6. China's Processing Trade:

A firm-level analysis¹

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Introduction

The processing trade, which has become hugely popular in China, 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 chapter 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 analyse why processing trade has developed rapidly in China in the past 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 (2000–06) from China to investigate various factors affecting processing trade. These include 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 dataset includes firm-level information. Each trade transaction is attributable to a particular firm. We investigate the number of products (that is, 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 and Pakes (1996) semi-parametric approach for estimating firm productivity. Furthermore, in carefully scrutinising processing trade in China, the present chapter contributes

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to the literature by providing a novel and orderly way of matching two powerful datasets—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 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 in Europe: Norway, France, Finland, Germany and the Netherlands. With regard to importer ownership, foreign-owned enterprises are the major importers of processing goods. Approximately 20 per cent of all processing firms import a single variety, whereas approximately 50 per cent import less than 10 varieties. The number of imported varieties has also declined over the years, suggesting heightened specialisation, greater domestic intermediate input, or both. Moreover, we find that processing firms are considered less productive than ordinary firms.

The rest of the chapter is organised as follows. Section two discusses the policy setting that supports processing trade in China. Section three explores various characteristics of China's processing trade. Section four offers 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 five concludes.

Policy Setting to Promote Processing Trade

China's foreign trade has grown rapidly in the past three decades, alongside overall economic activity. From a low level of openness (the ratio of exports and imports over GDP) in the early 1980s, China increased its openness ratio to about 70 per cent by 2006; the country's exports accounted for 39 per cent of its GDP at this point, whereas imports accounted for 31 per cent of its gross domestic product (Figure 6.1). Although China's exports declined by 16 per cent in 2009 due to the global financial crisis, it still surpassed Germany in that year to become the world's largest exporter of goods. Today, China's foreign trade volume (that is, the sum of exports and imports) accounts for more than 10 per cent of the global trade volume.

Figure 6.1 China's Exports and Imports as a Percentage of GDP, 1978–2010

Source: NBS (2011a).

Processing trade now constitutes a very large proportion—usually one-half—of China's total trade. This trade began in China in the late 1970s. In the early 1980s, processing imports accounted for only a small proportion of total imports; however, China's processing imports dramatically increased in the early 1990s, and began to surpass ordinary imports in 1994 (Figure 6.2a). Processing trade peaked at 64 per cent of total trade in 1997 and then consolidated at about 50 per cent for a decade. Processing trade declined to about 37 per cent during the most recent financial crisis.

Figure 6.2a China's Processing Imports and Ordinary Imports, 1981–2010

Source: NBS (2011a).

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 6.2b). This suggests that processing and assembly usually take a considerable amount of time in China—on this evidence, more than one year but less than two. 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 per cent, whereas processing imports declined to about 35 per cent, indicating a gradual increase in value-adding activities associated with processing trade.

Figure 6.2b China's Processing Exports and Ordinary Exports, 1981–2010

Source: NBS (2011a).

Classification by China's customs bureau shows 19 types of trade regimes: ordinary trade (code: 10), aid or donation from government or from international organisations (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 investment by foreign-invested enterprises (25), outward processing (27), barter trade (30), duty-free commodities (31), customs warehousing trade (33), entrepot trade by bonded area (34), imported equipment by export processing zone (35), and others (39). Table 6.1 shows the percentage of trade value for each customs regime in 2010.

Table 6.1 Proportion of 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	Entrepot trade by bonded area	7.826	2.313
35	Equipment imported into export processing zone	0.286	0.000
39	Other trade	0.141	0.972

Source: NBS (2011b).

Table 6.1 shows that processing imports accounted for approximately 45 per cent of total imports, whereas processing exports accounted for approximately 55 per cent of total exports in 2010. Processing imports are supposedly transformed into processing exports after local assembly and processing; however, some firms consider their imported intermediate inputs as 'processing imports' on arrival in the ports but sell their final value-added products in the domestic market.⁴ Such behaviour reinforces the idea that the high share of processing exports is due to the addition of value involved in processing trade. Nevertheless, throughout this chapter, we rely on processing *imports* rather than on processing *exports* in measuring processing trade.

Besides ordinary trade, of the 18 other types of trade regime, processing with assembly and processing with intermediate inputs are the most important in China. As shown in Table 6.1, processing imports (exports) with assembly account for roughly 7.12 per cent of China's total imports (exports). In contrast,

4 Such imported intermediate inputs are not eligible for customs duty rebates.

processing imports with imported materials account for more than 22 per cent of total imports and 39.8 per cent 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 embodied 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 (that is, 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 100 per cent 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 may obtain a full duty rebate, indicating that firms engaged in processing using imported inputs face more credit constraints than pure assembly operations because they need to have sufficient cash flow to cover import duties (Feenstra et al. 2011). Table 6.1 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 exploring the rapid growth in China's processing trade over the past 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 (ETDZs), high-technology industrial development zones (HTIDZs) 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 South-East 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 favourable 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 enterprises (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 centres in China, with its own stock exchange.

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 special economic zones. This marked the second phase of trade liberalisation. Shortly thereafter, China established two more SEZs: Pudong SEZ and Hainan Island Special Economic Zone. Furthermore, China designated the Pearl River Delta and the Yangtze River Delta as economic development areas, and opened four northern ports to trade with Mongolia, Russia and North Korea in 1991 (Figure 6.3).

Figure 6.3 China's Free-Trade Zones

Source: Authors' own compilation from China's customs data (2010).

The third phase of China's trade liberalisation occurred in early 1992. China extended its open-door policy from the eastern coast to central and western China. Industrial cities in central and western China established various economic development zones and high-tech development zones. Table 6.2 shows that there were at least eight SEZs, 55 EPZs, 33 ETDZs, 49 HTIDZs and five bonded zones or export-oriented units (EOUs) by the end of 2010. Total processing imports in these free-trade zones accounted for more than 22 per cent of China's processing imports.

Table 6.2 Number of Special Economic Areas in China, up to 2010

Type of special economic area	Number	Proportion of processing imports
Special economic zones (SEZs)	8	3%
Export processing zones (EPZs)	55	11.2%
Economic and technological development zones (ETDZs)	33	12.8%
High-technology industrial development zones (HTIDZs)	49	4%
Bonded zones/export-oriented units (EOUs)	5	1%

Sources: Tian and Yu (forthcoming); 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 in the year 2000. Barely a year before China's accession to the World Trade Organisation (WTO), China built EPZs in several eastern coastal cities. Only processing firms were allowed in the zones and were granted various privileges, such as freedom from duties and minimal administrative restrictions. By 2010, China had established 55 export processing zones. Table 6.3 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 per cent of China's total processing trade. Jiangsu has the largest number of EPZs, with 12 of the 55 export processing zones. Kunshan EPZ in Jiangsu Province is the largest among all EPZs, contributing 2.62 per cent of China's total processing imports.

Table 6.3 Ranking of Export Processing Zones by Processing Imports in 2010

Ranking	Name	Percentage	Ranking	Name	Percentage
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: Authors' own compilation from China's customs data (2010).

Figure 6.4 presents a geographic distribution of EPZs in China. Processing imports are concentrated in three areas: Suzhou in Jiangsu Province and 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 make up more than 1 per cent 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 north of the Yangtze River. This suggests, to some degree, the Chinese Government's intention to promote processing trade in northern China.

Figure 6.4 Geographic Distribution and Proportion of Export Processing Zones in China, 2010

Note: Numbers shown in the figure represent the percentage of the export processing zone in total processing imports in China.

Source: Authors' own compilation from China's customs data (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 zones make up more than 3 per cent of the country's total processing trade, as illustrated in Table 6.4.

Table 6.4 Ranking of Special Economic Zones by Processing Imports in 2010

Ranking	Name	Percentage	Ranking	Name	Percentage
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: Authors' own compilation from China's customs data (2010).

Total processing imports from bonded areas are relatively small. There were five bonded areas in China in 2010: Tanggu, Pudong, Ningbo, Qingdao and Zhanjiang. Only the bonded area of Tanggu, located in Tianjin Province, yielded a relatively large share of processing imports (0.81 per cent). Contributions from other bonded areas are relatively economically insignificant. By way of comparison, high-technology industrial development zones (HTIDZs) yield approximately 4 per cent of China's total processing imports. As shown in Table 6.5, there are 49 HTIDZs in China today, the largest of which is Suzhou HTIDZ in Jiangsu Province, which accounts for 1.38 per cent of China's total processing imports, as exhibited in Table 6.5.

Table 6.5 Ranking of High-Technology Industrial Development Zones by Processing Imports in 2010

Ranking	Name	Percentage	Ranking	Name	Percentage
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: Authors' own compilation from China's customs data (2010).

Economic and technological development zones (ETDZs) are the leading zones for processing imports. As shown in Table 6.6, Suzhou ETDZ in Jiangsu Province accounts for 4.83 per cent 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 ETDZs (12.8 per cent) are higher than those from the 55 EPZs (11.5 per cent). One possible reason is that EPZs were established much later than ETDZs. This implies that the absorption of processing imports takes time to materialise. Jiangsu Province has outperformed other provinces in welcoming processing imports.

Table 6.6 Ranking of Economic and Technological Development Zones by Processing Imports in 2010

Ranking	Name	Percentage	Ranking	Name	Percentage
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: Authors' own compilation from China's customs data (2010).

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

The Characteristics of Processing Trade

In this section, we discuss various characteristics of processing trade: the top 10 countries from which China imports processing intermediate inputs, the top 10 industries of processing imports, the percentage distribution of processing imports by transport mode, the percentage 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 realise these comparisons, we rely on transaction-level trade data provided by China's customs bureau, which recorded about 3.3 million import transactions in 2010. The dataset includes information on the customs district, the location of the Chinese importer, customs regime, countries of departure/origin, location of Chinese consumers, transport modes, HS eight-digit codes, quantity and monthly values (measured in US dollars). This dataset does not, however, 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 (2000–06) from an earlier period, which include firm-level information.

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 6.7, China primarily imports from Japan, Korea and Taiwan Province. China also imports much from its entrepots, 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 suggests in part that China imports core intermediate inputs from Korea and Japan and then exports final value-added products to the United States and Europe.

Table 6.7 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

Notes: 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.

Source: Authors' own compilation from China's customs data (2010).

In terms of total import volume, the top 10 regions make up two-thirds of China's total imports and 80 per cent of China's processing imports. The remaining 20 per cent of processing imports are 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.

Top Products of Processing Imports

As shown in Table 6.8, the electrical machinery and transport equipment industry yields the largest volume of processing imports, accounting for approximately 40 per cent of China's total. Along with this industry, four other industries—machinery and mechanical appliances, optical and photographic instruments, mineral fuels and oils, and plastic—account for approximately 70 per cent of China's total processing imports. These five industries import a huge volume of intermediate inputs; however, it is still worthwhile investigating whether these industries adopt a large volume of domestic inputs.

Table 6.8 Ranking of Imports by Industry in 2010

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

Notes: Here proportions denote the ratio of processing (or total) imports by HS two-digit industry over China's total processing (total) imports in 2010.

Source: Authors' own compilation from China's customs data (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 utilise data on intermediate inputs maintained by China's customs bureau and China's input-output data for 2005 to calculate the ratio of imported intermediate inputs. As shown in Figure 6.5, the five aforementioned industries use a large amount of imported intermediate inputs (for example, the ratio for machinery is 30 per cent, whereas the ratio for non-metal minerals is 17 per cent).

Figure 6.5 Ratio of Imported Intermediate Inputs, 2006

Source: Cited in Yu (2011a).

Transportation Modes

There is ample evidence showing electrical machinery and transport equipment commodities are 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 chapter: sea (or river if applicable), railway, truck, air, post and others. The last column of Table 6.9 shows that 62.52 per cent 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 along its eastern Pacific coast. The second most common transport mode is air (19.63 per cent) and then by truck (15.72 per cent).

Table 6.9 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

Note: 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.

Source: Authors’ own compilation from China’s customs data (2010).

The leading transport modes for all processing imports are the same as above. Sea shipment accounts for 41 per cent, whereas air shipment and truck shipment account for 29.56 per cent and 27.42 per cent, 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. The value of imports was used as a measurement, however, not the quantity of goods. The average per-unit price of commodities sent by air shipment is usually higher than that for commodities sent by truck.

The Most Important Ports

We switch our interest to customs ports in China with 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 were Shanghai, Shenzhen, Nanjing, Qingdao, Huangpu in Guangzhou, Guangzhou, Tianjin, Gongbei in Shanghai, Dalian and Beijing (Table 6.10). Except for Beijing, these ports are seaports or river ports (for example, Nanjing) located on the eastern Pacific coast. The port of Shanghai is the largest port not only for processing imports but also for ordinary imports. Moreover, Shanghai's port is the largest port for total imports, followed by Shenzhen—a special economic zone located in Guangdong Province.

Table 6.10 The Top 10 Ports with Largest Volume of 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: Authors' own compilation from China's customs data (2010).

The top three ports with the largest share of processing imports are Shanghai, Shenzhen and Nanjing, comprising more than 55 per cent 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 per cent of China's total ordinary imports. This suggests that China's processing imports are more concentrated than its ordinary imports.

The Most Strongly Demanded Locations

We next 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 port to reduce transport costs. To verify this conjecture, we determine the top 10 strongly demanded cities/districts using China's transaction-level trade data for 2010 (Table 6.11).

Table 6.11 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

Note: Sometimes a city is displaced more than once since it could contain firms in different zones such as an EPZ, ETDZ or and HTIDZ.

Source: Authors' own compilation from China's customs data (2010).

Shenzhen, Pudong and Suzhou prove to be the top three districts with the most processing imports; however, they account for only 18 per cent of total processing imports. The leading destinations for processing imports are different from the leading destinations for ordinary imports (that is, 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 in Beijing replaces Shenzhen and Pudong as the top import destination in 2010, receiving 6.41 per cent of total imports in China.

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 of the highest quality? Which goods have the highest 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 6.6 shows the top 10 countries that ship goods with the highest quality to China. Interestingly, nine of these 10 countries (regimes) are located in Europe. The top five countries are: Norway, France, Finland, Germany and the Netherlands. The United States ranks sixth. Meanwhile, the top five countries (regimes) with the highest quality of *ordinary* imports are Cayman Islands, Finland, Germany, Panama and Austria. Cayman Islands is capable of exporting high-quality products due to its 'tax-haven' privileges. Certain countries can export their products to Cayman Islands, which serves as an entrepot, for eventual shipment to China.

Figure 6.6 The Top 10 Countries with Highest Quality of Processing Goods Shipped to China

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

Source: Authors' own compilation from China's customs data (2010).

Table 6.12 lists industries that lead in terms of importing high-quality raw materials for processing. Imports for 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 6.12 Top 10 Industries with Highest Quality of 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	3493
85	Electrical machinery and equipment and parts thereof	2890
30	Pharmaceutical products	1064
92	Musical instruments, parts and accessories	878
81	Other base metals, cement, articles thereof	727

Source: Authors' own compilation from China's customs data (2010).

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 for 2010 to answer this question.

Table 6.13 Proportion of Imports by Ownership of Firms in 2010

Firm type	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

Note: Here proportions denote the ratio of processing (ordinary or both) imports by ownership of firms of China's total processing (ordinary or both) imports in 2010.

Source: Authors' own compilation from China's customs data (2010).

As shown in Table 6.13, more than half of processing imports are attributable to foreign-invested enterprises. Another 17 per cent of processing imports are attributable to Sino-foreign joint ventures (either contractual or equity joint ventures). State-owned and private enterprises account for only a relatively small proportion (12.2 per cent and 10.2 per cent, respectively). Meanwhile, state-owned enterprises (SOEs) are the most important type of firms involved in ordinary imports (third column of Table 6.13). Combining both processing and ordinary imports (last column of Table 6.10), foreign-invested enterprises are the most important type of importers (37.86 per cent), followed by state-owned enterprises (28.16 per cent).

The Scope of Activity Conducted by Import Processing Firms

How many varieties do processing firms import? Compared with ordinary importing firms, do processing firms import more varieties? Answering these questions requires a dataset containing firm-level information. China's 2010 customs dataset (the most recently released version) does not include such information. As a compromise, we have to rely on an older dataset. We therefore adopt China's transaction-level trade data for 2000–06, which include firm-level information, such as firm name, address, zip code and telephone numbers.

Figure 6.7 Four Types of Firms in China

Note: Dotted lines represent firms' processing imports (exports) whereas solid lines denote firms' non-processing (that is, ordinary) imports (exports).

Sources: Cited from Yu (2011a).

Before investigating the importation scope of processing firms, we need to provide a formal definition of such firms. Yu (2011b) classified firms in China into four types, as shown in Figure 6.7: 1) non-importing firms that do not use any foreign intermediate inputs; 2) non-processing importing firms that use some foreign intermediate inputs but do not sell their final products abroad; 3) hybrid (or regular) processing firms that 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 chapter, we define both hybrid and pure processing firms as processing importers. In other words, a firm engaging in some processing imports is labelled as a processing firm.

Table 6.14a The Scope of Importing Firms by Year, 2000–06

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

Source: Authors' own calculation from China's customs data (2000–06).

Table 6.14a reports the scope of processing trade by year. In 2000–06, about 20 per cent of firms imported only a single variety, and about 10 per cent imported two varieties. In 2000, about 45 per cent imported less than five varieties, whereas about 50 per cent imported less than 10 varieties. Another 31 per cent imported more than 10 but less than 50 varieties. The other 3.24 per cent imported more than 50 but less than 1000 varieties. Only 0.23 per cent of the firms imported more than 1000 varieties, with 3497 the highest number of varieties imported.

Table 6.14a also shows the dynamic pattern for each cohort. In the same period, the proportion of firms importing less than five varieties increased from 45 per cent to 54 per cent. Similarly, the proportion of firms importing less than 10 varieties increased from 60 per cent to 68 per cent. In contrast, the proportion of firms importing more than 10 varieties but less than 50 varieties declined from 31.2 per cent to 24.5 per cent. The highest number of varieties imported also declined, to 2839 in 2006.

Table 6.14b The Scope of Processing Importing Firms by Year, 2000–06

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

Source: Authors' own calculation from China's customs data (2000–06).

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 per cent) was higher than that of single-variety non-processing importers (23.6 per cent). In the same year, the proportion of processing firms (4.42 per cent) importing more than 50 varieties was lower than that of non-processing firms (6.88 per cent), as shown in Tables 6.14a and 6.14b.

Figure 6.8 The Maximum Scope for Importing Firms and Processing Importing Firms

Source: Authors' own compilation from China's customs data (2000–06).

Figure 6.8 shows that the number of varieties that firms import has declined 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. A lower variety of imports could reflect increased specialisation or it could reflect an increased sourcing of domestically produced intermediate goods, or both.

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 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 five countries with the highest quality of goods shipped to China for processing are all located in Europe: Norway, France, Finland, Germany and the Netherlands. In terms of types of importer ownership, foreign-invested enterprises are the top importers of processing goods. About 20 per cent of processing firms import only a single variety, and about 50 per cent import less than 10 varieties. Furthermore, the number of imported varieties declines over time. An important question, however, is still unanswered: do processing firms have higher (or lower) productivity than non-processing firms? We now seek to answer this question.

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

To explore the productivity performance of processing firms, we need data on processing firms' output level and labour input. 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 dataset. Below, we begin by describing the two datasets, and we present a detailed technique for their merging. Thereafter, we discuss the performance of the matched dataset. Indeed, the two datasets are widely accepted in the study of China's foreign trade and firm heterogeneity. Yet, as far as we know, beyond our own work there is not yet on offer a detailed and reliable means of matching these two datasets. Thus, our chapter aims to fill a research gap on the heterogeneity of Chinese firms.

Transaction-Level Trade Dataset

Extremely disaggregated transaction-level monthly trade data for 2000–06 are obtained from China's General Administration of Customs. Each transaction is described at the HS eight-digit level. The number of monthly observations increased from about 78 000 in January 2000 to more than 230 000 in December 2006. As shown in column one of Table 6.15, the annual number of observations was more than 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 two of Table 6.15 shows that 286 819 firms engaged in international trade during this period.

For each transaction, the dataset compiles three types of information: 1) five variables on basic trade information, including value (measured in current US dollars), 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).

Firm-Level Production Dataset

The sample used in this chapter comes from a rich firm-level panel dataset covering about 230 000 manufacturing firms per year for the period 2000–06. The number of firms doubled from 162 885 in 2000 to 301 961 in 2006. The data, including full information on three accounting items—that is, balance, loss and benefit, and cash flow—are collected through an annual survey of manufacturing enterprises and maintained by China’s National Bureau of Statistics (NBS). On average, the annual entire value of industrial production covered by this dataset accounts for about 95 per cent of China’s total annual industrial production. Aggregated data on the industrial sector in the *China Statistical Yearbook* from the NBS are compiled from this dataset. The dataset includes more than 100 financial variables listed in the balance sheets of all firms covered. Briefly, two types of manufacturing firms are covered: all SOEs and all non-SOEs with annual sales more than RMB5 million. The number of firms increased from more than 160 000 in 2000 to 301 000 in 2006. As shown in column three of Table 6.15, the number of firms included in the dataset at any time in 2000–06 is 615 951 in total.

The raw production dataset is, however, still quite noisy 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 RMB1, whereas the official requirement is a unit of RMB1000. Following Cai and Liu (2009) and Feenstra et al. (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 (for example, the opening month is later than December or earlier than January). Accordingly, the total number of firms covered in the dataset is reduced to 438 165, and about one-third of firms are dropped from the sample after this filtering process. As shown in column four of Table 6.15, the filter ratio is even higher in the initial years: about one-half of firms in 2000 are dropped.

Matching Method

Although the two available datasets have rich information on production and trade, matching them is challenging. Both datasets contain firm identification numbers; however, the coding systems in these datasets are completely different. For example, the length of firm identifications in the transaction-level dataset

is 10 digits, whereas that in the firm-level dataset is only nine 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 datasets by firm name and year. If a firm has the exact same Chinese name in both datasets in a particular year, it 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 dataset, we come up with 83 679 matching firms; this number is further reduced to 69 623 with the more accurate filtered production dataset.

In the second stage, we use another matching technique as a supplement. Here, we rely on two other common variables to identify firms: 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 dataset includes both area codes and a hyphen in phone numbers, whereas the firm-level production dataset does not. Therefore, we use the last seven digits of the phone number to serve as the proxy for firm identification for two reasons. First, in 2000–06, 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 dataset, phone numbers are 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 sub-string neatly solves this problem.

A firm might not include its name information in either the trade or the production dataset. Similarly, a firm could lose its phone and/or zip code information. To be sure that our matched dataset can cover as many common firms as possible, we then include observations in the matched dataset if a firm occurs in *either* the name-adopted matched dataset *or* the phone-and-post-adopted matched dataset. The number of matched firms increases to 90 558 when the raw production dataset is used, as shown in column seven of Table 6.15. Our matching performance is comparable with (or even better than) that of other similar studies. For example, Ge et al. (2011) used the same datasets and similar matching techniques, but ended up with 86 336 matching firms. Meanwhile, if we match the more rigorously filtered production dataset with the firm-level dataset, we end up with 76 823 firms in total, as shown in the last column of Table 6.15.

Table 6.15 Matched Statistics: Number of firms

Year	Trade data		Production data		Matched data			
	Transactions	Firms	Raw	Filtered	w/raw	w/filtered	w/raw	w/filtered
	(1)	(2)	Firms (3)	Firms (4)	Firms (5)	Firms (6)	Firms (7)	Firms (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 years	118 333 831	286 819	615 951	438 165	83 679	69 623	90 558	76 823

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

Source: Authors' own compilation from China's customs data (2010) and firm-level production dataset.

How does our matched dataset perform? Table 6.16 compares several key firm-level variables between the matched dataset and the full-sample production dataset. The matched sample clearly has higher means for sales, exports, number of employees, log of capital–labour ratio and even the log of labour productivity compared with the full sample, suggesting that the merged sample is skewed towards large firms. By construction, the full-sample firm-level production dataset contains only large firms (that is, with annual sales larger than \$770 000), and our matched dataset contains about 70 per cent of total exports. Thus, our matched dataset is sufficiently representative of large Chinese exporting firms.

Table 6.16 Comparison of the Merged Dataset and the Full-Sample Production Dataset

	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–labour ratio	3.62	−5.71	9.87	3.53	−6.22	11.14
Log of labour productivity	3.86	−7.75	10.78	3.84	−8.96	10.79

Note: Variables = matched dataset full-sample production dataset.

Source: Cited from Qiu and Yu (2012).

Productivity for Processing Firms

With a matched trade and firm-level production dataset, we are now ready to explore the productivity of processing firms. Labour productivity is a simple and straightforward measure of productivity; however, labour productivity cannot measure the contribution of input factors other than labour. 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–Douglass production function to introduce technology improvement (Equation 6.1).

Equation 6.1

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

In Equation 6.1 Y_{it} , M_{it} , K_{it} , L_{it} is firm i 's output, materials, capital and labour at year t , respectively. To measure a firm's TFP, π_{it} , one needs to estimate Equation 6.1 by taking a log function first (Equation 6.2).

Equation 6.2

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

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 Equation 6.3.

Equation 6.3

$$TFP_{it} = \ln Y_{it} - \ln \hat{Y}_{it}.$$

This approach, however, 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 maximise profit. Thus, TFP could have reverse endogeneity in its input factors. The lack of such a consideration would make the maximised choice of firms biased. In addition, the dynamic behaviour 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 dataset, the firms observed are those that have already survived. Meanwhile, firms with low productivity, which collapsed and exited the market, are excluded from the dataset. 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 were 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 dataset is wasted, and the dynamic behaviour 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 realisation of the unobserved productivity shock, v_{it} , relies on its contemporaneous value, firm i 's investment is modelled 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) (Equation 6.4).

Equation 6.4

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

In Equation 6.4, $EF_{it}(IF_{it})$ is a dummy variable measuring whether firm i exports (imports) at year t . Therefore, the inverse function of investment is

Equation 6.5

$$v_{it} = \tilde{I}^{-1}(\ln K_{it}, I_{it}, EF_{it}, IF_{it}).$$

Unobserved productivity also depends on log capital and firm i 's export decisions.⁵ Accordingly, Equation 6.2 can now be written as Equation 6.6.

Equation 6.6

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

In Equation 6.6, $g(\ln K_{it}, I_{it}, EF_{it})$ 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 dataset covers the period 2000–06, so we include a WTO dummy (that is, one for a year after 2001 and zero for before) to characterise the function $g(\cdot)$ as follows (Equation 6.7).

Equation 6.7

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

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 accurately estimate the following specification (Equation 6.8).

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

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

Equation 6.8

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

In Equation 6.8, $\hat{p}r_i$ 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 6.8 requires the estimated coefficients of the log-capital in the first and second terms to be identical. Therefore, nonlinear least squares seem to be the most desirable econometric technique (Arnold 2005; Pavcnik 2002). 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 (Equation 6.9).

Equation 6.9

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

As discussed above, the revised Olley–Pakes approach assumes that capital responds to an unobserved productivity shock with a Markov process, whereas other input factors do so without any dynamic effects; however, labour could be correlated with unobserved productivity shocks as well (Akerberg et al. 2006). This consideration might fit with China's case very closely, given that China is a country with abundant labour. When facing unobserved productivity shocks, firms might prefer adjusting their labour rather than their capital to reoptimise their production behaviour. We then use the Blundell and 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 realisations, the system GMM approach models TFP to be affected by all types of firm i 's inputs in both current and past realisations.⁷ In particular, this model has a dynamic representation as follows (Equation 6.10).

Equation 6.10

$$\begin{aligned} \ln y_{it} = & \gamma_1 \ln L_{it} + \gamma_2 \ln L_{i,t-1} + \gamma_3 \ln K_{it} + \gamma_4 \ln K_{i,t-1} + \gamma_5 \ln M_{it} \\ & + \gamma_6 \ln M_{i,t-1} + \gamma_7 \ln y_{i,t-1} + \varsigma_i + \zeta_t + \omega_{it}, \end{aligned}$$

7 Note that the first-difference GMM introduced by Arellano and Bond (1991) also allows a firm's output to depend on its past realisation. Such an approach would, however, lose instruments for the factor inputs because the lag of output and factor inputs is 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.

In Equation 6.10, ζ_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 labour 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 6.17 summarises 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 6.17 presents differences in the estimated coefficients for labour, materials and capital using both the Olley–Pakes methodology and the system GMM approach. The last row of Table 6.17 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 labour ($\alpha_l^{OP} = .052, \alpha_l^{GMM} = .240$). Summarising all the estimated elasticity, the implied scale elasticity is 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 the 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). The elasticity of capital input is, however, 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.

8 As discussed by Blundell and Bond (1998), even if there is a transient measurement error in some of the series (that is, $\omega_{it} \sim MA(1)$), the system GMM approach can still reach consistent estimates of the coefficients in Equation 6.6.

9 Note that here, firm exit means a firm either stops trading and exits the market or has an annual sales figure lower than the 'large-scale' amount (RMB5 million in sales per year) and dropped from the dataset. Owing to dataset restrictions, we cannot distinguish the difference between the two.

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

11 Note that here we use the industrial deflator as a 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.

Table 6.17 Estimates of Olley–Pakes Input Elasticity of Chinese Firms

HS 2-digit	Labour		Materials		Capital	
	OP	GMM	OP	GMM	OP	GMM
Animal products (01–05)	.056** (3.32)	.053 (.87)	.888** (55.36)	.970** (17.71)	.048** (1.80)	–.022 (–.43)
Vegetable products (06–15)	.007 (.49)	.031** (8.55)	.891** (68.05)	.571** (9.82)	.052** (5.49)	.019 (.46)
Foodstuffs (16–24)	.036** (2.23)	–.020 (–.25)	.874** (68.48)	.595** (10.73)	.044 (1.07)	.027 (.46)
Mineral products (25–27)	.035* (1.70)	.241** (3.78)	.872** (51.00)	.671** (15.51)	.099** (2.69)	.089 (1.57)
Chemicals and allied industries (28–38)	.014** (1.98)	.127** (1.95)	.831** (121.70)	.488** (10.99)	.103** (7.79)	.071 (1.48)
Plastics/rubber (39–40)	.064** (8.49)	.321** (6.98)	.796** (107.17)	.298** (4.54)	.103** (5.59)	–.003 (–.08)
Raw hides, skins, leather and furs (41–43)	.102** (7.76)	.125* (1.85)	.810** (65.53)	.738** (11.55)	.090** (3.36)	.043 (.66)
Wood products (44–49)	.039** (4.29)	.041 (.46)	.855** (97.11)	.266** (6.83)	.012 (.47)	.118** (2.99)
Textiles (50–63)	.085** (19.50)	.157** (4.81)	.810** (192.59)	.653** (22.96)	.066** (10.38)	.043* (1.95)
Footwear/headgear (64–67)	.072** (5.93)	.138 (1.62)	.864** (73.17)	.703** (10.77)	.033** (5.43)	.108** (2.38)
Stone/glass (68–71)	.104** (9.14)	.233** (3.56)	.785** (67.02)	.448** (11.58)	.103** (8.19)	.063 (1.16)
Metals (72–83)	.045** (6.30)	.191** (4.22)	.832** (131.73)	.400** (11.67)	.109** (16.23)	.084** (2.72)
Machinery/electrical (84–85)	.065** (13.36)	.056 (1.15)	.825** (206.22)	.548** (13.43)	.150** (10.83)	.175** (4.97)
Transportation (86–89)	.042** (2.80)	.147* (1.70)	.883** (69.58)	.426** (8.81)	.043** (3.47)	.068 (1.08)
Miscellaneous (90–98)	.083** (10.32)	.195** (3.58)	.796** (110.01)	.276** (8.15)	.098** (10.70)	.007 (.22)
All industries	.052** (30.75)	.240** (17.05)	.820** (493.33)	.486** (44.54)	.117** (27.08)	.001 (.11)

* indicates significance at 5 per cent level

** indicates significance at 1 per cent level

Note: Numbers in parentheses are robust t-values.

Source: Authors' own estimation.

Our final interest is in comparing the productivity of processing firms and non-processing firms. As discussed in Figure 6.7, three types of firms that engage in both processing and non-processing activities are important: non-processing firms (that is, ordinary firms), pure processing firms and hybrid firms. Figure 6.9 shows the dynamic evolution of the productivity of these three firm types. The productivity of all these firms has increased over time in the new century. Processing firms have the lowest productivity and ordinary firms have the highest productivity, with the productivity of hybrid firms in between. This strongly suggests that processing firms, compared with non-processing firms, have lower productivity.

Figure 6.9 Chinese Firms' Log of Total Factor Productivity, 2000–06

Source: Authors' calculation and estimates from China's firm-level production data and transaction-level trade data.

Conclusions

This chapter aimed to provide an overview of China's processing trade using highly disaggregated data (firm-level data and transaction-level data) from the new century. We started by highlighting that processing trade plays a fundamental role in China's foreign trade, and then explored why processing trade has developed rapidly in the past three decades. China's free-trade policy has dramatically fostered processing trade. Various free-trade zones, such as export processing zones and economic and technological development zones, have served as important instruments boosting processing trade.

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

Similarly, to gain a rich understanding of processing trade, we carefully measured and calculated 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 levels 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 match is not perfect due to data format restrictions, but the resulting matched dataset is still sufficiently representative of China's trading firms.

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