)	(10.83)	(4.97)
Transportation (86-89)	.042**	.147*	.883**	.426**	.043**	.068
	(2.80)	(1.70)	(69.58)	(8.81)	(3.47)	(1.08)
Miscellaneous (90-98)	.083**	.195**	.796**	.276**	.098**	.007
	(10.32)	(3.58)	(110.01)	(8.15)	(10.70)	(.22)
All industries	.052**	.240**	.820**	.486**	.117**	.001
	(30.75)	(17.05)	(493.33)	(44.54)	(27.08)	(.11)

Notes: Numbers in parentheses are robust t-values, *(**) indicates significance at 5(1) % level.

Our final interest is on comparing the productivity of processing firms and non-processing firms. As discussed in Figure 7, three types of firms that engage in both processing and non-processing activities are important: non-processing firms (i.e., ordinary firms), pure processing firms, and hybrid firms. Figure 9 shows the dynamic evolution of the productivity of these three firms. The productivity of all these firms has increased over time in the new century. Processing firms have the lowest productivity and ordinary firms have highest productivity, with the productivity of hybrid firms in between. This strongly suggests that processing firms, compared with non-processing firms, have lower productivity.



Sources: China's Firm-Level Production data and transaction-level trade data. Authors' calculation and estimates.

Figure 9: Chinese Firm's Log of Total Factor Productivity (2000-2006)

5. Concluding Remarks

This paper aims to provide an overview of China's processing trade using highly disaggregated data (firm-level data and transaction-level data) in the new century. We start by highlighting that processing trade plays a fundamental role in China's foreign trade, and then explore why processing trade has developed rapidly in the last three decades. China's free-trade policy has dramatically fostered processing trade. Various free-trade zones, such as export processing zones and economic and technologic development zones, have served as an important instrument boosting processing trade.

With such background in hand, we then explore various characteristics of processing imports. We investigate China's processing imports from the industrial perspective, including the origin countries, main products, transport mode, entry ports, consumption destinations, and even quality of the commodities. We provide very detailed firm-level evidence on the scope of processing trade.

Similarly, to gain a rich understanding of processing trade, we carefully measure and calculate total factor productivity using the semi-parametric Olley–Pakes and GMM approaches. Our estimates show that the productivity of all firms has increased in the new century. However, processing firms usually have lower productivity than non-processing firms.

Last but not least, we also contribute to the literature by providing a careful and very precise method of matching firm-level production data with transaction-level trade data. The matching is not perfect due to data format restrictions, but the resulting matched data set is still sufficiently representative of China's trading firms.

References

Ackerberg, Daniel, Kevin Caves, and Garth Frazer (2006), "Structural Identification of Production Functions," UCLA mimeo.

Arellano, Manuel and Stepen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies* 58, pp. 277-97.

Amiti, Mary, and Jozef Konings (2007), Trade Liberalization, Intermediate Inputs, and

Productivity: Evidence from Indonesia, *American Economic Review* 93, pp. 1611-1638.

Arnold, Jens Metthias (2005), "Productivity Estimation at the Plant Level: A Practical Guide," mimeo.,, Bocconi University.

Blundell, Richard and Stepen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics* 87, pp. 11-143.

Cai, Hongbin and Qiao Liu (2009), Does Competition Encourage Unethical Behavior? The Case of Corporate Profit Hiding in China, *Economic Journal* 119, pp.764-795.

Feenstra, Robert, Li, Zhiyuan and Miaojie Yu (2010), "Export and Credit Constraints under Private Information: Theory and Empirical Investigation from China", miemo, University of California, Davis.

Ge, Ying, Huiwen Lai, and Susan Zhu (2011), “Intermediates Import and Gains from Trade Liberalization”, mimeo, University of International Business and

Economics, China

Hallak, J.C. (2006), “Product Quality and the Direction of Trade,” *Journal of International Economics*, 68, pp. 238-265.

Keller Wolfgang and Stephen R. Yeaple (2009), "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States," *Review of Economics and Statistics* 91(4), pp. 821-831.

Khandelwal, Amit (2010), “The Long and Short (of) Quality Ladders,” *Review of Economic Studies*, 77(4), pp. 1450-1476.

Marschak, Jacob and Andrews, William (1944), "Random Simultaneous Equations and the Theory of Production," *Econometrica* 12(4), pp. 143-205.

Melitz, Marc (2003), "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica* 71(6), pp. 1695-1725.

Olley, Steven and Ariel Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica* 64(6), pp. 1263-1297.

Pavcnik, Nina (2002), "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants, " *Review of Economic Studies* 69(1), pp. 245-276.

Qiu, D. Larry and Miaojie Yu (2012), “Exporter Scope, Productivity, and Trade Liberalization: Theory and Evidence from China”, miemo, Peking University.

Tian, Wei and Miaojie Yu (2012)，“A Trade Tale of Two Countries: China and India”, *Journal of China and Global Economics*, forthcoming.

Tybout, James (2003), "Plant and Firm-Level Evidence on "New" Trade Theories," In *Handbook of International Trade*, ed. James Harrigan and Kwao Choi, pp. 388-415. New York: Blackwell Publishing Ltd.

Van Biesebroeck, Johannes (2005), "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms," *Journal of International Economics* 67(2), pp. 373-391.

Yu, Miaojie (2011), "Moving Up the Value Chain in Manufacturing for China", in Huang Yiping and Juzhong Zhuang (eds.), *Can China Avoid the Middle-Income Trap*? ADBI, Japan, forthcoming.

Yu, Miaojie (2011), "Processing Exports, Firm's Productivity and Tariff Reductions: Evidence from Chinese Products," mimeo, Peking University.