Made and Created in China: The Role of Super Processors*

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December 2022

Abstract

This paper examines the main participants of China's processing trade regime—firms that engage in both processing and ordinary exports, even at the product-destination level. By matching several datasets from China, including a unique sample of transaction-level customs data, we uncover three empirical regularities. First, these firms, which we refer to as "super processors," exhibit superior performance in various margins such as revenue and physical productivity. Second, even within firms, there is a tight link between export mode choice and brand ownership—own-branded products are typically exported under ordinary trade while products under other firms' brands are exported under processing trade. Third, there is a price premium associated with selling one's own-branded products. To rationalize these findings, we present a simple theoretical framework where firms with multi-attributes (i.e., "making" and "creating") endogenously determine their specialization within a production network.

JEL codes: F12, F13, F14

Keywords: heterogeneous firms, production networks, processing trade

*We are grateful to Suzanne Bijkerk, Maarten Bosker, Julia Cajal Grossi, Mi Dai, Jonathan Eaton, Julian Emami Namini, Inga Heiland, Laura Hering, Sacha Kapoor, Vladimir Karamychev, Kala Krishna, Franceso Lippi, Andreas Moxnes, Monika Mrázová, Ezra Oberfield, Vincent Rebeyrol, Frédéric Robert-Nicoud, Yu Shi, Felix Tintelnot, Lorenzo Trimarchi, Bauke Visser, Yikai Wang, Zi Wang, Weisi Xie, Stephen Yeaple, and Zhihong Yu for helpful comments. We also thank seminar participants at the China International Conference in Economics, Erasmus University Rotterdam, Graduate Institute of Geneva, Norwegian Business School, Pennsylvania State University, University of Namur, University of Nottingham, and University of Oslo for useful feedback. Yanlin Zhou provided excellent research assistance. Yuan Zi acknowledges funding received from the European Research Council under the European Union's Horizon 2020 research and innovation program (grant agreement 715147).

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1 Introduction

"[W]hereas during the later part of the twentieth century and early twenty-first century, the world became used to reading the Made in China *label on every conceivable type of product, mankind is increasingly getting used to a ubiquitous* Branded in China *tag. What is clear is that China has fallen in love with brands."*

-John M.T. Balmer and Weifeng Chen, *Advances in Chinese Brand Management,* 2017

China's trade as percentage of its GDP rose from below 10% in the late 1970s to over 60% just before the Great Recession (World Bank, 2018). During this period, Chinese firms specialized in relatively low value-added stages of production and supplied foreign multinationals largely through processing trade, as epitomized by the "Made in China" tag. While processing trade accounted for the majority of China's total exports and was the key driver of China's export boom, relatively little attention has been paid to its main participants—exporters that engaged in both processing and ordinary exports. We find that these 'mixed' firms, which are ubiquitous across sectors, made up about a fifth of processing exporters, and contributed to over 60% of total Chinese processing exports, explaining about half of China's export surge during 2000-2006. Even though they are considered to be "perhaps the most interesting type of firm[s]" (Yu, 2015), they were never carefully investigated in the literature.

In this paper, we unpack the "black box" of mixed firms to shed light on Chinese exporters' performance and specialization within a production network. This is important as these firms were the driving force behind China's export boom by engaging in both processing and ordinary activities, hinting to policy implications that aim to foster export growth. We find that mixed exporters are larger and have higher revenue and physical productivity compared to firms that engage in only ordinary (i.e., pure ordinary exporters) or only processing (i.e., pure processors) activities. Importantly, unlike what is suggested in the literature, these "super processors" are not 'mixed' because they sell different products under different export modes: the majority of their exports consists of the same product being sold to the same destination under both processing and ordinary trade modes.

Even though being highly processing-oriented, mixed exporters' superior labor and revenue productivity does not generalize to pure processing exporters. On the other hand, pure processing exporters have significantly higher physical productivity when compared to pure ordinary exporters. In addition, using a novel transaction-level customs data with detailed product and brand information, we find that firms tend to export their own-branded products using ordinary trade mode, and there is a price premium associated with selling one's own-branded product. This finding suggests that a firm's export mode not only reflects its position inside a production network, but is also closely related to its efficiency across different stages of production (i.e., manufacturing versus branding, or synonymously in this paper, "making" versus "creating"), which ultimately determines its measured performance at various margins. This exercise also reveals that focusing on a single-measure of productivity would miss out on how specific firm attributes determine firms' specialization patterns along a value chain.

To rationalize our empirical findings, we build a parsimonious model in a unified yet intuitive framework. Our model features an endogenous production network in which firms are heterogeneous in both manufacturing and branding abilities. In equilibrium, firms with good blueprints but low manufacturing ability outsource production and become downstream firms that do not manufacture, and those with intermediate manufacturing ability and blueprint quality become pure ordinary exporters. Firms with higher manufacturing ability but low blueprint quality become pure processing exporters, and firms with exceptional blueprint quality and manufacturing ability become mixed exporters, i.e., firms that both export their own brands and serve as manufacturing suppliers for foreign firms. As such, our model rationalizes the observed ranks at various margins between mixed, pure ordinary, and pure processing exporters.

Our work is related to three strands of the international trade literature. First, our empirical findings on mixed exporters are related to a large body of work on the characteristics of processing exporters in China (Fernandes and Tang, 2015; Yu, 2015; Dai et al., 2016; Kee and Tang, 2016; Li et al., 2018).[1] Different from these studies which mainly focus on processing firms and how they differ from ordinary exporters, we document the dominant role of exporters that engage in both ordinary and processing exports. We also provide novel empirical facts that shed light on firms in supply-chain trade by relating for the first time exporters' brand ownership and choice of trade mode, using a unique transaction-level trade data on firms' branding information.

Instead of disentangling all the mechanisms behind processing trade, this paper highlights the key feature of processing firms, i.e, they are typically contract-taking suppliers of foreign downstream firms. Thus, we view policies such as duty exemptions as factors that simply increase a firm' propensity to engage in processing activities. By doing so, we complement the works of Feenstra and Hanson (2005), Fernandes and Tang (2012), Dai et al. (2016), Manova and Yu (2016), Brandt and Morrow (2017), Defever and Riaño (2017), and Deng (2021) who emphasize the role of different policy factors that shape firms' export mode choice.[2]

Second, our paper connects to the literature that study firms with multiple heterogeneities, including Antràs and Helpman (2004), Hallak and Sivadasan (2013), Harrigan and Reshef (2015), Manova and Yu (2017), Ariu et al. (2019), and Huang et al. (2022).[3] None of these papers,

[1]Fernandes and Tang (2015) find that processing firms are less diversified in products and destinations when compared to ordinary exporters, and Yu (2015) shows that their productivity does not change considerably with trade liberalization. Dai et al. (2016) find that compared to non-exporters and ordinary exporters, processing firms have lower revenue productivity, skill intensity, and profitability, and they pay lower wages and spend little on R&D. Kee and Tang (2016) show that China's processing exporters began to use domestic inputs instead of imported materials during 2000-2007. Li et al. (2018) calculate physical total factor productivity (TFP) based on quantity data and find that processing exporters are significantly more productive than non-exporters.

[2]Dai et al. (2016), Brandt and Morrow (2017), Defever and Riaño (2017), and Deng (2021) emphasize the role of special duty drawbacks; Feenstra and Hanson (2005) and Fernandes and Tang (2012) emphasize foreign firms' outsourcing decisions; Manova and Yu (2016) highlight the importance of credit constraints.

[3]Antràs and Helpman (2004) study how firm-level productivity and sector-level headquarter-intensity affect firms' choices of ownership structure and supplier locations. Hallak and Sivadasan (2013) explore how differences in firms'

however, emphasize the role of heterogeneities that enable firms to self-select into different stages of the production network. Combining rich Chinese firm-level trade and production data with a novel transaction-level data with branding information, we show that the intuitive set-up of our model rationalizes a rich set of empirical regularities on Chinese firms.

Finally, our stylized model contributes to the literature on firms' sourcing decisions in international and regional trade, e.g., Antràs et al. (2017), Lim (2018), Bernard et al. (2019b), Kikkawa et al. (2022), and Dhyne et al. (2021).[4] These papers emphasize that sourcing decisions are important in explaining firm performance, shock transmissions, aggregate gains from trade, and business cycle fluctuations. Our paper shows that it is also useful to take the network feature into account to explain exporters' performance under processing trade.

The rest of the paper is organized as follows. Section 2 describes the data and the processing trade regime in China. Section 3 presents our empirical findings regarding exporters' performance, export mode, and brand ownership. Section 4 develops a model that rationalizes these findings. Finally, Section 5 concludes.

2 Data and the Processing Trade Regime in China

2.1 Data

We use four main datasets in this paper. The first is China's 2000-2006 customs data that shows firms' monthly transactions of exports and imports at the product-country level, where products are defined at the 8-digit Harmonized Schedule (HS8) level. Since our analysis is focused on manufacturing firms, we remove intermediaries (i.e., wholesalers and retailers) from the dataset.[5] The customs data allows us to observe each firm's ordinary and processing exports at the product-country level. Thus, we are able to divide firms into three mutually exclusive groups: pure processing exporters, pure ordinary exporters, and mixed exporters who are engaged in both activities.

Our second dataset is a rich sample of transaction-level customs data for 2018. Unlike the commonly used 2000-2006 customs data, this sample is directly obtained from the Chinese customs

process versus product productivity can explain the empirical observation that exporters produce higher-quality products. Harrigan and Reshef (2015) let firms differ in productivity and skill-intensity to explain the positive correlation of globalization and wage inequality. Manova and Yu (2017) focus on multi-product firms with different productivity and scope for quality, and study how firms allocate activity across products in line with a product hierarchy based on quality. Bernard et al. (2018) study how productivity and relationship capability can explain the matching between buyers and sellers in Belgium. Bernard et al. (2019a) document carry-along trade and emphasize demand-scope complementarities. Ariu et al. (2019) study complementarities between trade in goods and services, and finally, Huang et al. (2022) study how upstream market structure affects downstream sourcing behavior.

[4]Building on Tintelnot (2017), Antràs et al. (2017) study firms' optimal sourcing decisions across countries, and predict that the intensive and extensive margins of sourcing are positively related to firm productivity. Redefining countries as locations within a country, Bernard et al. (2019b), Kikkawa et al. (2022), and Dhyne et al. (2021) adapt the framework of Antràs et al. (2017) to the context of domestic production networks and study how geography, markups, and endogenous firm-to-firm connections affect shock transmissions and firm performance, respectively. Lim (2018) quantifies the importance of endogenous network adjustment for business cycles. Chaney (2016), Bernard and Moxnes (2018), and Johnson (2018) provide excellent reviews of the network models in international trade.

[5]To remove intermediaries, we follow the approach taken by Ahn et al. (2011) and exclude firms whose names include words such as "import," "export," "trading," "business," "supply chain," "warehousing," or "investment."

without any aggregation, which enables us to observe all the information in firms' customs clearance records. In particular, these records contain highly detailed product and brand information for each export transaction.[6] In this database, we observe firm ID, firm name, value and quantity of exports, export destination, product specification (both in 10-digit HS code and description), and export mode. The product specification is a long string variable that provides detailed information on the type of product, and its brand name and brand ownership, which we group into three categories: no brand, domestic brands (domestically created or purchased), and foreign brands (including original equipment manufacturers). The dataset consists of 862,567 daily transactions which make up around $38 billion worth of exports in 34 HS8 products by 29,138 firms, covering product categories from 13 out of 68 HS2 manufacturing sectors.[7] The wide variety of products, which are listed in Table A.1, includes goods that make up a large share of exports such as car tires, refrigerators, and mobile phones.

The third and fourth datasets we use are the annual industry survey (AIS) and the production survey compiled by China's National Bureau of Statistics (NBS) for 2000-2006. The AIS data report firm-level balance sheet information such as sales, value-added, number of employees, capital stock, R&D expenses, advertisement expenses, material costs, and ownership structure, which allows us to examine firms' performance along various margins.[8] The production survey contains firm-product level information on output quantity, which enables us to compute firm-level quantity-based (i.e., physical) TFP.[9] Both datasets cover all state-owned enterprises (SOEs) and private firms that have annual sales of at least five million RMB. We merge both datasets with the 2000-2006 customs data based on firm names, telephone numbers, and zip codes. Our matching procedure results in covering about 58% of aggregate exports, which is similar to the match rate of existing studies.[10]

2.2 The Processing Trade Regime in China

In this subsection, we briefly describe the institutional details of processing trade based on our interviews with senior officials at Chinese customs and owners of various processing firms.[11] These details and their reflection in the data help put our empirical findings in context.

Processing trade generally refers to the business activity of importing all, or part of, raw materials from abroad and re-exporting the finished products after manufacturing within a country. Processing trade widely exists in international commerce, although many countries' customs do not

[6]The Chinese government began to require firms to report the brand information in customs declaration forms in 2018. This policy change was issued in the No. 69 General Administration of Customs Announcement on Amending the "Regulations on the Customs Declaration of Imports and Exports of the People's Republic of China" in 2017, and became effective on January 1, 2018.

[7]Of the 34 products, 30 are from March and the rest are from January and April 2018.

[8]We follow the data cleaning procedures proposed by Brandt et al. (2012) and exclude firms with missing or negative (or zero) capital stock, value-added, or employment data, and ones that have less than 8 employees.

[9]See Li et al. (2018) for a more detailed description of the production survey and its link with the AIS survey.

[10]See the Appendix of Chen et al. (2017) for a more detailed explanation of the matching procedure.

[11]We are particularly grateful to Jie Zhang and Li Liang from the research department of the statistical division of Chinese Customs, Jianming Gao and Tommy Yu from Fujian Business Association, and Chunmei Wu for their valuable inputs.

distinguish it from other trade modes. China separately classifies processing trade in its customs data and treats these transactions with different policies as a consequence of the country's gradual opening-up and dual-track reforms. Viewed as a way to help firms integrate into global value chains and manufacture goods for foreign firms, China provides numerous preferential conditions for processing trade such as tax rebates and tariff waivers on intermediate goods and capital equipment that are used exclusively in the production of exported goods. Combined with the relatively cheap labor force of China that attracted firms in developed countries to outsource manufacturing to China, processing trade helped China become an export powerhouse.[12]

Note that preferential access to processing trade also has a cost. In order to deter firms from evading taxes and tariffs, processing trade is subject to much tighter governmental supervision compared to ordinary trade: processing contracts are required to provide detailed information on inputs, outputs, and production processes, and be registered and approved in advance by the Chinese customs before any transaction takes place. These transactions are then subject to stricter customs checks.[13] Ultimately, these policies helped to select businesses that the Chinese government targeted: 84% of processing exports in our transaction sample can be explained by firms making products for foreign brands, as we show in the next subsection. In other words, the majority of processing contracts are for Chinese firms "making" goods for foreign contractors, which we take as the *de facto* definition of processing trade throughout the paper.

A key feature of processing trade is that it is defined by *contracts*, not by firms (see order No. 113 of the General Administration of Customs of PRC). This reflects a form of governmental supervision: the Chinese customs approves a firm's filing of a processing transaction if it satisfies certain requirements; then, this transaction becomes subject to the relevant policies.[14] A firm can, for example, engage in processing trade and sell domestically at the same time, but only its processing transactions will be subject to processing-specific benefits and regulations. Thus, while we define exporters that export solely through the processing regime as pure processors, we identify mixed exporters as firms that report both ordinary and processing trade to the Chinese customs.

[12] In 1988, China' total trade accounted for less than 1% of global trade and over 50% of it was in agriculture and primary goods. From 1978 to 2000, processing trade increased over 64 times while ordinary trade increased by only three times. In 1981, processing trade counted for only 6% of China's total trade, but by 1996 it exceeded 50% of China's total trade.

[13] One way to avoid complicated customs procedures is to operate in export processing zones. However, these zones are highly exclusive and only suitable for firms working for extremely stable contractors with fixed inputs and outputs. In 2000-2006, out of the 74,184 processing exporters, only 0.9% were located in export processing zones, and 96% of these firms were either foreign-owned or joint ventures.

[14] We thank to Jie Zhang and Li Liang from the research department of the statistical division of Chinese Customs for this clarification.

3 Empirical Findings

3.1 Mixed Exporters in China

In this subsection, we unpack the "black box" of mixed exporters—firms that engage in both processing and ordinary exports. We find that mixed firms made up about a fifth of processing exporters, and contributed to over 60% of total Chinese processing exports, explaining about a half of China's export surge during 2000-2006. In particular, two findings stand in contrast to the existing literature. First, we do not find evidence that would support the view that there is a linear upgrade from processing to hybrid and to ordinary trade: most industries' top exporters are mixed firms. Second, mixed firms are not 'mixed' because they sell different products under different export modes: the majority of their exports consists of the same product being sold to the same destination under both processing and ordinary trade modes. In what follows, we present these findings in steps, which lead us to further examine various firm characteristics across exporter types in the next subsection.

The customs data show that even though the number of mixed exporters was only 21% of the total number of exporters, they made up 54% of exports in 2005. Pure processors and pure ordinary exporters, on the other hand, made up 24% and 19% of exports in 2005 respectively.[15] Mixed firms' exports also made up the bulk (48%) of China's export boom in 2000-2006, with the rest of the growth explained almost equally by exports of pure ordinary firms (21%) and pure processors (24%).

As shown in Table 1, firms tend to remain the same type across years. Pure ordinary exporters change their type less than 7% of the time, whereas pure processors and mixed firms change their type less than 20% of the time. Firms usually do not switch directly between pure ordinary and pure processing, whereas other types of switches are observed with a similar level of magnitude. This finding dispels the concern that switching is frequent in our data.[16]

Table 1: Transition Matrix

Type	PO_{it+1}	PP_{it+1}	Mix_{it+1}
PO_{it}	93.5	0.27	6.23
PP_{it}	1.32	84.1	14.58
Mix_{it}	11.3	6.59	82.11

Notes: PO_{it}, PP_{it}, and Mix_{it} that indicate whether firm i is a pure ordinary exporter, pure processor, or a mixed exporter in year t respectively. The matrix shows the probability of switching from one type to another in China during 2000-2006.

[15] The rest is made by firms that did not fit into one of the three groups as they engaged in other export modes such as re-exporting, and made up about 3% of exports. Note that we exclude intermediaries, which made up 18% of exports in 2005.

[16] The switching between modes across years, albeit an interesting avenue for future research, is out of the scope of this paper.

We present firm-level statistics for mixed exporters in Table 2, with the full sample in panel (a) and the merged sample in panel (b). The figures in both panels are similar, and thus we refer to statistics in panel (b) from here on. Row 1 shows that the median (mean) share of processing exports in a mixed firm's total exports is 66% (58%). Corresponding shares at the firm-HS8 and firm-HS8-country levels in rows 2 and 3 are similarly high, suggesting that mixed exporters' main activity is processing trade. Nevertheless, mixed exporters contribute substantially to China's ordinary trade as well—in 2005, they made up 63% and 42% of China's processing and ordinary exports, respectively. Moreover, in 51 of the 68 HS2 manufacturing sectors, the top firm in terms of export value was a mixed exporter. Looking at the top three firms in each sector, there was at least one mixed exporter in 66 sectors.

Table 2 row 4 shows that the median (mean) share of processing exports done via the 'pure-assembly' (as opposed to 'import-and-assembly') regime is 0% (22%), revealing that mixed exporters generally purchase their own inputs for their exports (as opposed to receiving these inputs free-of-charge from their customers).

One may conjecture that these firms are 'mixed' because they export multiple products, some under processing trade and others under ordinary trade, potentially due to differences in input tariff schemes. Surprisingly, a careful look at the data reveals that this is not the main explanation. In Table 2 panel (b), we show that the *number* of products exported under both trade regimes, on average, accounts for 37% of mixed firms' total number of exported products (row 5). In terms of values, the median (mean) *value* share of products that are exported through both ordinary and processing modes (mixed HS8) in a mixed firm's exports is 89% (71%) (row 7). In other words, mixed exporters tend to sell their core product(s) under both trade regimes.

Table 2: Mixed Exporters

	(a) All mixed exp.			(b) Merged mixed exp.		
	Median	Mean	Sd.	Median	Mean	Sd.
(1) Processing share	0.64	0.58	0.36	0.66	0.58	0.36
(2) Processing share, mixed HS8	0.71	0.62	0.34	0.74	0.63	0.34
(3) Processing share, mixed HS8-country	0.68	0.62	0.32	0.70	0.63	0.32
(4) Pure-assembly share	0.00	0.26	0.42	0.00	0.22	0.39
(5) Share of mixed HS8	0.29	0.37	0.31	0.31	0.37	0.30
(6) Share of mixed HS8-country	0.19	0.25	0.24	0.20	0.24	0.23
(7) Value share of mixed HS8	0.87	0.68	0.37	0.89	0.71	0.35
(8) Value share of mixed HS8-country	0.59	0.53	0.37	0.62	0.55	0.36

Notes: This table shows the processing intensity (processing exports/total exports) of mixed exporters in rows 1-3, the share of their processing exports done via the *pure-assembly* (as opposed to *import-and-assembly*) regime in row 4, and their composition of exports (mixed exports/total exports) in rows 5-8, at different levels of aggregation. Panel (a) reports figures for the entire sample of 50,952 mixed exporters, whereas panel (b) reports figures for the subsample of 24,470 mixed exporters that can be matched to the AIS data (merged) for 2000-2006.

One can argue that there might still be different kinds of products within an HS8 code. This is less of a concern since China's product classification at the HS8 level is highly detailed: for example, there are seven different HS8 under the internationally-standardized HS6 code 520811 *Plain weave, unbleached, weighing not more than 100g/m*^{2}, that specify the type of cotton used (e.g., medical gauze). This level of detail mitigates the concern that an exporter is mixed due to its multi-product nature. Moreover, even when we look at the more disaggregate product-country level (panel (b) rows 6 and 8), we find that the median (mean) share of the same products that are sold to the same destination using both export modes is 20% (24%), with a value share of 62% (55%).

The fact that firms serve the same products or the same product-destinations under both trade regimes suggests that their choice of trade mode cannot be primarily driven by trade policies that ex-ante are only different across products, firms, or destinations. For example, if input tariff exemptions for processing trade makes it cheaper for a firm to export a certain product under the processing trade regime, it should export this product only via the processing trade regime. These findings do not change if we consider 'pure-assembly' and 'import-and-assembly' separately; the data shows that mixed firms' and pure processors' average share of 'pure-assembly' in their processing exports were very similar in 2000-2006 (22% versus 16%). Also, the government is seldom directly involved with mixed firms: the data shows that only 7% of mixed firms are state-owned enterprises. The top-5 HS2 sectors that mixed exporters engage in are the same top-5 sectors for pure ordinary and pure processing firms (HS: 62, 61, 85, 84, 39), suggesting that mixed exporters are ubiquitous across sectors.

The non-trivial existence of mixed exporters is intriguing. The theoretical literature typically assumes either that processing is a different sector (Brandt et al., 2021; Deng, 2021) or that heterogeneous firms as in Melitz (2003) sort themselves into processing or ordinary trade based on productivity differences combined with a variable-fixed cost trade-off (Brandt and Morrow, 2017; Defever and Riaño, 2017). Mixed exporters, although not the focus of these aforementioned papers, are generated by bringing in some product- or destination-specific shock to fixed costs. In that case, mixed exporters would never sell the same product to a given destination via both export modes.

3.2 Export Mode and Firm Characteristics

Following the well-established literature on exporter premia pioneered by Bernard and Jensen (1995, 1999, 2004), we investigate whether firms that engage in different export modes have significantly different characteristics. Lu (2010) showed that China was exceptional since it did not have the exporter premia that was found for virtually all other countries. Dai et al. (2016) showed that this lack of exporter premia was due to processing exporters, whose productivity lagged behind that of non-exporters. Several other papers including Fernandes and Tang (2015), Li et al. (2018), and Brandt et al. (2021) focused largely on the differences between ordinary and processing exporters. In the following, we build on this earlier work by focusing on mixed firms and their comparison to other types of exporters. Specifically, we bring in production and novel transaction-level trade data with brand information to understand the source of performance differences between firms.

We run the following regression using the merged exporters database:

$$Y_{it} = \beta_1 PP_{it} + \beta_2 Mix_{it} + \delta_{ht} + \epsilon_{it}, \tag{1}$$

where Y_{it} is an outcome variable (e.g., $\ln(empl.)_{it}$, where $empl.$ is for employment) for firm i in year t, PP_{it} and Mix_{it} are dummies for pure processing and mixed exporters respectively (pure ordinary exporters is the omitted group), and δ_{ht} are sector-year fixed effects, where sectors are classified according to the two-digit Chinese Industry Classification (CIC) reported in the AIS database. Finally, ϵ_{it} is the error term, and we cluster standard errors at the sector level. Each row of Table 3 shows results from a separate regression, and coefficients can be interpreted as relative to pure ordinary exporters. All regressions except for row 1 include $\ln(empl.)$ as a control variable for firm size. Panel (b) excludes firms with foreign ownership.

Table 3 panel (a) row 1 shows that compared to pure ordinary firms, pure processors and mixed firms have, on average, 30% and 38% more employment respectively. The statistical difference between the two coefficients (Prob.$> F = 0.07$) reveals that mixed exporters are also larger than pure processors. This size premium remains when we exclude foreign firms in panel (b): pure processors and mixed exporters are 21% and 38% larger than pure ordinary exporters respectively.

The existing empirical literature, including Mayer and Ottaviano (2008) and Bernard et al. (2012) for European and US firms respectively, find that larger firms tend to have higher labor productivity and revenue TFP ($TFPR$). Does this result hold for mixed exporters? Table 3 panel (a) row 2 shows that mixed firms have 14% higher labor productivity (i.e., value added per employee) than pure ordinary firms, whereas pure processors have 22% lower labor productivity than pure ordinary firms.[17] Row 3 shows that the ranking we obtained based on labor productivity remains when we consider $TFPR$ calculated using the Olley-Pakes (1996) methodology.[18]

As is well documented in the literature, $TFPR$ reflects not only firms' technical (or manufacturing) efficiency (quantity-based TFP, or $TFPQ$), but also their prices. In particular, focusing on the Chinese leather shoes industry, Li et al. (2018) find that exporters' $TFPQ$ is higher than non-exporters', while their $TFPR$ is lower than non-exporters'. What is the rank of mixed firms' $TFPQ$ among exporters? To answer this question, we compute $TFPQ$ focusing on the 36 of the 693 manufacturing 5-digit products for which we can obtain reliable quantity information. The estimation methodology and the list of products can be found in Appendix A and Table A.2 respectively.[19] Consistent with Li et al. (2018), we find that compared to pure ordinary exporters,

[17] In a similar vein, Dai et al. (2016) show that pure processing exporters are less productive than non-exporters, who are less productive than non-processing and "hybrid" exporters.

[18] As explained in Appendix A, we use only single-product firms to compute $TFPQ$, and thus for meaningful comparison, the regressions for $TFPR$ and $TFPQ$ consist of single-product producers only and include product-year fixed effects. Our $TFPR$ results are robust to using the Levinsohn-Petrin (2003) methodology.

[19] Our methodology is similar to the one used by Li et al. (2018) but differs slightly since instead of following De Loecker et al. (2016) and use a translog production function, we use the Olley-Pakes (1996) methodology with a

Table 3: Mixed Exporter Premia

(a) All exporters	PP_{it}		Mix_{it}		Obs.
(1) ln($empl.$)$_{it}$	0.30***	(0.07)	0.38***	(0.04)	208,514
(2) ln($labor\ prod.$)$_{it}$	-0.22***	(0.03)	0.14***	(0.03)	197,661
(3) $TFPR_{it}$	-0.14**	(0.07)	0.12***	(0.04)	9,297
(4) $TFPQ_{it}$	0.02*	(0.01)	0.03***	(0.01)	9,297
(5) ln($R\&D\ exp.$)$_{it}$	-0.81***	(0.15)	-0.27***	(0.05)	208,514
(6) ln($advert.\ exp.$)$_{it}$	-1.00***	(0.13)	-0.37***	(0.06)	193,919
(b) Excl. foreign firms	PP_{it}		Mix_{it}		Obs.
(1) ln($empl.$)$_{it}$	0.21***	(0.06)	0.38***	(0.04)	159,938
(2) ln($labor\ prod.$)$_{it}$	-0.05	(0.04)	0.21***	(0.03)	152,073
(3) $TFPR_{it}$	-0.02	(0.06)	0.14***	(0.04)	7,037
(4) $TFPQ_{it}$	0.04**	(0.02)	0.04***	(0.01)	7,037
(5) ln($R\&D\ exp.$)$_{it}$	-0.78***	(0.17)	-0.24***	(0.06)	159,938
(6) ln($advert.\ exp.$)$_{it}$	-0.95***	(0.14)	-0.33**	(0.06)	149,466

Notes: This table reports the results of running specification (1). Each row is a separate OLS regression of the dependent variable shown in column 1 on dummy variables PP_{it} and Mix_{it} that indicate whether firm i is a pure processor or a mixed exporter in year t respectively (pure ordinary is the omitted group). ln($R\&D\ exp.$)$_{it}$ and ln($advert.\ exp.$)$_{it}$ are calculated by $\ln(x+1)$ to avoid dropping zeros. $TFPR_{it}$ and $TFPQ_{it}$ refer to TFP calculated using revenue and quantity data respectively (see the text for details). Rows 1-2 and 5-6 include sector-year fixed effects, and all except those in the first row control for firm size. Rows 3-4 focus on single-product producers only and thus include product-year fixed effects. Coefficients for the two dummy variables are significantly different from each other in all rows except for row 4 in both panels. Standard errors clustered by 2-digit CIC industries are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

pure processors have higher $TFPQ$ on average (row 4 of Table 3 panel (a)). In addition, mixed exporters have the highest physical productivity on average (though not statistically significantly different from that of pure processors).[20] Note that processing intensity as captured by the share of processing in total exports varies across mixed exporters with a mean of 58% and a standard deviation of 36%. In Appendix Table A.3 we restrict the sample to mixed exporters to focus on the intensive margin, and find qualitatively similar results for processing intensity.

In the following, we summarize our finding regarding firms' performance:

Finding 1: Mixed exporters are larger than pure processors, who are larger than pure ordinary exporters in terms of employment. Mixed exporters have higher labor and revenue productivity than pure ordinary exporters, who have higher labor and revenue productivity than pure processors. However, mixed exporters and pure processors have higher physical productivity than pure ordinary exporters.

If we view a mixed firm as a combination of a pure processing and a pure ordinary firm, we would

Cobb-Douglas production function to control for selection. This difference, and our larger coverage of sectors, can explain the discrepancy that while we find mixed exporters and pure processors to have the highest $TFPQ$, they find that pure processors' $TFPQ$ is higher than that of "hybrid" firms.

[20] In unreported results, we regress productivity on the processing share of exports, and find a linear and positive relationship with $TFPQ$ and a non-linear inverted-U relationship with $TFPR$. These results confirm the ones above with exporter-type dummies.

expect that mixed firm characteristics lie between that of pure processing and pure ordinary firms, which stands in contrast with our findings. One obvious rationalization would be that processing transactions have lower prices due to, for example, input tariff exemptions or transfer pricing (Li et al., 2018), which would disproportionately distort the average export price of pure processors, and hence render the lowest $TFPR$. This could explain why the production efficiency ($TFPQ$) is greater for pure processors compared to ordinary exporters, but not why mixed exporters have the highest $TFPQ$.

An alternative hypothesis is that processing firms contribute to relatively less value-added stages of production (e.g., manufacturing), and thus get a lower share of profits when compared to their foreign buyers (Feenstra and Hanson, 2005; Dai et al., 2016; Manova and Yu, 2016). Given that most value-added comes from firms' non-manufacturing activities such as innovation and marketing, processing firms can be efficient in production yet have low $TFPR$. On the contrary, ordinary producers can claim more profits thanks to their branding activities, and hence can survive even with a relatively low $TFPQ$. This view also gives a natural explanation to the existence of mixed exporters: they are firms that excel in both manufacturing and non-manufacturing activities. This hypothesis is also consistent with the fact that many prominent Chinese firms produce their own-branded products while at the same time manufacture goods for other firms (Deng, 2021).[21]

To identify the dominant explanation among the two hypotheses, we use the 2018 customs sample to examine the relationship between product trade mode, price, and brand ownership of firms. As described in the data section, the 2018 customs dataset allows us to extract the brand ownership information for each export transaction, and label it as no brand, foreign brand, or domestic (own) brand. As shown in the last row of Table 4, 12.4%, 56.4%, and 32.7% of export value are due to transactions that have no brand, foreign brand, and domestic brand, respectively. Importantly, we find a tight link between the choice of processing trade mode and the production of foreign branded goods. Table 4 shows that 84% of processing exports in the sample consist of foreign branded products, while only 33% of ordinary exports consist of foreign branded products. This confirms the conjecture that processing transactions are typically viewed as local manufacturers supplying customized products to their buyers (Manova and Yu, 2016).

We run the following transaction-level regression:

$$D_{ifhc} = \beta P_{ifhc} + \delta_{hc} + \epsilon_{ifhc}, \tag{2}$$

where D_{ifhc} is a dummy indicating whether firm f's export transaction i of product h (at the HS10 level) to country c is for its own Chinese domestic brand (as opposed to foreign or no brand), P_{ifhc} is a dummy for processing trade (as opposed to ordinary trade), δ_{hc} are HS10-country fixed effects to control for product-destination determinants of processing trade policy and brand ownership (e.g.,

[21] For instance, *Shenzhou International*, a large Chinese textile manufacturer with its own brand, does processing for world-renowned brands such as *Adidas*, *Nike*, and *Uniqlo*. *Galanz*, a prominent home appliance producer to brands such as *De'Longhi*, *General Electric*, and *Sanyo*, also exports its own-branded microwaves and air conditioners.

FDI policy), and ϵ_{ifhc} is the error term. We cluster standard errors at the firm level. Table 5 column 1 shows that processing transactions are 13 percentage points less likely to involve products with domestic brands when compared to ordinary transactions. In column 2, we include firm-product-country fixed effects, which implies that we are comparing transactions of the same HS10 sold to the same destination by the same firm.[22] Column 2 shows that the coefficient remains negative and significant at the 10% level: mixed firms' processing exports are 3.2 percentage points less likely to include their own-branded products when compared to their ordinary exports of the same product to the same destination. Hence, we arrive at the following finding:

Finding 2: Ordinary transactions tend to involve firms' exports of their own-branded products, whereas processing transactions tend to involve firms' exports of their customers' branded products.

Table 4: Export Mode and Brand Ownership: Summary Statistics

	(1) No brand	(2) Foreign brand	(3) Domestic brand
Ordinary exports	14.3%	33.5%	52.2%
Processing exports	7.0%	83.9%	9.1%
Total	12.4%	56.4%	32.7%

Notes: This table reports the share of export modes in no brand, foreign brand, and domestic brand categories in columns 1, 2, and 3 respectively, using the 591,270 manufacturing export transactions in the 2018 customs data sample (after excluding the 271,297 transactions made by intermediaries). We extract brand ownership information for each transaction from the reported string product specification using an algorithm to classify transactions as no brand, foreign brand, or domestic (own) brand. We classify the 45 export modes reported in the dataset into three broader groups: ordinary exports, processing exports, and other exports.

In column 3, we regress the log unit value of transactions on brand ownership, controlling for export mode, and including product-country fixed effects. We find a positive relationship between brand ownership and unit values, even when we include firm-product-country fixed effects in column 4. The estimated coefficient indicates that a domestically branded product of a firm is about 9% more expensive than that same firm's sales of the same product to the same destination but under a different brand (significant at the 5% level). The positive correlations between non-processing export mode and brand ownership, as well as between brand ownership and brand premium support the hypothesis that price differences between processing and ordinary exporters can be explained by their specialization within a value chain. This results in the following finding:

Finding 3: There is a price premium associated with selling one's own-branded product.

Now let us turn to the first explanation that emphasized input price differences among exporters.

[22]There is enough variation even at this level as the average (median) number of transactions for each firm-product-country in our regression sample is 9.7 (2). Note also that 7% of the 15,078 firms in our regression sample are mixed, with the rest consisting of pure ordinary (82%) and pure processing firms (11%). The mixed firm-product-country flows make up 15% of total flows, with the rest consisting of pure ordinary (51%) and pure processing flows (34%).

If the observed $TFPR$ and $TFPQ$ differences between firms are due to processing exports being subject to lower input tariffs or preferential tax policies, then the export price for processing goods should be mechanically lower. However, the above conjecture would imply that within a firm-product-destination, processing exports should have a lower unit value, which contradicts our finding in Table 5 column 4. If transfer pricing is driving the results (i.e., processing exporters artificially lowering the price of export transactions between enterprises under common ownership or control), then we would expect to see a less stark difference in $TFPQ$ between processing and ordinary firms once we exclude foreign firms, which are more likely to engage in transfer pricing—the results in Table 3 suggest the opposite. Therefore, we conclude that the higher average price of exporters' own products is more likely due to brand premium instead of input tariff exemptions or transfer pricing.

Table 5: Export Mode and Brand Ownership: Regressions

Dependent var.:	D_{ifhc}		$\ln uv_{ifhc}$	
	(1)	(2)	(3)	(4)
P_{ifhc}	-0.126***	-0.032*	-0.072	0.092**
	(0.039)	(0.016)	(0.162)	(0.044)
D_{ifhc}			0.197*	0.088**
			(0.110)	(0.038)
Product-country FE	Yes	No	Yes	No
Firm-product-country FE	No	Yes	No	Yes
R^2	0.30	0.85	0.81	0.92
Obs.	445,437	427,567	419,009	402,169

Notes: This table reports the results of running specification (2). D_{ifhc} indicates whether transaction i of firm f in product h (at the HS10 level) to destination c is a domestic own-brand transaction, P_{ifhc} indicates whether this transaction is classified under processing trade, and $\ln uv_{ifhc}$ is the log unit value of this transaction. Standard errors clustered by firms are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Finally, we provide suggestive evidence that a firm's choice of export mode is indeed associated with its branding activities. Table 3 panel (a) rows 5 and 6 reveal that R&D investment and advertisement expenditures across firms are in the following decreasing order: pure ordinary exporters, mixed exporters, and pure processors. In fact, 85% of pure processors did not have any R&D or advertising expenses in 2005. This is in line with anecdotal evidence that pure processors tend to specialize in manufacturing for other firms, and thus do not need to invest in R&D or spend on advertisement, which are ultimately done by their customers. In panel (b) rows 5 and 6, we exclude foreign firms since the majority of their R&D and advertising are likely to be done in their headquarter-countries, and thus are not perfectly observed in our data—the results are similar. In Appendix Table A.3, we find that for mixed exporters, as processing intensity increases, R&D and advertisement expenditures decrease as expected.

4 A Simple Model to Rationalize the Findings

The empirical findings presented above lead us to view mixed exporters as firms that are superb in both manufacturing efficiency and branding ability. These two abilities jointly determine firms' export and specialization patterns and affect their observed characteristics. In this section, we provide a parsimonious model of multi-attribute firms to rationalize our findings. In particular, we highlight two modeling pieces that help explain our results: (i) two-dimensional heterogeneity in "making" and "creating" (i.e., manufacturing and branding), and (ii) a positive but low profit margin in manufacturing. To emphasize the sufficient model structure that matches our empirical findings, rest of the model is as stylized as possible. We provide derivations of the main results in Appendix B.

4.1 Model Setup

Consider an economy where consumer preferences are Cobb-Douglas over two sectors: a homogeneous sector producing one unit of product with one unit of labor, and a differentiated sector that is the focus of our analysis. A fraction β of income is spent on the differentiated sector and the preference across varieties is CES with elasticity of substitution $\sigma > 1$. The sector constitutes a continuum of firms, and each firm owns a blueprint to produce a single differentiated variety. The demand for variety j is:

$$q_j = A_1 z_j p_j^{-\sigma},$$

where A_1 is the aggregate demand shifter and z_j reflects the quality of the blueprint owned by firm j. Other things equal, varieties with better blueprints attract more demand. The price p_j refers to the price of variety j.

To link with our empirical findings, we distinguish between the "making" and "creating" of a variety. A variety's blueprint quality (i.e., creating) is associated with the firm who owns the blueprint. A variety's manufacturing efficiency (i.e., making), on the other hand, is tied to the production efficiency of the firm that makes it. We specify firms' making decision as the following. Production requires only labor, which is inelastically supplied (L).[23] As a manufacturer, firm j can produce both for its own and for other firms' blueprints. Its marginal cost of production is $1/t_j$ when it produces its own variety, but when making for other firms, as every production contract is unique and has different manufacturing requirements, we assume that this production efficiency is subject to uncertainty. Specifically, for every blueprint, firm j draws a production efficiency from a Fréchet distribution with a level parameter t_j and a shape parameter θ, where $\theta > \sigma - 1$. That is, t reflects on average how good firm j is in manufacturing.

Analogously, as a blueprint holder, firm j can organize its production in-house or outsource

[23] In reality, pure manufacturing firms are often involved in only one part of the value chain, while sourcing the rest of the inputs. This can be incorporated into the model by assuming that production requires labor and intermediate goods, but such treatment does not affect the main implications of the model, and hence we abstract from 'intermediate' goods for simplicity.

production to other firms. It observes the t of all firms, but needs to pay a fixed cost f in terms of labor to discover a supplier's actual efficiency in manufacturing for its blueprint. In other words, blue-print holders make the decision of matching before they observe the realized blueprint-specific productivity of each supplier. In addition, outsourcing requires an additional f_o units of labor to coordinate production. A blueprint holder optimally chooses the number of reached suppliers, draws blueprint-specific productivity from each supplier, and selects the one with the lowest marginal cost of production as its manufacturer. We assume that ex-post gains are shared through Nash bargaining, and the bargaining power of the manufacturer is γ.[24]

There is an unbounded pool of prospective entrants who learn about their blueprint quality z and core manufacturing ability t after incurring a fixed entry cost f_E. We assume that z and t are drawn from two distributions $G_z(z)$ and $G_t(t)$ with supports $(0, \bar{z}]$ and $(0, \bar{t}]$, respectively. Once firms draw their abilities, they decide whether (i) to bring own blueprint to production (in-house or outsource) and/or (ii) be active in manufacturing for other firms' blueprints. Bringing one's own blueprint to production requires an additional fixed cost f_B. Finally, there is a constant probability δ that forces a firm to exit in each period.

When it comes to international trade, it is natural to distinguish the trade costs associated with goods that are *made* domestically and exported, and goods that are *owned* by domestic firms and sold abroad. We assume that iceberg trade costs are associated with the "making" locations, i.e., $\tau_t > 1$ units are required to be shipped for one unit of domestic manufactured variety to be consumed in the foreign country, regardless of whether the blueprint is foreign or domestic. The fixed cost of exporting is typically associated with getting access to a certain market, and thus we assume that selling to foreign markets requires an additional cost f_X borne by domestic blueprint holders, regardless of where the goods are made. The homogeneous good is freely traded.

4.2 Firm Specialization

The model yields a natural specialization pattern of firms within a value chain. From a blueprint holder's perspective, conditional on outsourcing, the least productive supplier that a profit-maximizing firm j contacts solves:

$$\underline{t}_j \equiv \underline{t}(z_j) = f(A(1-\gamma)\Gamma(\frac{\theta+1-\sigma}{\theta})z_j)^{-1}\frac{\theta}{\sigma-1}\Theta(z_j)^{1-\frac{\sigma-1}{\theta}}, \tag{3}$$

where $A = \frac{1}{\sigma}(1-\frac{1}{\sigma})^{\sigma-1}\beta L P^{\sigma-1}$, Γ stands for the gamma function, and $\Theta(z_j) = N\int_{\underline{t}_j(z_j)}^{\bar{t}} \iota dG_t(\iota)$ measures firm j's "sourcing pool." Intuitively, the more suppliers that firm j contacts, the more likely it finds a manufacturer producing its variety at a low cost. Firms with better blueprints benefit more from contracting with a productive manufacturer, and hence $\underline{t}_j$ decreases in z_j.

[24]The model predictions are robust to different assumptions of market structure such as Bertrand competition in manufacturing.

If firm j chooses to outsource (O) the production of its variety, the expected profit is given by:

$$\pi_j^O = \frac{(1-\gamma)}{\sigma} A z_j E(c_j^{1-\sigma}) \left(1 - \frac{\sigma-1}{\theta} \frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota)}{\int_{\underline{t}_j}^{\bar{t}} t dG_t(\iota)} \right) - f_B - f_o, \tag{4}$$

where $E(c_j^{1-\sigma}) = \Gamma(\frac{\theta+1-\sigma}{\theta})\Theta(z_j)^{\frac{\sigma-1}{\theta}}$. If firm j chooses to produce in-house (I), its expected profit is:

$$\pi_j^I = A z_j t_j^{\sigma-1} - f_B.$$

Therefore, firm j will choose to produce its variety in-house if $\pi_j^I \geq \pi_j^O$ and $\pi_j^I > 0$, outsource if $\pi_j^O > \pi_j^I$ and $\pi_j^O > 0$, and exit otherwise. This yields three cutoff curves, and firm j would find it optimal to:

(1) outsource its variety if $z_j > z_1, z_j < \psi^{-1}(t_j)$,

(2) produce in-house if $z_j > \phi(t_j), z_j \geq \psi^{-1}(t_j)$, and

(3) exit otherwise,

where z_1 solves $\pi_j^O(z_1) = 0$, $\psi(z) = ((1-\gamma)E(c^{1-\sigma})(1 - \frac{\sigma-1}{\theta}\frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota)}{\int_{\underline{t}_j}^{\bar{t}} t dG_t(\iota)}) - f_o)^{\frac{1}{\sigma-1}}$ and $\phi(t) = \frac{f_B}{At^{\sigma-1}}$. As visualized in Figure 1 panel (a), when production is outsourced, firm j's own manufacturing ability does not matter. As a result, the cutoff between exit and outsource is a straight vertical line. Blueprint quality and manufacturing ability are complements in production, and thus the cutoff between in-house production and exit, $\phi^{-1}(z)$, is downward sloping. Lastly, since higher blueprint quality means a greater return from outsourcing, a firm with a higher z is more likely to outsource given the same manufacturing ability. Therefore, the cutoff $\psi(z)$ between in-house production and outsourcing is upward sloping.

As firms with better blueprints search for more potential suppliers, the active manufacturer with the least productivity has to be the firm that is reached by the blueprint holder with the best blueprint quality $\bar{z}$.[25] This yields the manufacturing cutoff $\underline{t}_M$, above which firms will be active in producing for other firms' blueprints:

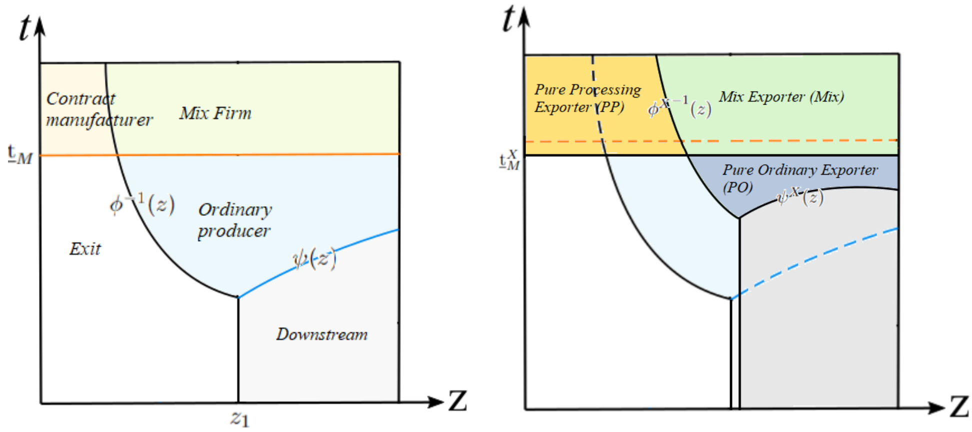
$$\underline{t}_M \equiv \underline{t}(\bar{z}) = f(A(1-\gamma)\Gamma(\frac{\theta+1-\sigma}{\theta})\bar{z})^{-1}\frac{\theta}{\sigma-1}\Theta(\bar{z})^{1-\frac{\sigma-1}{\theta}}. \tag{5}$$

This is illustrated as the orange horizontal line in panel (a) of Figure 1.

Putting the decisions of outsourcing and own-production together, the model gives rise to firms' specialization based on their heterogeneity in two dimensions. As shown in panel (a) of Figure 1, firms with low z become pure contract manufacturers (light yellow area), and firms with high z and high t also produce their own variety and become mixed firms (light green area). Firms with intermediate z and t produce solely for their own blueprint, becoming ordinary producers (light

[25] Because the manufacturing abilities are drawn from a Fréchet distribution, the least productive manufacturer would have a positive chance of being the cheapest supplier. With a continuum of firms, the supplier's production in equilibrium is positive by law of large numbers.

Figure 1: Firm Specialization



(a) Closed economy specialization

(b) Open economy specialization

blue area). Firms with high z but low t outsource production and become downstream firms that do not manufacture (grey area). Firms with both low z and t exit (white area).

With international trade, the cutoff contract manufacturer for foreign firms satisfies $\underline{t}_M^X = \tau_t^\theta \underline{t}_M^*$. Since a large share (40%) of pure processors did not have any domestic sales in our sample period, we assume that the foreign blueprint qualities are higher such that the export processing cutoff is lower (i.e., $\underline{t}_M^X < \underline{t}_M$). For domestic varieties, the model yields three additional export cutoff curves and two new equilibrium decisions: export with in-house production and export with outsourced production. Note that the cutoff between in-house production and outsourcing for exporting firms $\psi^X(z)$ is strictly above $\psi(z)$, since improved market access always leads to greater gains from outsourcing. As depicted in Figure 1 panel (b), with international trade, a subset of entrants survive and a smaller subset of them export. Active manufacturing firms have higher manufacturing ability than firms that exit, while processing exporters have even higher manufacturing ability. If a firm has high manufacturing ability but low blueprint quality, it becomes a pure processing exporter. Similarly, those with the 'worst' blueprint quality exit, better ones operate in the domestic market, and the even better ones export and become pure ordinary exporters. If a firm excels in both manufacturing ability *and* blueprint quality, it becomes a mixed exporter.

4.3 Linking the Model to Empirics

Our model generates a rich set of firm types, but for the sake of empirical relevance, we focus on pure processing exporters (PP), pure ordinary exporters (PO), and exporters that engage in both activities (Mix). We now discuss how our framework can rationalize the empirical findings in Section 3.

Physical Productivity Physical TFP measures a firm' efficiency in transforming inputs into quantity outputs, which corresponds to the manufacturing ability t in our model. The processing export cutoff $\underline{t}_M^X$ ensures that t_{PO} is always lower than t_{PP} and t_{Mix}, and the downward sloping cutoff curve $\phi^{X^{-1}}$ ensures that by selection there are always more firms with greater t being mixed than pure processing exporters. Therefore our model naturally generates the $TFPQ$ ranking observed in data: mixed exporters on average have the highest physical productivity, followed by processing exporters, which are followed by ordinary exporters.

Revenue and Labor Productivity The log labor productivity of a firm j is given by $LP(z_j, t_j) = ln\left(\frac{\pi^I(z_j,t_j)+\pi^M(t_j)+l(z_j,t_j)}{l(z_j,t_j)}\right)$, which can be expressed as an employment weighted average of its labor productivity of being a blueprint producer and a contract manufacturer.[26] Manufacturing is often considered as the least value-added stage in a value chain, and this translates into a low γ in our model. If γ is sufficiently small, processing exporters exhibit the lowest labor productivity. Mixed exporters with superior manufacturing ability naturally exhibit greater labor productivity for their ordinary part of the production compared to ordinary exporters. However, greater manufacturing ability also implies more demand from outsourcing, which reduces the aggregate labor productivity of mixed firms. When the first force dominates, our model naturally generates the labor productivity ranking observed in the data: $E_{Mix}(LP) > E_{PO}(LP) > E_{PO}(LP)$.

The model can also rationalize the ranking for the revenue TFP. To be consistent with the Olley-Pakes estimation of $TFPR$, we can instead assume that varieties are produced using labor and capital with a Cobb-Douglas technology, with a share parameter on labor being α. In this case, the revenue TFP of firm j is given by:

$$TFPR(z_j, t_j) = ln(\frac{\pi^I(z_j, t_j) + \pi^M(t_j)}{{l_j}^{\alpha}{k_j}^{1-\alpha}}) \propto ln(\frac{\pi^I(z_j, t_j) + \pi^M(t_j)}{l_j}) = LP_j,$$

in equilibrium, where w_K is the rental price of capital. The ranking is therefore the same as that of labor productivity, which is consistent with the data.

R&D and Advertisement Expenditures In the data, we find that pure ordinary exporters spend more on R&D and advertising than mixed exporters, who spend more than pure processing exporters. Suppose that firms draw their blueprint quality and manufacturing ability sequentially. After observing its z, a firm can choose whether to incur an additional cost $f^{RD}(a)$ to improve its blueprint quality to $za^{\frac{1}{\sigma-1}}$ before observing its manufacturing ability t.[27] Standard assumption that $f^{RD'} > 0$ and $f^{RD''} > 0$ applies, and hence f^{RD} is an increasing function of z in equilibrium. As Figure 1 panel (b) illustrates, there are relatively more processing exporters with lower z compared to mixed and ordinary exporters, and thus the model predicts that pure processing exporters spend the least on R&D and advertising. Compared to mixed exporters, the downward-sloping cutoff $\phi^{X^{-1}}$ selects relatively more high z firms to become pure ordinary exporters. However, the upward-sloping outsourcing cutoff ψ^X at the same time also pushes more high z firms to become

[26] $LP(z_j, t_j)$ can be expressed as $\ln\left(\frac{\pi^I(z_j,t_j)}{l^B(z_j,t_j)}s^B + \frac{\gamma}{(\sigma-1)}(1-s^B)+1\right)$, where l^B and s^B are the level and share of employment used for producing j's own variety, respectively.

[27] In this case, the blueprint quality distribution remains orthogonal to the distribution of t, and thus all other predictions derived from the model still hold.

downstream firms (hence out of the comparison sample). When the first effect dominates, our model also rationalizes the observation that pure ordinary exporters spend more on R&D and advertising than mixed exporters.

Employment On average, mixed exporters have greater employment compared to pure processing exporters for two reasons. First, mixed exporters employ more labor for manufacturing other firms' varieties because they have greater t on average. Second, mixed exporters have additional labor for producing their own varieties. The employment ranking between processing and ordinary exporters is also intuitive. The key is to recognize that the production, and hence the employment of processing exporters, can be viewed as that of a "compound firm," whose production efficiency is given by manufacturers, but whose blueprint quality is given by outsourced blueprint holders. Therefore, this "compound firm" can have on average greater t and z compared to that of pure ordinary exporters, and thus greater employment, generating the observed employment rankings in the data.

5 Conclusion

In this paper, we analyzed the mostly neglected 'mixed' exporters that were the driving force behind China's export boom in 2000-2006 by engaging in both processing and ordinary exports. Importantly, unlike what is suggested in the literature, these firms are not 'mixed' because they sell different products under different export modes: the majority of their exports consists of the same product being sold to the same destination under both processing and ordinary trade modes. This finding suggests that factors other than policy instruments such as duty exemptions also determine firms' selection into different trade modes.

We found that these mixed "super processors" are larger and have higher revenue and physical productivity than other exporters. Our finding that ordinary trade transactions are more likely to consist of firms' own brands, which have a price premium, indicated that a firm's export mode not only reflects its position inside a production network, but is also closely related to its efficiency across different stages of production, which ultimately determines its measured performance at various margins.

To rationalize our empirical findings, we provided a simple theoretical framework where firms that are heterogeneous in two dimensions ("making" and "creating") endogenously determine their specialization within a production network. The model predicted that, in equilibrium: firms with intermediate manufacturing ability and blueprint quality become ordinary exporters; firms with high manufacturing ability but low blueprint quality become pure processing exporters; and firms with exceptional blueprint quality and manufacturing ability become mixed exporters. As such, our model was able to rationalize the observed ranks at various margins between the three types of exporters. Overall, our results highlighted that firms can be good at different stages of the value chain, and these heterogeneous abilities do not necessarily translate into a single measure for firm performance.

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Appendix A Calculating Physical TFP

To calculate physical TFP, we use the firm-product level production survey conducted by the NBS in China. This survey records information on products produced by all SOEs and private firms that have annual sales of at least five million RMB in 2000-2006.[28] To be able to assign an export mode for each firm, we merge this database with the merged Chinese customs-AIS dataset using unique firm IDs. Then, to obtain reliable productivity estimates at the firm level, we focus on single-product firms. Counting by the number of firm-product-year observations, single-product firms account for 56% of observations. Considering the relatively large amount of single-product observations, we expect that focusing on these observations will not severely bias our results. To ensure that the sample size is large enough to perform the estimation, we keep product categories with at least 2,000 firm-year observations and at least four years of existence.[29] Moreover, for each product category we require that there are at least 50 yearly observations. This results in a sample of 36 products (out of 693 manufacturing products) and 145,832 firm-year observations. Table A.2 lists the 36 products with their brief descriptions.

A.1 Methodology and Estimation

Our goal is to compare the production efficiency of exporters with different export modes. Following Foster et al. (2008), we use quantity data to get rid of the estimation bias caused by heterogeneity in output pricing. Since we do not have information on firms' inputs, the input price dispersion may also bias our productivity estimates. To deal with this concern, we follow De Loecker et al. (2016) and use output prices to control for the input price dispersion. Note that for the final sample with single-product firms, 19% of firms exit before the end of our sample period. This attrition rate can potentially cause a selection bias as first pointed out by Olley and Pakes (1996). To deal with this concern, we also control for firm exit.[30] We outline the estimation framework below.

The log-linearized Cobb-Douglas production technology for firm i in period t is assumed to be in the form of:

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma m_{it} + \omega_{it} + \varepsilon_{it}, \tag{6}$$

where q_{it} is output quantity of firm i in year t, k_{it} is fixed assets, l_{it} is the number of employees, m_{it} is materials, ω_{it} is physical productivity, and ε_{it} is the productivity shock that is exogenous to the firm's production decision. We aim to estimate ω_{it}, which is observable to the firm but not to the econometrician.

Most of the existing literature has estimated TFP using deflated revenue data. However, these output price deflators are usually at the industry level, and thus they ignore the heterogeneity in firms' prices within an industry. As a consequence, the estimated productivity contains information

[28]See Li et al. (2018) for a detailed description of the production survey.

[29]As a robustness check, we change the threshold to 1,000 and results are qualitatively the same.

[30]In addition to using a Cobb-Douglas instead of a translog production function, our methodology slightly differs from Li et al. (2018) as we control for selection using the Olley-Pakes method.

on output prices, causing revenue productivity ($TFPR$) to be systematically different than physical productivity ($TFPQ$). The quantity data helps us to control for the output price dispersion if we can observe firms' input usage. Unfortunately, like in most other production survey datasets, we do not have information on the amount (in quantities) of each input used for production. However, we do observe the total expenditure on materials, denoted by $\tilde{m}_{it}$. Letting p_{Mit} be the log of material prices, we immediately have:

$$m_{it} = \tilde{m}_{it} - p_{Mit}. \tag{7}$$

If we use the industry-level material price index p_{Mjt} to deflate material expenditures, the material input used in the production function can be written as:

$$\bar{m}_{it} = \tilde{m}_{it} - p_{Mjt}. \tag{8}$$

Plugging (8) into (7), we can express the quantity of materials as:

$$m_{it} = \bar{m}_{it} + p_{Mjt} - p_{Mit}.$$

Therefore, we can rewrite the production function as:

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma \bar{m}_{it} + \omega^*_{it} + \varepsilon_{it}, \tag{9}$$

where:

$$\omega^*_{it} = \omega_{it} + \gamma(p_{Mjt} - p_{Mit}).$$

This implies that the productivity obtained will contain information on input prices: $p_{Mjt} - p_{Mit}$. This input price bias can potentially create misleading results about the productivity differences for different types of exporters, especially if this input price is also correlated with export mode. This is of particular concern because processing exporters can use imported materials duty-free (as long as the output that uses these materials is exported).

The existing literature has also documented the necessity of controlling for input prices in estimating production functions (Ornaghi, 2006). Taking advantage of the quantity and revenue data, we control for the firm's input price using its output price. The underlying assumption is that the output price contains information on the firm's input price within a narrowly defined product category. Specifically, denoting p_{it} as the output price, the input price is assumed to be a non-parametric function of p_{it} and other firm characteristics:

$$p_{Mit} = f(p_{it}, \mathbf{X}_{it}). \tag{10}$$

This allows us to express physical material input as:

$$m_{it} = \tilde{m}_{it} - f(p_{it}, \mathbf{X}_{it}).$$

Thus, the production function we estimate is given by:

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma \tilde{m}_{it} + \gamma f(p_{it}, \mathbf{X}_{it}) + \omega_{it} + \varepsilon_{it}. \tag{11}$$

In our estimations, we use sales and quantity data to construct output price in the following way:

$$p_{it} = \log\left(\frac{R_{it}}{Q_{it}}\right), \tag{12}$$

where R_{it} and Q_{it} are firm i's sales in values and quantities respectively in year t. We follow the Olley-Pakes methodology except that in the first-stage estimation, in addition to k_{it}, l_{it}, and $\tilde{m}_{it}$, we add polynomials of logged output prices to control for material prices. We also control for firm exit as a function of polynomials of capital stock, investment, and year dummies. This allows us to address the potential selection bias caused by less productive firms exiting the sample. To account for heterogeneity in production technology, we perform the estimation product by product.[31] Once we estimate the production function coefficients, we then compute our physical productivity ($TFPQ$) estimates, which are used in the regressions in Table 3.

[31] The production function estimation results are available upon request.

Appendix B Theory Appendix

Solving the model

Conditional on blueprint holder j being connected with i, the probability that a manufacturer i is the lowest-cost supplier is:

$$\lambda_{ij} \equiv \lambda(z_j, t_i) = \frac{t_i}{\Theta(z_j)}, \tag{13}$$

where $\Theta(z_j) \equiv \Theta_j = N \int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota)$. Given the well-known properties of the Fréchet distribution, the probability that the least-cost supplier's marginal cost of production is smaller than c is given by $Pr(c_j \leq c) = 1 - e^{-\Theta_j c^\theta}$ and expected marginal cost of production of j is therefore $E(c_j) = \Theta_j^{\frac{-1}{\theta}} \Gamma(\frac{\theta+1}{\theta})$ and $E(c_j^{1-\sigma}) = \Gamma(\frac{\theta+1-\sigma}{\theta})\Theta_j^{\frac{\sigma-1}{\theta}}$. The measure of reached suppliers equals:

$$n_j = N \int_{\underline{t}_j}^{\bar{t}} dG_t(\iota).$$

Firm j's net profits (from its own blueprint) when production is outsourced is given by:

$$\pi_j^O = (1-\gamma) A z_j E(c_j^{1-\sigma}) - n_j f - f_B - f_o, \tag{14}$$

where $A = \frac{1}{\sigma}(1-\frac{1}{\sigma})^{\sigma-1} \beta L P^{\sigma-1}$. Taking the first derivative with respect to $\underline{t}_j$ of the above equation, we get:

$$\frac{\sigma-1}{\theta}(1-\gamma) A z_j \Gamma(\frac{\theta+1-\sigma}{\theta}) N^{\frac{\sigma-1}{\theta}} \left(\int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota) \right)^{\frac{\sigma-1}{\theta}-1} \underline{t}_j = Nf. \tag{15}$$

This yields the optimal cutoff $\underline{t}_j$ that satisfies:

$$\underline{t}_j \equiv \underline{t}(z_j) = f((1-\gamma) A z_j E(c_j^{1-\sigma}))^{-1} \frac{\theta}{\sigma-1} \Theta(z_j). \tag{16}$$

Note that the first order condition (15) implies:

$$(1-\gamma) A z_j E(c_j^{1-\sigma}) \times \frac{\sigma-1}{\theta} \frac{\underline{t}_j}{\Theta(z_j)} = f, \tag{17}$$

in equilibrium. Using equation (17) to substitute f in (14), we get the expected profit of j if the firm chooses to outsource the production of its variety:

$$\pi_j^O = (1-\gamma) A z_j E(c_j^{1-\sigma}) \left(1 - \frac{\sigma-1}{\theta} \frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota)}{\int_{\underline{t}_j}^{\bar{t}} t dG_t(\iota)} \right) - f_B - f_o. \tag{18}$$

On the other hand, if firm j chooses to produce in house (I), its expected profit is:

$$\pi_j^I = A z_j t_j^{\sigma-1} - f_B.$$

Clearly, from the blueprint holder's perspective, firm j chooses to produce its variety in-house iff $\pi_j^I \geq \pi_j^O > 0$, outsource iff $\pi_j^O > \pi_j^I > 0$, and exit otherwise. This yields three cutoffs:

$$\pi^I(z,t) = 0 \quad \Rightarrow \quad z = \frac{f_B}{At^{\sigma-1}},$$

$$\pi^O(z_1) = 0,$$

$$\pi^O(z) = \pi^I(z,t) \quad \Rightarrow \quad t = ((1-\gamma)E(c^{1-\sigma})(1 - \frac{\sigma-1}{\theta}\frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota)}{\int_{\underline{t}_j}^{\bar{t}} t dG_t(\iota)}) - f_o)^{\frac{1}{\sigma-1}}.$$

Therefore, firm j as a blueprint holder would find it optimal to outsource its variety if:

$$z_j > z_1, z_j < \psi^{-1}(t_j), \tag{19}$$

and produce in house if:

$$z_j > \phi(t_j), z_j \geq \psi^{-1}(t_j), \tag{20}$$

where z_1 solves $\pi_j^O(z_1) = 0$, $\psi(z) \equiv ((1-\gamma)E(c^{1-\sigma})(1 - \frac{\sigma-1}{\theta}\frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota)}{\int_{\underline{t}_j}^{\bar{t}} t dG_t(\iota)}) - f_o)^{\frac{1}{\sigma-1}}$ and $\phi(t) \equiv \frac{f_B}{At^{\sigma-1}}$. On the other hand, the actively producing firm with the least manufacturing ability can only be reached by firms with the best blueprint quality $\bar{z}$ (in comparative statics below we show formally that $\frac{\partial \underline{t}_j}{\partial z_j} < 0$). This yields the manufacturing cutoff $\underline{t}_M$, above which firms will be active in producing for other firms' blueprints:

$$\underline{t}_M \equiv \underline{t}(\bar{z}) = f(A(1-\gamma)\Gamma(\frac{\theta+1-\sigma}{\theta})\bar{z})^{-1}\frac{\theta}{\sigma-1}\Theta(\bar{z})^{1-\frac{\sigma-1}{\theta}}. \tag{21}$$

Firm i's expected profit from manufacturing other firms' blueprints is given by:

$$\pi_i^M \equiv \pi^M(t_i) = \sum_{\{j:\underline{t}_j \leq t_i\}} \gamma\lambda_{ij} A z_j E(c_j^{1-\sigma}).$$

Intuitively, π_i^M equals the sum of expected profits from contracting with potential blueprint holders times the probability that the firm actually matches with each of these blueprint holders.

From the above analyses we solved for firms' decisions given the aggregate price index P and the mass of entrants N. Additionally, the aggregate price (AP) index is given by:

$$P^{1-\sigma} = N\left(\int_{z_1}^{\bar{z}}\int_0^{\psi(z)} z_j\tilde{p}(z_j)^{1-\sigma}g(z,t)dtdz + \int_{z_1}^{\bar{z}}\int_{\psi(z)}^{\bar{t}} z_j p_j^{1-\sigma}g(z,t)dtdz + \int_{z_2}^{z_1}\int_{\phi^{-1}(z)}^{\bar{t}} z_j p_j^{1-\sigma}g(z,t)dtdz\right), \tag{22}$$

where $p_j = ((1-\frac{1}{\sigma})t_j)^{-1}$ and $\tilde{p}(z_j)^{1-\sigma} = (1-\frac{1}{\sigma})^{\sigma-1}E(c(z_j)^{1-\sigma})$, and $g(.)$ is the corresponding probability density function of distribution $G(.)$ that is specified in the main text. Note that although the actual marginal cost of production for an outsourced variety is a random variable, since there is a continuum of varieties the law of iterated expectations applies, and thus we can write the aggregate price index as such.

The free entry condition (FE) is given by:

$$\int_{\underline{t}_M}^{\bar{t}} \pi^M(t)dG_t(t) + \int_{z_1}^{\bar{z}}\int_0^{\psi(z)} \pi^O(z)g(z,t)dtdz + \int_{z_1}^{\bar{z}}\int_{\psi(z)}^{\bar{t}} \pi^I(z,t)g(z,t)dtdz + \int_{z_2}^{z_1}\int_{\phi^{-1}(z)}^{\bar{t}} \pi^I(z,t)g(z,t)dtdz = \delta f_E, \tag{23}$$

where $\pi^M(t)$ is the profit from being a contract manufacturer, and z_2 is the blueprint quality cutoff of firms that produce in-house, i.e., z_2 solves $\pi_j^I(z_2, \bar{t}) = 0$. Therefore, we have two equations to solve for two unknowns and hence reach the equilibrium. Similar to the case with international trade, given the mass of entrants and the aggregate price indices in both countries, firms' optimal sourcing and operating decisions can be determined. By plugging the associated variables as functions of N, N^*, P, P^* into the aggregate price equations and the free entry conditions for home and foreign, we can solve for the equilibrium.

Comparative statics for z_j, P, and A It is easy to show that the second-order condition of the optimization problem requires that $\theta > \sigma - 1$. Recall that the optimal cut-off for sourcing is:

$$\underline{t}_j \equiv \underline{t}(z_j) = f((1-\gamma)Az_j\Gamma(\frac{\theta+1-\sigma}{\theta}))^{-1}\frac{\theta}{\sigma-1}\Theta(z_j)^{1-\frac{\sigma-1}{\theta}}. \tag{24}$$

Note that A and z_j always show up multiplicatively, and hence it is sufficient to do comparative statics for one of them. Without loss of generality, we focus on z_j. We first examine how the cutoff $\underline{t}_j$ changes with respect to changes in z_j:

$$\frac{\partial \underline{t}_j}{\partial z_j} \propto \frac{\partial({z_j}^{-1}\Theta(z_j)^{1-\frac{\sigma-1}{\theta}})}{\partial z_j} \propto \left[-z_j^{-1}{\Theta_j}^{1-\frac{\sigma-1}{\theta}} + \frac{\partial \Theta_j^{1-\frac{\sigma-1}{\theta}}}{\partial z_j} \right], \tag{25}$$

where:

$$\frac{\partial \Theta_j^{1-\frac{\sigma-1}{\theta}}}{\partial z_j} = \left(1 - \frac{\sigma-1}{\theta}\right)\Theta_j^{-\frac{\sigma-1}{\theta}}\frac{\partial \Theta_j}{\partial \underline{t}_j}\frac{\partial \underline{t}_j}{\partial z_j}.$$

Now suppose $\frac{\partial \underline{t}_j}{\partial z_j} > 0$, then the right-hand side of equation (25) will be negative because $\frac{\partial \Theta_j}{\partial \underline{t}_j} < 0$ and $\theta > \sigma - 1$. This leads to a contradiction, which implies that $\frac{\partial \underline{t}_j}{\partial z_j} < 0$. Then, it is straightforward to show that $\frac{\partial \Theta_j}{\partial z_j} > 0$. As $E(c_j) = \Theta_j^{\frac{-1}{\theta}}\Gamma(\frac{\theta+1}{\theta})$ and $E(c_j^{1-\sigma}) = \Gamma(\frac{\theta+1-\sigma}{\theta})\Theta_j^{\frac{\sigma-1}{\theta}}$, it is immediate that $\frac{\partial E(c_j)}{\partial z_j} < 0$, $\frac{\partial E(c_j^{1-\sigma})}{\partial z_j} > 0$. Finally, by the envelope theorem we know that $\frac{\partial \pi_j^O}{\partial z_j} > 0$. As A and z_j enter the function multiplicatively, we immediately know that $\frac{\partial \pi_j^O}{\partial A} > 0$, $\frac{\partial \underline{t}_j}{\partial A} < 0$. As $A{=}\beta L P^{\sigma-1}$and $\sigma > 1$, applying the chain rule we get $\frac{\partial \pi_j^O}{\partial P} > 0$, $\frac{\partial \underline{t}_j}{\partial P} < 0$.

Appendix Tables and Figures

Table A.1: List of Products in the 2018 Customs Sample

HS code	Product specification
39232100	Ethylene polymer bags and bags (for transport or packaging of goods)
40112000	Tires for passenger cars or trucks
42022200	Handbags made of plastic or textile materials (with or without straps)
54075200	Dyed other polyester textured filament woven fabric
61099090	T-shirts
61102000	Pullovers
62019390	Cold weather clothes
62034290	Trousers, breeches
62043200	Cotton-made women's tops
63014000	Blankets and traveling rugs of synthetic fibers
73239300	Table, kitchen or other household articles and parts made of stainless steel
84151021	Air conditioners
84181020	Refrigerators (200 to 500 liters)
84183029	Cabinet freezers (temperature>-40 degree Celsius)
84714140	Microcomputers
84715040	Other microprocessor processing components
84717010	Hard disk drivers for automatic data processing machines
84717030	Optical drive for automatic data processing equipment
85030090	Motor stator and other motor (set) parts
85164000	Electric irons
85165000	Microwaves
85171100	Cordless telephones
85171210	GSM & CDMA digital wireless phones
85177060	Laser transceiver modules for optical communication equipment
85183000	Headphones
85219012	DVD players
85299090	High frequency tuner for satellite television reception and other purposes
85340090	Printed circuit with four layers or less
85366900	Plugs and sockets with voltage $\leq$ 1000 volts
85414020	Solar batteries
85416000	Assembled piezoelectric crystals
87120030	Mountain bikes
90138030	LCD panels
94051000	Chandeliers

Notes: This table lists the 34 products used in the 2018 customs sample. The original customs data is at the 10-digit HS (HS10) level; we report the product specification at the 8-digit level (HS8) to save space. Even at the HS8 level, the product specification is highly disaggregated and clearly defined. The English product specifications are translated from `http://www.i5a6.com/hscode/`.

Table A.2: Products in the Estimation Sample

Product code	Product name	Obs.
01567	Rice	3,777
01623	Wheat flour	6,373
01765	Refined edible vegetable oil	5,039
01994	Fresh, frozen meat	2,493
02079	Aquatic products	2,311
02305	Mixed feed	8,797
02517	Cans	2,227
03796	Yarn	9,675
04166	Printed and dyed cloth	4,206
05036	Silk	2,802
05098	Silk products	4,096
05883	Light leather	2,032
05901	Leather shoes	7,322
06982	Machine made paper	2,865
07307	Machine made cardboard	2,437
07432	Paper products	4,198
08364	Toys	2,333
13989	Paint	2,672
16866	Chemical raw material	2,723
20122	Chinese-patented drugs	5,280
21696	Plastic products	16,323
22108	Cement	4,477
22559	Folded standard brick	2,432
23245	Glass products	3,045
23325	Ceramics	3,922
23936	Refractory products	2,437
26035	Pig iron	3,775
26719	Ferroalloy	2,949
27092	Copper (copper processed material)	3,027
28677	Aluminum	2,128
31438	Stainless steel products	2,608
31872	Pump (liquid pump)	3,025
31969	Bearings	2,868
32426	Casting	3,974
41305	Power supply cable	2,052
44497	Sub-assemblies & parts	3,132

Notes: This table lists the 36 products used in our $TFPQ$ estimation. This set is a subsample of the 693 manufacturing products in the dataset, selected according to the criteria described in Appendix A. The English product specifications are translated from `http://www.i5a6.com/hscode/`.

Table A.3: Mixed Exporter Premia - Intensive Margin

(a) All exporters	proc.share$_{it}$		Obs.
(1) ln(*empl.*)$_{it}$	0.26***	(0.07)	66,326
(2) ln(*labor prod.*)$_{it}$	0.03	(0.08)	62,505
(3) $TFPR_{it}$	-0.03	(0.06)	2,697
(4) $TFPQ_{it}$	0.02	(0.02)	2,697
(5) ln(*R&D exp.*)$_{it}$	-0.43***	(0.08)	66,326
(6) ln(*advert. exp.*)$_{it}$	-0.61***	(0.11)	60,645
(b) Excl. foreign firms	proc.share$_{it}$		Obs.
(1) ln(*empl.*)$_{it}$	0.19***	(0.06)	48,869
(2) ln(*labor prod.*)$_{it}$	0.10	(0.09)	46,032
(3) $TFPR_{it}$	-0.03	(0.07)	1,969
(4) $TFPQ_{it}$	0.02	(0.02)	1,969
(5) ln(*R&D exp.*)$_{it}$	-0.46***	(0.10)	48,869
(6) ln(*advert. exp.*)$_{it}$	-0.64***	(0.12)	44,773

Notes: Each row is a separate OLS regression of the dependent variable shown in column 1 on proc. share$_{it}$: the share of processing of mixed firm i in year t. ln(*R&D exp.*)$_{it}$ and ln(*advert. exp.*)$_{it}$ are calculated by $\ln(x+1)$ to avoid dropping zeros. $TFPR_{it}$ and $TFPQ_{it}$ refer to TFP calculated using revenue and quantity data respectively (see the text for details). Rows 1-2 and 5-6 include sector-year fixed effects, and all except those in the first row control for firm size. Rows 3-4 focus on single-product producers only and thus include product-year fixed effects. Standard errors clustered by 2-digit CIC industries are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.