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Made and created in China: the role of processing trade

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Abstract

This paper examines the main participants of China's processing trade regime – firms that engage in both processing and ordinary exports. By matching several datasets from China, including a unique sample of transaction-level customs data with firms' branding information, we uncover three stylized facts. First, these "mixed" firms exhibit superior performance in various margins such as revenue and physical productivity. Second, even within firms, there is a 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. We find evidence for the model's main prediction that firms in China intensified their branding activities when faced with favorable processing trade policies upstream.

Keywords: Heterogeneous firms; production networks; processing trade

JEL classification: *F*12; *F*13; *F*14

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

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> is increasingly getting used to a ubiquitous *Branded in China* tag. What is clear is that China has fallen in love with brands." (Balmer and Chen, 2017)

China's trade as a percentage of its GDP rose from below 10 percent in the late 1970s to over 60 percent just before the Great Recession (World Bank, 2018). During this period, Chinese firms supplied foreign multinationals by specializing in relatively low value-added stages of production, as epitomized by the "Made in China" tag. This phenomenon is changing. After decades of efforts to become "the factory of the world", China's large manufacturing base is now a breeding ground for firms with innovative ideas. Between 2000 and 2014, Chinese firms' share of the technology improvement budget dedicated to in-house R&D rose from 78 percent to 84 percent (Wei et al., 2017); Chinese firms' domestic patent filings and trademark applications grew, on average, by over 30 percent each year, with an even faster growth since 2008 (Eberhardt et al., 2016; Deng et al., 2020). An unexplored angle of this switch from "Made in China" to "Created in China" is the role of processing trade, which lets firms forego paying tariffs on imports that they process to export.

Surprisingly, a significant number of top companies are "mixed" exporters (i.e., firms that engage in both processing and ordinary exports). For example, Greenworks, a prominent gardening equipment manufacturer based in China, initially produced equipment for companies such as Costco, Toro, and Walmart, but in 2009, it launched its own-branded gardening machinery. The company derives almost all of its revenues from exports, and its own-branded products made up roughly half of its total revenues in 2019. Similarly, China Pet Foods, the largest pet food producer in China, serves as an original equipment manufacturer/original design manufacturer (OEM/ODM) for renowned pet food brands such as Globalinx Pet and Spectrum Brands. Since 2014, China Pet Foods has also introduced its own-branded pet food line, which accounted for 28 percent of its total revenues in 2022.[1] These mixed firms, which are ubiquitous across sectors, made up about a fifth of processing exporters, and contributed to over 60 percent 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 start by unpacking the "black box" of mixed firms to examine their performance and specialization within a production network.[2]

[1] The sources of these statistics are the annual reports of Greenworks and China Pet Foods.

[2] To fix ideas, throughout the paper, we refer to exporters engaged in both processing and ordinary trade as "mixed exporters (firms)", to those engaged only in processing as "pure

We find that mixed exporters are larger and have higher revenue and physical productivity compared with firms that engage in only ordinary (i.e., pure ordinary exporters) or only processing (i.e., pure processors) activities. Importantly, 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.

Even though they are highly processing-oriented, mixed exporters' superior labor and revenue productivity do not generalize to pure processing exporters. Nevertheless, pure processing exporters have significantly higher physical productivity when compared with pure ordinary exporters. In addition, using 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 that 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), which ultimately determines its measured performance in various margins.

Next, we build a parsimonious model to rationalize our empirical findings. 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 become ordinary exporters, those 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). Thus, our model rationalizes the observed ranks at various margins between mixed, pure ordinary, and pure processing exporters. The model also yields the prediction that facilitating processing trade raises the *ex ante* expected profits from manufacturing, leading to a greater mass of potential suppliers, which benefits sourcing firms with good ideas.

In the last part of the paper, we empirically test the model's main prediction. To this end, we use China's pilot "paperless" processing supervision program implemented in 2000–2006 as a quasi-natural experiment. The paperless program significantly reduced the burden of red tape on processing activities by replacing processing-related paperwork with the customs' automatic, online administration system.[3] This policy shock is suitable for our study and gives

processors" or "pure processing exporters (firms)", and to those engaged only in ordinary trade as "pure ordinary exporters (firms)". We use "upstream" and "downstream" in the standard input–output sense, with downstream firms being closer to the final stage of production.

[3] The details of this policy are given in Section 5.1.

us a clean identification, as it affects only the costs of processing trade, leaving other costs of a firm unchanged. By exploiting the staggered introduction of the policy to different regions in China, and by comparing firms around the qualification cutoff, we document that the paperless processing program increased firm-level processing exports by 28 percent. We also find that the policy induced downstream firms to intensify their branding activities: the number of trademarks for above-median productive domestic firms increased by about 1 percent on average. Thus, our results highlight that processing trade not only led goods to be “Made in China”, but also “Created in China”, by providing a breeding ground of suppliers for firms with good ideas.

Our work is related to several strands of the trade literature. Primarily, our stylized facts 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).[4] Different from these studies, which focus on processing firms and how they differ from ordinary exporters, we document the dominant role of mixed 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 the characteristics of different types of exporters with their brand ownership and choice of trade modes, using unique transaction-level trade data on firms’ branding information.

This paper does not intend to disentangle all the mechanisms behind processing trade. Instead, we highlight the fact that processing firms are typically contract-taking suppliers of foreign downstream firms. Thus, we view policies such as duty exemptions as factors that simply increase a firm’s propensity to engage in processing activities. As a result, 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 factors that shape a firm’s export mode choice.[5] We rely on rich transaction- and

[4]Fernandes and Tang (2015) find that processing firms are less diversified in products and destinations when compared with ordinary exporters, and Yu (2015) shows that their productivity does not change considerably with trade liberalization. Dai et al. (2016) find that compared with 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.

[5]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; and Manova and Yu (2016) highlight the importance of credit constraints.

firm-level Chinese data and a unique quasi-natural experiment, the pilot paperless processing supervision program, to shed light on the implications of processing policy, and thus also complement the work that examines the welfare implications of processing trade through the lens of various quantitative trade models (e.g., Defever and Riaño, 2017; Brandt et al., 2021; Deng, 2021; Deng and Wang, 2021).[6]

Our simple theoretical framework is inspired by the literature on firms' sourcing decisions in international and regional trade (Antràs et al., 2017; Lim, 2018; Bernard et al., 2019b; Dhyne et al., 2021; Kikkawa et al., 2022).[7] Our framework is related to the literature in which firms are modeled with multiple heterogeneities, including Antràs and Helpman (2004), Hallak and Sivadasan (2013), Harrigan and Reshef (2015), Manova and Yu (2017), Bernard et al. (2018, 2019a), Ariu et al. (2019), and Huang et al. (2022).[8] None of these papers, however, emphasizes the role of heterogeneities that enable firms to self-select into different stages of the production network. Combining Chinese firm-level trade and production data with novel transaction-level data with branding information, we show that the intuitive set-up of our

[6]Defever and Riaño (2017) analyze the welfare implications of subsidies with export share requirements in a quantitative export model. Brandt et al. (2021) quantify the welfare effects of duty exemptions under China's processing trade based on a multi-industry Ricardian model. Deng (2021) quantifies the welfare implications of processing policy with the presence of learning-by-processing. Deng and Wang (2021) introduce increasing returns to scale in input production in a similar framework and quantify the processing-trade-induced Dutch disease.

[7]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), Dhyne et al. (2021), and Kikkawa et al. (2022) adapt the framework of Antràs et al. (2017) to the context of domestic production networks and study how geography, endogenous firm-to-firm connections, and markups affect shock transmissions and firm performance, respectively. Lim (2018) quantifies the importance of endogenous network adjustments for business cycles. Chaney (2016), Bernard and Moxnes (2018), and Johnson (2018) provide excellent reviews of the network models in international trade.

[8]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' 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 with 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 the complementarity between trade in goods and services, and Huang et al. (2022) study how upstream market structure affects downstream sourcing behavior.

model rationalizes a set of stylized facts, and provides new insights on processing-promoting policies.

Finally, our analysis of the policy to promote paperless processing connects to the body of literature that examines the impact of trade policy changes on vertically linked industries. This literature has shown that input tariff liberalization has benefited downstream firms in terms of productivity (Amiti and Konings, 2007), exports scope and quality (Bas and Strauss-Kahn, 2015; Fan et al., 2015; Feng et al., 2016), innovation (Liu and Qiu, 2016; Chen et al., 2017b), and product growth (Goldberg et al., 2010). A closely related body of literature has uncovered that foreign direct investment (FDI) liberalization has positive spillovers to upstream (Javorcik, 2004) and downstream (Arnold et al., 2011, 2016) industries, inducing export upgrading in some settings (Harding and Javorcik, 2012). Similarly, we find that liberalizing trade policy upstream benefits domestic downstream firms. However, our proposed mechanism is via increased domestic upstream supply rather than cheaper imported inputs, and we focus on a particular form of outcome, which is the establishment of new brands, as opposed to productivity or the introduction of new varieties typically examined in the existing literature.

The rest of the paper is organized as follows. In Section 2, we describe the data. In Section 3, we present the set of stylized facts regarding exporters' performance, export mode, and brand ownership. In Section 4, we develop a model that rationalizes the empirical findings, and in Section 5, we empirically examine the effect of processing trade on firms' branding activities by exploiting China's paperless processing trade program. Finally, we conclude in Section 6.

2. Data and processing trade in China

2.1. Data

We use four main datasets in this paper. The first consists of China's 2000–2006 customs data that show firms' monthly transactions of exports and imports at the product–country level, where products are defined at the eight-digit harmonized schedule (HS8) level. As our analysis is focused on manufacturing firms, we remove intermediaries and wholesalers from the dataset.[9] The customs data allow us to observe each firm's ordinary and processing exports at the product–country level. This enables us to divide firms into three mutually exclusive groups: pure processing exporters, pure

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

ordinary exporters, and mixed exporters who are engaged in both processing and ordinary exports.

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 without any aggregation. In particular, these records contain highly detailed product and brand information for each export transaction.[10] 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).[11] The dataset consists of 862,567 daily transactions, which make up around \$38 billion worth of exports in 34 HS8 products exported by 29,138 firms, covering product categories from 13 out of 68 HS2 manufacturing sectors.[12] The wide variety of products, which are listed in Table A.1 in the Online Appendix, include goods that make up a large share of exports such as car tires, refrigerators, and mobile phones.

The third dataset we use is the Annual Industry Survey (AIS) 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, advertising expenses, material costs, and ownership structure, which allow us to examine firms' performance along various margins.[13]

The fourth dataset we utilize is the Production Survey dataset, also compiled by NBS for 2000–2006. This dataset provides firm–product level information on output quantity, allowing us to compute firm-level quantity-based (i.e., physical) TFP.[14] Both AIS and the Production Survey

[10] The Chinese government began to require firms to report 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 1 January 2018.

[11] No brand indicates missing or confidential data.

[12] Our transaction-level data were purchased from a data company for RMB 5,000 per month and HS8 category (reported at the HS10 level). Due to budget constraints, we selected 34 product categories that make up a sizable share of China's exports. Of the 34 products, 30 are from March and the rest are from January and April 2018.

[13] 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 fewer than eight employees.

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

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 percent of aggregate exports, which is similar to the match rate of existing studies.[15]

We utilize two additional datasets for our empirical analysis. The first is the yearly firm-level trademarks data collected by the State Administration for Industry and Commerce in China, which we merge with the AIS data using unique firm identifiers provided by Deng et al. (2020).[16] The second is the dates when each Chinese regional customs authority adopted the pilot paperless processing trade program, which we constructed using China's publicly available customs notices.

2.2. Processing trade 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.[17] 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 distinguish it from other trade modes. China classifies processing trade separately 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.[18]

[15] See the Appendix of Chen et al. (2017b) for a more detailed explanation of the matching procedure.
[16] We are grateful to Ran Jing for sharing the data. See Deng et al. (2020) for a detailed description of the trademarks dataset.
[17] We are particularly grateful to Jie Zhang and Li Liang from the research department of the statistical division of Chinese Customs, and Jianming Gao and Tommy Yu from the Fujian Business Association for their valuable inputs.
[18] According to publications from the Ministry of Commerce of China, in 1988, China's total trade accounted for less than 1 percent of global trade and over 50 percent of it was in agriculture and primary goods. From 1978 to 2000, processing trade increased by 64 times while ordinary

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 stricter governmental supervision compared with 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.[19] Ultimately, these policies helped to select businesses that the Chinese government targeted: 84 percent of processing exports in our transaction sample can be explained by firms making products for foreign brands, as we show in the next section. 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 the People's Republic of China). This reflects a form of governmental supervision. The Chinese customs approves a firm's filing of a processing transaction if it satisfies certain requirements. In turn, this transaction becomes subject to the relevant policies.[20] 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.

3. Stylized facts

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. The customs data show that even though the number of mixed exporters was only 21 percent of the total number of exporters, they made up 54 percent of exports in 2005. Pure processors and pure ordinary exporters, however, made up 24 percent and 19

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trade increased by only three times. In 1981, processing trade made up only 6 percent of China's total trade, but by 1996 it exceeded 50 percent of China's total trade.

[19]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 percent were located in export processing zones, and 96 percent of these firms were either foreign-owned or joint ventures.

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

Table 1. Transition matrix

Type	PO_{it+1}	PP_{it+1}	Mix_{it+1}
Pure ordinary (PO_{it})	93.50	0.27	6.23
Pure processing (PP_{it})	1.32	84.10	14.58
Mixed (Mix_{it})	11.30	6.59	82.11

Notes: PO_{it}, PP_{it}, and Mix_{it} indicate whether firm i is a pure ordinary exporter, a 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.

percent of exports in 2005, respectively.[21] Mixed firms' exports also made up the bulk (48 percent) of China's export boom in 2000–2006, with the rest of the growth explained almost equally by exports of pure ordinary firms (21 percent) and pure processors (24 percent).

As shown in Table 1, firms tend to remain the same type across years. Pure ordinary exporters change their type less than 7 percent of the time, whereas pure processors and mixed firms change their type less than 20 percent 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.[22]

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 65 percent (58 percent). 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 percent and 42 percent 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.

Row 4 of Table 2 shows that the median (mean) share of processing exports done via the "pure-assembly" (as opposed to "import-and-assembly") regime is 0 percent (21 percent), revealing that mixed exporters generally

[21] The rest is made up 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 percent of exports. Note that we exclude intermediaries, which made up 18 percent of exports in 2005.

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

Table 2. Mixed exporters

	(a) All mixed exporters			(b) Merged mixed exporters		
	Median	Mean	SD	Median	Mean	SD
(1) Processing share	0.64	0.58	0.36	0.65	0.58	0.36
(2) Processing share, mixed HS8	0.71	0.62	0.34	0.73	0.63	0.34
(3) Processing share, mixed HS8–country	0.68	0.62	0.32	0.69	0.62	0.32
(4) Pure-assembly share	0.00	0.26	0.42	0.00	0.21	0.39
(5) Share of mixed HS8	0.29	0.37	0.31	0.30	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.

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 percent 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 percent (71 percent) (row 7). In other words, mixed exporters tend to sell their core product(s) under both trade regimes.

One can argue that there might still be different kinds of products within an HS8 code. This is less of a concern because 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 100 g/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 percent (24 percent), with a value share of 62 percent (55 percent).

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 make it cheaper for a firm to export a certain product under the processing trade regime, then the firm 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 show that mixed firms' and pure processors' average shares of pure-assembly in their processing exports were similar in 2000–2006 (21 percent versus 16 percent). Also, the government is seldom directly involved with mixed firms: the data show that only 7 percent of mixed firms are state-owned enterprises. Moreover, the top five HS2 sectors that mixed exporters engage in are the same top five 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 as 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 with other types of exporters. Specifically, we bring in production- and 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:

$$Y_{it} = \beta_1 PP_{it} + \beta_2 Mix_{it} + \delta_{ht} + \epsilon_{it}. \quad (1)$$

Table 3. Mixed exporter premia

	PP_{it}		Mix_{it}		Obs.
(a) All exporters					
(1) ln $(empl.)_{it}$	0.315***	(0.039)	0.396***	(0.025)	208,514
(2) ln $(labor\ prod.)_{it}$	−0.211***	(0.025)	0.151***	(0.019)	197,661
(3) $TFPR_{it}$	−0.142***	(0.067)	0.120***	(0.043)	9,297
(4) $TFPQ_{it}$	0.025***	(0.013)	0.034***	(0.011)	9,297
(5) ln $(R\&D\ exp.)_{it}$	−0.767***	(0.085)	−0.252***	(0.034)	208,514
(6) ln $(advert.\ exp.)_{it}$	−0.976***	(0.081)	−0.380***	(0.039)	193,919
(7) ln $(trademarks)_{it}$	−0.461***	(0.031)	−0.184***	(0.021)	208,514
(8) ln $(capital\ int.)_{it}$	−0.010***	(0.044)	0.277***	(0.031)	208,073
(9) $skill\ int._{it}$	−0.035***	(0.007)	0.004***	(0.003)	39,120
(b) Excluding foreign firms					
(1) ln $(empl.)_{it}$	0.225***	(0.038)	0.394***	(0.027)	159,938
(2) ln $(labor\ prod.)_{it}$	−0.065***	(0.029)	0.208***	(0.020)	152,073
(3) $TFPR_{it}$	−0.018***	(0.062)	0.144***	(0.044)	7,037
(4) $TFPQ_{it}$	0.044***	(0.021)	0.040***	(0.012)	7,037
(5) ln $(R\&D\ exp.)_{it}$	−0.755***	(0.096)	−0.230***	(0.037)	159,938
(6) ln $(advert.\ exp.)_{it}$	−0.939***	(0.088)	−0.343***	(0.041)	149,466
(7) ln $(trademarks)_{it}$	−0.452***	(0.039)	−0.191***	(0.022)	159,938
(8) ln $(capital\ int.)_{it}$	0.090***	(0.041)	0.302***	(0.033)	159,583
(9) $skill\ int._{it}$	−0.028***	(0.008)	0.009***	(0.003)	29,557

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}, which indicate whether firm i is a pure processor or a mixed exporter in year t, respectively (pure ordinary is the omitted group). ln $(R\&D\ exp.)_{it}$, ln $(advert.\ exp.)_{it}$, and ln $(trademarks)_{it}$ 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 5–8 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. Row 9 includes sector fixed effects only as the sample is restricted to 2004. 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 three-digit CIC industries are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Here, Y_{it} is an outcome variable (e.g., $\ln(empl.)_{it}$, where $empl.$ is 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 three-digit Chinese Industry Classification (CIC) reported in the AIS database.[23] Finally, ϵ_{it} is the error term, and we cluster standard errors at the sector level.[24] Each row of Table 3 shows results from a separate regression, and coefficients can be interpreted as relative to

[23] We use the three-digit classification as this is the most disaggregate level of classification that we are able to concord overtime to have a consistent set of (162) sectors in our sample period.
[24] Clustering at the firm level produces significantly lower standard errors.

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.

Row 1 of Table 3(a) shows that compared with pure ordinary firms, pure processors and mixed firms have, on average, 32 percent and 40 percent more employment, respectively. The statistical difference between the two coefficients (Prob. $> F = 0.02$) 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 23 percent and 39 percent larger than pure ordinary exporters, respectively. Note that processing intensity as captured by the share of processing in total exports varies across mixed exporters with a mean of 58 percent and standard deviation of 36 percent. In Table A.3 in the Online Appendix, we restrict the sample to mixed exporters, and find qualitatively similar results for the correlation of processing intensity and employment.

Next, we turn to productivity. Row 2 of Table 3(a) shows that mixed firms have 15 percent higher labor productivity (i.e., value-added per employee) than pure ordinary firms, whereas pure processors have 21 percent lower labor productivity than pure ordinary firms.[25] Row 3 shows that the ranking we obtained based on labor productivity remains when we consider revenue-based total factor productivity (*TFPR*) calculated using the Olley–Pakes methodology (Olley and Pakes, 1996).[26]

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 that of non-exporters, while their *TFPR* is lower than that of non-exporters. To assess the *TFPQ* rank across exporters, we compute *TFPQ* focusing on the 36 of the 693 manufacturing five-digit products for which we can obtain reliable quantity information. The estimation methodology and the list of products can be found in Online Appendix A and Table A.2, respectively.[27] Consistent with

[25] Similarly, 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. However, they only consider revenue-based TFP measures, and hence do not discover that processing firms are highly productive, even more than ordinary firms, when focusing on physical TFP.

[26] As explained in Online Appendix A, we use only single-product firms to compute quantity-based TFP (*TFPQ*), and thus 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 methodology (Levinsohn and Petrin, 2003).

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

Li et al. (2018), we find that compared with pure ordinary exporters, pure processors have higher *TFPQ* on average (row 4 of Table 3(a)). In addition, mixed exporters have the highest physical productivity on average (though not significantly different from that of pure processors).[28]

To summarize, these findings indicate that 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.

The finding that processing exporters have the lowest *TFPR* could be explained by the fact that processing firms contribute to relatively low value-added stages of production (e.g., manufacturing), and thus get a lower share of profits when compared with 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). 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.

To explore whether ownership of brands can explain the results we find for *TFPR* and *TFPQ*, we employ the 2018 customs sample and examine the relationship between product trade mode, price, and brand ownership of firms. As described in Section 2.1, the 2018 customs dataset allows us to extract the brand ownership information for each export transaction, and label it as no brand (i.e., missing or confidential), foreign brand, or domestic (own) brand. The last row of Table 4 shows that 10.4 percent, 60.3 percent, and

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.

[28]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 results above with exporter-type dummies.

Table 4. Export mode and brand ownership: summary statistics

	No brand (1)	Foreign brand (2)	Domestic brand (3)
Ordinary exports	14.3%	33.4%	52.2%
Processing exports	7.0%	83.9%	9.1%
Total	10.4%	60.3%	38.3%

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 wholesalers and intermediaries). We extract brand ownership information for each transaction from the reported string product specification, which we then classify as no brand (i.e., missing or confidential), 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.

38.3 percent of export value are due to transactions that have no brand, foreign brand, and domestic brand, respectively, in our sample. 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 percent of processing exports in this customs sample consist of foreign-branded products, while only 9 percent consist of domestic-branded products. This pattern stands in sharp contrast to the one for ordinary trade, where domestic brands account for over half of exports.[29]

To summarize, while processing transactions are commonly perceived as instances where local manufacturers supply customized productions to foreign contractors (Manova and Yu, 2016), our data enable us to confirm this conjecture empirically. To do that, we run the following transaction-level regression:

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

Here, 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

[29] Among the 9 percent of processing exports sold under domestic brands, 77 percent are conducted by domestic private firms, while the remainder is handled by foreign-owned enterprises. Unfortunately, we lack information on the foreign downstream buyers, so we cannot ascertain the reasons for these transactions. One possibility is that these transactions are carried out by Chinese multinationals with factories overseas or their affiliated firms in Hong Kong, which are considered foreign firms in Chinese statistics. However, it is not surprising that 33 percent of ordinary exports consist of foreign-branded products. Any contracted trade without relationship-specific inputs from overseas will generally be conducted via the ordinary regime. Multinationals with horizontal FDI will also trade via the ordinary regime. In terms of ownership, 52 percent of this trade is conducted by domestic Chinese firms, 17 percent by foreign firms, and 17 percent by joint ventures.

Table 5. Export mode and brand ownership: regressions

Dependent variable	D_{ifhc}		$\ln uv_{ifhc}$			
	All		All		Foreign	Domestic
	(1)	(2)	(3)	(4)	(5)	(6)
P_{ifhc}	−0.126***	−0.032***	−0.072	0.092*	0.128*	0.028***
	(0.040)	(0.007)	(0.194)	(0.049)	(0.073)	(0.009)
D_{ifhc}			0.197*	0.088*	0.176*	0.269***
			(0.112)	(0.050)	(0.092)	(0.007)
Product–country FE	Yes	No	Yes	No	No	No
Firm–product–country FE	No	Yes	No	Yes	Yes	Yes
Obs.	445,437	427,567	419,009	402,169	215,527	197,304
R^2	0.30	0.85	0.81	0.92	0.92	0.84

Notes: The first two columns report 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, and P_{ifhc} indicates whether this transaction is classified under processing trade. In Columns 3–6, the dependent variable is $\ln uv_{ifhc}$, the log unit value of transaction i. Standard errors clustered by eight-digit HS code–country are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

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., FDI policy), and ϵ_{ifhc} is the error term. We cluster standard errors at the firm level. Column 1 of Table 5 shows that processing transactions are 13 percentage points less likely to involve products with domestic brands when compared with 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.[30] Column 2 shows that the coefficient remains negative and significant at the 10 percent level: mixed firms' processing exports are 3.2 percentage points less likely to include their own-branded products when compared with their ordinary exports of the same product to the same destination. These results echo and reinforce the suggestive evidence in Table 4, highlighting that ordinary transactions typically feature firms exporting their own-branded products. In contrast, processing transactions tend to involve firms exporting products branded by their customers, even when considering variations within the firm, destination, and products. This finding

[30]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 percent of the 15,078 firms in our regression sample are mixed, with the rest consisting of pure ordinary (82 percent) and pure processing firms (11 percent). The mixed firm–product–country flows make up 15 percent of total flows, with the rest consisting of pure ordinary (51 percent) and pure processing flows (34 percent).

also supports the hypothesis that the low *TFPR* of processing exporters is due to their specialization in manufacturing as opposed to branding, indicated by their relatively high *TFPQ*. This can also explain why we observe high *TFPR* for ordinary and mixed exporters, who tend to sell their own-branded products.

To see whether there is a relationship between brand ownership and prices, in Column 3 of Table 5, 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 percent more expensive than that same firm's sales of the same product to the same destination but under a different brand. Note that, as shown in Column 4, there is also a 9 percent price premium for processing exports. When the sample is divided between foreign and domestic firms, we observe a 13 percent price premium for foreign enterprises and a 3 percent price premium for domestic firms as shown in Columns 5 and 6, respectively.

Given that processing exports are often shipped to large multinationals, one may argue that the price difference we find reflects discounts for large orders. In other words, Chinese firms may export their own brands in smaller quantities and may avoid offering such discounts to foreign buyers. To dispel this concern, we follow Khandelwal et al. (2013) and estimate quality and quality-adjusted prices in Online Appendix B. We then run the quality-adjusted unit-price regressions to control for the quantity of sales for each transaction. Table A.4 presents the results. After adjusting for quality, the price premium associated with brand ownership drops significantly and becomes negative for foreign firms, suggesting that the higher price of foreign own-branded products is due to their superior quality; this result might also indicate that foreign firms engage in transfer pricing. However, the price premium for domestic firms remains positive and quantitatively similar to our baseline. The positive correlations between ordinary export mode and brand ownership, as well as between brand ownership and price premium for domestic firms support the hypothesis that price differences between processing and ordinary exporters can be largely explained by their specialization within a value chain.

One might also be concerned that 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 might be mechanically lower. However, this would imply that within a firm–product–destination, processing exports should have a lower unit value, which contradicts our finding in Table 5. In sum, we conclude that the price premium of processing exports primarily originates from domestic enterprises, which cannot be explained by factors such as quantity discounting, quality differences, transfer pricing, or differences in tariffs.

We further provide some suggestive evidence that a firm's choice on export mode is indeed associated with its branding activities. Rows 5, 6, and 7 of Table 3(a) reveal that R&D investment, advertising expenditures, and number of trademarks across firms are in the following decreasing order: pure ordinary exporters, mixed exporters, and pure processors. In fact, 85 percent of pure processors did not have any R&D or advertising expenses in 2005. Whereas the average number of trademarks for pure ordinary and mixed exporters is 2.8, this figure is only 0.8 for pure processors. 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 and trademarks or spend on advertising, which are ultimately done by their customers. In rows 5, 6, and 7 of Table 3(b), we exclude foreign firms as the majority of their R&D, advertising, and trademark expenses are likely to be done in their headquarter-countries, and find similar results. In Table A.3, we find that for mixed exporters, as processing intensity increases, R&D investment, advertising expenditures, and the number of trademarks decrease as expected.

Finally, rows 8 and 9 of Table 3(a) show the capital and skill intensity of different exporters in our sample, respectively. We measure capital intensity by taking the log of the fixed assets to employment ratio, and measure skill intensity by the share of workers with a college degree in a firm's total workforce.[31] Row 8 reveals that the capital intensity of mixed exporters is the highest, followed by pure processors (when excluding foreign firms) and pure ordinary firms. Regarding skill intensity, mixed exporters seem to (weakly) lead as well, followed by pure ordinary, and then by pure processing exporters. These results are qualitatively similar when we focus on the processing intensity of mixed exporters in Table A.3 in the Online Appendix.

4. A simple model of two-way heterogeneity and sourcing

The preceding sections indicate that mixed exporters excel in both production and branding, explaining their export choices and performance across various margins. In this section, we introduce a concise model elucidating the export decisions and characteristics of processing, ordinary, and mixed exporters. We emphasize two key model elements: (i) a two-dimensional heterogeneity in production and branding; and (ii) the positive yet comparatively lower

[31] We follow Chen et al. (2017a) to classify education levels into skills. Note that the education data are available only for 2004, so these regressions include sector fixed effects only.

profitability of manufacturing. For a more detailed explanation of the model, please refer to Online Appendix C.

4.1. Model set-up

There are a large number of industries, with each firm in each industry ω undertaking one task of production. Specifically, they acquire varieties from the upstream domestic industry $\omega - 1$ as a CES aggregate, using labor and Cobb–Douglas (CD) technology to transform them into type-ω varieties.[32] Every firm is endowed with a blueprint that corresponds to a single differentiated variety. Firm j can produce its own blueprint or manufacture for other firms, where the latter is considered processing trade in cross-border transactions. The representative household has CES preferences over the most downstream varieties, with the shape parameter being σ.

Firms vary in manufacturing abilities and blueprint qualities. Firm j has a production efficiency of t_j when producing from its own blueprint. When producing for other firms, it draws production efficiency from a Fréchet distribution with level parameter t_j and shape parameter θ. The blueprint quality of the firm is given by z_j, serving as a demand shifter. Firm j can choose between in-house production and outsourcing. Outsourcing incurs beachhead labor costs (f_0) and fixed costs (f) for each connected supplier. The supplier with the lowest marginal production cost is then selected as the contracted manufacturer. *Ex post* gains are distributed through Nash bargaining, with the bargaining power of the contracted manufacturer denoted by γ.[33]

The remaining model settings are standard. In each industry, there is an unbounded pool of potential entrants who discover their blueprint quality and manufacturing ability after incurring a fixed entry cost f_E. To simplify, we assume independence in the drawing of z and t from two distributions $G_z(z)$ and $G_t(t)$ with supports $(0, \bar{z}]$ and $(0, \bar{t}]$ respectively.[34] Once firms draw their abilities, they decide whether to produce their own products or be active in manufacturing for other firms. Introducing one's blueprint to production involves an additional fixed cost f_B. To focus on the model's essential components, we adopt the assumption of a small open economy, and all trade is free except for processing, with an iceberg trade cost $\tau_t \geq 1$.

[32] As it does not affect model predictions, unless otherwise stated, we simply assume that all production functions are of nested CD–CES structure and that all CD share parameters are β, all CES shape parameters are σ, and $(\sigma - 1)/\theta > 1$.

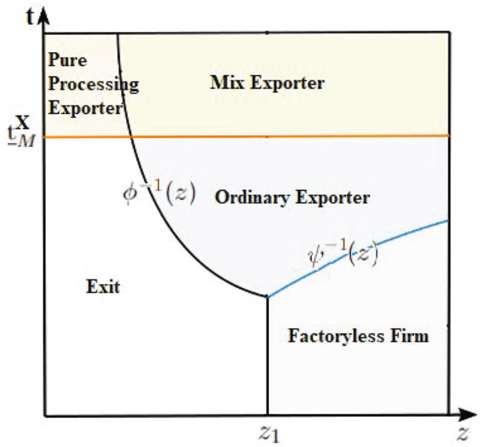
[33] We refer the interested reader to the previous version of the paper (Chen et al., 2020), where we consider Bertrand competition in manufacturing.

[34] In Online Appendix C.5, we show that our results do not rely on this independence assumption. In particular, if z and t are positively correlated, which is the case empirically, then the model's predictions discussed in this paper continue to hold.

4.2. Firm specialization

Given the set-up of the model, we can visualize the specialization of firms in Figure 1.[35] To focus on exporters, assume that all trade is free for the time being. If a firm opts for in-house production, both its blueprint quality and manufacturing ability positively correlate with profitability. Therefore, the marginal firm that chooses in-house production and makes zero profits must either have a good blueprint quality or a high production efficiency. This implies a downward-sloping cutoff curve between exit and becoming an ordinary exporter, depicted as $\phi^{-1}(z)$ in Figure 1.

Figure 1. Firm specialization



If a firm opts for outsourcing, its profit is no longer tied to its own manufacturing ability but relies on the abilities of potential suppliers, determined by the firm's optimal sourcing decisions. As shown in Online Appendix C.1, given the complementarity of blueprint quality and manufacturing ability in shaping profitability, firms with superior blueprint quality will incur greater fixed costs and reach more potential suppliers. This has two immediate implications. First, because the firm's own manufacturing capabilities do not matter when outsourcing, the cutoff between exit and outsourcing must be a vertical line (z_1 in Figure 1). Second, which firms are selected as contracted manufacturers is not related to their own blueprint quality, and thus the processing cutoff must be a horizontal line ($\underline{t}_M^X$ in Figure 1). Finally, as firms with better blueprints are more likely to outsource

[35] Technical details are presented in Online Appendix C.2.

given a certain level of manufacturing ability, the cutoff curve between in-house production and outsourcing is upward sloping, represented as $\psi^{-1}(z)$ in Figure 1.

Putting the decisions of contracted making and own production together, the model gives rise to firms' specialization based on their heterogeneity in two dimensions: firms with low z become pure processing exporters (PP, light yellow area in Figure 1), and firms with high z and high t become mixed firms (Mix, light green area). Firms with intermediate z and t only produce their own blueprint and become ordinary exporters (PO, light blue area), firms with high z but low t outsource production and become factory-less service firms (gray area), and firms with both low z and t exit (white area).

4.3. Export choices and firm performance

We now discuss how the model aligns with the observed rankings of *PO*, *PP*, and *Mix* firms across different performance dimensions, as presented in Section 3.

Physical TFP. Physical TFP gauges a firm's efficiency in converting inputs into quantity outputs, corresponding to manufacturing ability t in the model. The processing export cutoff ensures that t_{PO} is always lower than t_{PP} and t_{Mix}, and the downward-sloping curve $\phi^{-1}(z)$ ensures a larger number of firms with greater t being mixed rather than pure processing exporters. Consequently, the model reproduces the observed *TFPQ* ranking in the data: mixed exporters exhibit the highest average physical productivity, followed by processing, and then ordinary exporters.

Revenue TFP and labor productivity. The log labor productivity of firm j is given by

$$LP(z_j, t_j) = \ln\left(\frac{\pi^I(z_j, t_j) + \pi^M(t_j) + l(z_j, t_j)}{l(z_j, t_j)}\right),$$

where π^I, π^M, and $l(z_j, t_j)$ represent profits from one's own blueprint, profits from manufacturing for other firms, and employment, respectively. Manufacturing, often considered the least value-added stage in the value chain, corresponds to a low γ value in our model. When γ is sufficiently small, processing exporters exhibit the lowest labor productivity. Mixed exporters have higher labor productivity in their own blueprint production compared with ordinary exporters. However, their increased manufacturing capacity results in more processing, reducing their overall labor productivity. When the first force dominates, our model naturally produces the observed labor productivity ranking in the data: $E_{Mix}(LP) > E_{PO}(LP) > E_{PO}(LP)$. Moreover, the revenue-based TFP formula can be written as

$$TFPR(z_j, t_j) = \ln\left(\frac{\pi^I(z_j, t_j) + \pi^M(t_j)}{{l_j}^{\beta}{M_j}^{1-\beta}}\right) \propto \ln\left(\frac{\pi^I(z_j, t_j) + \pi^M(t_j)}{l_j}\right) = LP_j,$$

where M_j is the upstream input usage. The ranking for *TFPR* is therefore the same as that of labor productivity, consistent with the observed data.

R&D and advertising. The data suggest that pure ordinary exporters invest more in R&D and advertising than mixed exporters, who in turn invest more than pure processing exporters. A simple extension of the model provides an explanation. Suppose firms draw their blueprint quality before manufacturing capacity. After observing its z, a firm can choose whether to pay an additional cost a^2 to improve blueprint quality to $za^{1/(\sigma-1)}$,[36] and thus a is an increasing function of z in equilibrium. As processing exporters have the lowest blueprint quality, they spend the least on R&D and advertising. While comparing mixed and ordinary exporters, the downward-sloping cutoff ϕ^{-1} selects relatively more high-z firms to become pure ordinary exporters. However, the upward-sloping outsourcing cutoff ψ^{-1} also pushes more high-z firms to become factory-less firms (hence out of the comparison sample). When the first effect dominates, the model can explain the ranking of R&D and advertising expenditures observed in the data.

Trademarks. Trademarks identify goods as manufactured by a particular person or company and confer an exclusive right to use a specific brand (Baroncelli et al., 2005); hence, we can view them as registered blueprints. If we extend the model to allow firms, after observing z, to pay an additional registration fee to prevent potential piracy, which occurs with a fixed probability, then firms with better blueprints are more likely to own trademarks. Thus, the number of trademarks owned by the three types of exporters is ranked in the same order as R&D and advertising expenditures, consistent with the data.

Employment. Mixed exporters employ more people than pure processing exporters because of their greater t values. Additionally, mixed exporters also employ labor to produce their own products. In comparing pure

[36] 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.

processing firms with ordinary firms, note that processing exporters can be considered "composite firms" whose manufacturing ability is determined by the manufacturer but whose blueprint quality is determined by the outsourced blueprint holder. As a result, pure processing exporters can have on average larger t and z, and hence more employment, than pure ordinary exporters.

4.4. Processing-promoting policy

Having demonstrated that our model can explain the observed rankings of PO, PP, and Mix firms across various margins, the next question naturally follows: does the model offer new insights into processing trade policy? In particular, does encouraging "making" have any positive effects on "creating"? This is a particularly important issue given the substantial investments made by many countries, including China, to promote processing trade. In this subsection, we explore the impact of processing-promoting policy and derive testable predictions from our model.

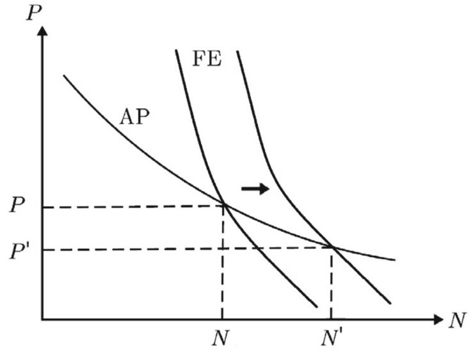
Similar to previous subsections, we emphasize the intuition in the main text, reserving technical details for the Online Appendix. In Online Appendix C.3, we demonstrate that the equilibrium of a specific industry can be determined by jointly solving the aggregate price index (AP) and the free entry condition (FE) as functions of P and N. Both curves exhibit a downward slope, with the FE curve intersecting the AP curve once from above, guaranteeing the uniqueness of the equilibrium.

With the processing-promotion policy reducing trade costs for foreign varieties manufactured domestically, firms' expected profits from manufacturing rise. To maintain the free entry condition, domestic firms' expected profits from bringing their blueprint into production must decrease, shifting the FE curve outward. Simultaneously, the small open economy assumption ensures that the change in processing policy has no direct impact on blueprint holders. Therefore, the AP curve remains unchanged. Illustrated in Figure 2, these collectively result in an increased equilibrium N and a decreased P, leading to a lower input price for downstream firms.

This finding contrasts with the conventional belief that promoting processing trade crowds out more productive ordinary firms and decreases overall efficiency. The latter perspective naturally arises when ignoring mixed exporters and viewing processing producers as less productive firms through the lens of single-attribute firm models.[37] Recognizing variability in both production and branding, promoting processing exports leads to

[37]This perspective is implicitly incorporated in the empirical findings of Dai et al. (2016) and in the models proposed by Brandt and Morrow (2017) and Deng and Wang (2021).

Figure 2. Promoting processing trade



increased sourcing and specialization, ultimately enhancing the overall industry efficiency.

How does promoting processing trade affect different firms? An increase in potential suppliers benefits firms in the same industry with superior blueprints. However, when these firms outsource their own blueprint production, they become either pure processing or factory-less service firms, with the latter exiting manufacturing altogether. Simultaneously, the least-performing ordinary firms exit. Consequently, within the same industry, our model's prediction is challenging to empirically distinguish it from the standard crowding-out effect.

Nevertheless, as our model predicts a decline in the sector's aggregate price index, it provides opposing predictions for adjustments by downstream firms compared with existing models. The reduction in input prices is particularly advantageous for downstream firms with high blueprint quality, given the complementarity between input costs and blueprint quality, as in, for example, Kugler and Verhoogen (2012). Focusing on branding, the margin we are most interested in, the model predicts that promoting processing trade will increase branding activities of downstream firms with better blueprints. Linking blueprints to trademarks (as discussed in Section 4.3) and blueprint quality to observables,[38] we propose the following proposition that we test empirically.

Proposition 1. *Promoting processing trade, conditional on employment, will make downstream firms with higher labor productivity more likely to apply for trademarks.*

[38]In Online Appendix C.4, we demonstrate that a firm's labor productivity increases in z given employment.

5. The impact of the processing-promoting policy

In this section, we empirically examine whether encouraging "making" affects "creating". Anecdotal evidence suggests that such a positive spillover is not rare: the success of Xiaomi, now the world's fourth-largest smartphone company, crucially relied on its world-leading suppliers such as Inventec and Zepp – companies that predominantly engaged in processing trade. LifEase, a Chinese online retailer akin to MUJI, works directly with renowned OEMs for brands such as Adidas, Burberry, Gucci, and Rimowa to produce its own-branded items. As mentioned before, another well-known case is Shenzhou International, a Chinese apparel manufacturer established in 1990. Initially, the majority of the company's income was due to exports to Japan, with processing for Uniqlo contributing to 60 percent of its revenues. As domestic sportswear brands gained prominence, Shenzhou diversified its manufacturing to Chinese brands such as Li Ning and Teppu. Between 2007 and 2021, its revenue from mainland China saw a consistent annual growth rate of around 24 percent, leading mainland China to become Shenzhou's primary market.[39]

We examine whether promoting processing trade helps downstream firms to eventually come up with their own-branded products by exploiting China's experimentation with paperless processing trade in 2000–2006. This policy shock is highly suitable for our study as it affects only the cost of processing exports, leaving other exporting costs of a firm unchanged. To the best of our knowledge, this paper is the first to examine the effect of this policy.

5.1. China's paperless processing trade

We first present the shock and the empirical context. China's customs authorities closely monitor the supply chain for processing trade because of special duty drawbacks granted to processing exporters. To complete the record-filing procedures for organizing process trade, operating firms have to fill in grueling paperwork that details their financial condition and upstream and downstream connections for each contract, and then wait to be approved by the local customs authority.[40]

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[39] The sources of these statistics are the annual reports of Shenzhou International Group Holdings Limited.

[40] When applying for the record-filing of processing trade goods, enterprises are required to submit several documents as stipulated by Article 12 of the Measures for the Supervision and Administration of Processing Trade Goods by the Customs of the People's Republic of China. These documents include a valid approval document issued by the competent authority allowing processing trade operations, a "Certificate of Production Capacity of Processing Trade Enterprises" issued by the competent authority if the enterprise has its own processing

In order to make processing trade less costly for firms, China began to experiment with an online supervision system in 2000. By connecting firms' computer management systems to the customs' online administration system, the Chinese customs can efficiently supervise enterprises throughout the entire process of filing, modification, verification, and import–export declaration for processing trade. By making the procedures paperless, the burden of red tape on processing firms is significantly reduced. As quoted from a news article by *International Business Daily*: " . . . the traditional methods, from preparing the contract to getting approval, takes at least two weeks—sometimes one needs to visit several governmental offices hundreds of times. After adopting online supervision, the application takes less than an hour. As a result, the company's customs clearance costs are reduced by more than 20 percent, and the clearance speed is greatly improved."[41]

The pilot program for paperless processing trade targeted Class A firms – firms that had at least $10 million worth of exports.[42] Favorable to our setting, this threshold of $10 million was set by the Chinese authorities in 1999 for administrative purposes and is unrelated to the paperless processing trade program. Because paperless supervision requires firms to have an Enterprise Resource Planning (ERP) system (a computer software for business management), the government naturally targeted large firms for the pilot program as most of these firms had already installed ERP systems. The $10 million threshold therefore provides a simple and established selection criterion, and we are unaware of any trade-related or policy programs in China that have used this criterion during our sample period. Other contemporaneous policy changes, such as corporate tax reform and R&D subsidies, did not use this $10 million threshold, and they all differed from the exact timing of the paperless policy. This policy experiment had a staggered introduction to different prefectures: between 2000 and 2006, customs authorities of

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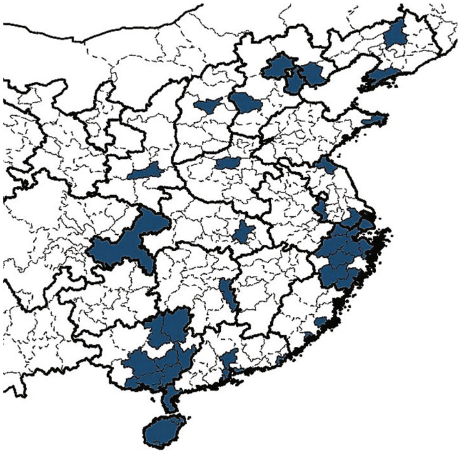
capabilities, and, in cases of entrusted processing, a contract for entrusted processing signed between the operating enterprise and the processing enterprise, accompanied by the "Certificate of Production Capacity of Processing Trade Enterprises" issued by the local customs for the processing entity. Additionally, contracts signed between the operating enterprise and foreign parties must be provided, along with any other certificates and materials that the customs deems necessary. This underscores the comprehensive documentation required to obtain processing trade qualifications.

[41] The original article is in Chinese and can be found at http://jm.ec.com.cn/article/jmzx/jmzxdfjm/jmzxguangzhou/200409/498189_1.html; translated by the authors.

[42] See http://www.people.com.cn/zixun/flfgk/item/dwjjf/falv/6/6-1-50.html (in Chinese) for the official firm classification notice, and http://www.fdi.gov.cn/1800000121_39_1919_0_7.html (in Chinese) for the official notice that explains the pilot program that targets Class A firms. We observe firms' eligibility, but not whether they actually adopt the program. We exclude the electronics sector from our analysis as firms in this industry had a lower threshold ($5 million) to qualify for the pilot program.

Figure 3. Adoption of the pilot paperless processing trade program



Notes: This map shows the 50 Chinese prefectures that adopted the pilot online supervision system during 2000-2006.

50 (out of 334) prefectures in 18 (out of 34) provinces of China adopted the pilot program, as illustrated in Figure 3. By the end of 2006, inspired by the success of the pilot program, the policy was rolled out nationwide and was made available to all processing firms, regardless of size. Both before and after the implementation of the policy, processing firms were under the jurisdiction of the customs office where the firms are located.

5.2. The direct impact of paperless processing trade

We first show that the pilot paperless program has been effective in increasing processing exports. In particular, we compare firms within a \$1 million bandwidth at the right and left side of the \$10 million threshold before and after the introduction of the paperless program. By incorporating a bandwidth, our approach resembles a regression discontinuity (RD) design with difference-in-differences (DD), similar to Bøler et al. (2015) who examine the effect of R&D policy in Norway using a difference-in-differences approach, and to Jia (2014) who analyzes the effect of treaty ports on Chinese prefectures by selecting a control group based on balancing checks. As emphasized by Lemieux and Milligan (2008), selecting an appropriate control group in DD and thus having a DD–RD type of estimation is crucial to obtain unbiased treatment effect estimates, given that the pre-treatment processing export trends of the treatment and control groups are parallel. This approach also allows us to take advantage of our panel data structure, using several years before and after the policy adoption, which enables us to estimate lagged effects. Moreover, our use of firm fixed effects allows us to focus strictly on within-firm variation, making DD–RD more robust to confounders when compared with a simple RD.

The direct impact of processing policy on processing trade is not our main interest; hence, we relegate our detailed empirical analysis and robustness checks to Online Appendix D. The balancing checks in Table A.5 reveal that our selected treatment and control group of firms are similar in almost all key aspects, while the full sample of firms are not. Figure A.1(b) shows that the pre-trends between our treatment and control groups are similar, with the \$10–11 million firms increasing their processing exports sharply in $t+1$. In contrast, the pre-trends between firms below and above \$10 million when using the full sample are very different (Figure A.1(a)). Our baseline estimation in Table A.6, Column 1, suggests that the pilot program increased firm-level processing exports by around 28 percent. Additional estimations in Tables A.6 and A.7 show that the result is robust to including a rich set of fixed effects, controlling for lagged processing shares, excluding foreign-owned firms, and using alternative bandwidths. Most importantly, our falsification tests with "false" thresholds yield point estimates that are insignificant and close to zero. Similarly, when focusing on ordinary instead of processing exports of mixed firms, the coefficient of interest is insignificant.

5.3. Downstream spillovers and trademarks

We now turn to the downstream spillovers of the pilot paperless processing trade program. We hypothesize that by promoting firms that are good at manufacturing, the policy will in turn benefit downstream firms that are good at "creating" to develop their own brands. Existing empirical research suggests that supplier–buyer relationships are highly localized (Bernard et al., 2019b), and thus we expect that downstream firms in the same prefecture as the affected suppliers would be more likely to benefit from the spillover and thus apply for new trademarks.

We first define the "treated processing exports" for each prefecture–sector–year (cst),

$$\text{Treated processing exports}_{cst} = \sum_{i \in A} \text{processing exports}_{icst},$$

where $i \in A$ are processing firms that are above the \$10 million threshold. Here sector s is defined based on the industry classification used in China's 2002 Input–Output (IO) table. To compute treated processing exports, we first concord HS8 from the customs data to the IO industry classification.[43]

[43] We thank Yu Shi for providing us with the HS8–IO industry correspondence table.

After adjusting for the one-to-many and many-to-many matches, we end up with a slightly more aggregated set of 74 IO industries. Then, we create a time-varying input shock as follows:

$$\text{Input shock}_{cnt} = \sum_{s} \omega_{ns} * \text{Treated processing exports}_{cst}.$$

Here ω_{ns} is the cost share of upstream industry s in downstream industry n, which we calculate based on the Chinese 2002 IO table. We then run the following specification:

$$Y_{icnt} = \exp\Big(\beta \ \ln(\text{Input shock})_{cnt} \times \text{Productive}_i + \lambda \ln(empl.)_{it} + \psi \ln(capital)_{it} + \gamma_i + \delta_{nt} + \phi_{ct}\Big) \times \epsilon_{icnt}. \tag{3}$$

Here Y_{icnt} is the number of effective trademarks a firm has,[44] and Productive_i indicates whether the firm's initial log labor productivity is above the median value.[45] We include $\ln(empl.)_{it}$ and $\ln(capital)_{it}$ to control for firm-level employment and capital stock, firm fixed effects γ_i to control for unobserved firm-level characteristics, sector–year fixed effects δ_{nt} to control for sector-specific supply and demand shocks, and prefecture–year fixed effects ϕ_{ct} to control prefecture-wide policy changes that might affect trademark applications.[46] Standard errors are clustered two-way at the prefecture and sector level. Because of the count nature of our dependent variable, we estimate specification (3) using a Poisson pseudo-maximum likelihood (PPML) model.[47]

Our identification strategy assumes that the initiation of the pilot paperless processing experiment by a prefecture's customs is exogenous to the branding activities of non-processing firms in the same region. We acknowledge that lobbying and simultaneous policy changes might threaten our identification assumption. However, our extensive review of policy documents indicates that the introduction of the policy was part of a broader agenda to enhance customs efficiency and was not influenced by specific local factors or interests. To address the concern that other temporal factors may also influence firms' branding activities, we include sector–year and prefecture–year fixed

[44]Trademarks are the legal basis for brands and thus we are using the number of effective trademarks as a proxy for firms' branding activity.

[45]To make sure that we retain zeros, we add 1 to Input shock_{cnt} before taking the natural log and including it in our regressions.

[46]Slightly more than a third of firms in our dataset have at least one effective trademark in 2000–2006. The average number of effective trademarks is 1.6, with a standard deviation 9.6.

[47]For our PPML estimations, we use the Stata package *ppmlhdfe* of Correia et al. (2020), which is robust to convergence issues inherent in maximum-likelihood estimation with multiple high-dimensional fixed effects.

effects in our specification. Also, by excluding pure processing firms, we aim to avoid confounding effects from unobserved productivity shocks to local processing exporters that could also influence branding activities. Our sample modifications do not change our results qualitatively, underscoring the robustness of our findings.

Table 6 presents the estimation results. As suggested in Column 1, we find that the adoption of the pilot program is positively associated with the number of trademarks of downstream firms, although the coefficient is statistically insignificant. This is intuitive, as almost 60 percent of below-median productive firms had at most one trademark between 2000 and 2006. Nevertheless, we expect that a greater input exposure to the pilot program should help productive firms to boost their trademark activity due to potential complementarities between productivity and sourcing. Hence, in Column 2, we interact the input shock variable with the Productive_i dummy, and find an interaction coefficient of 0.003, significant at the 1 percent level. The coefficient indicates that a one standard deviation (5.866) increase in $\ln(\text{Input shock})_{cnt}$ raises the number of trademarks of a productive firm by 0.012 ((0.003 − 0.001) × 5.866), which is 1.2 percent of the median number of trademarks (1). In Column 3, to allow for a more flexible effect, instead of the Productive_i dummy, we interact Input shock_{cnt} with the firm's demeaned initial labor productivity, $\ln(\textit{labor prod.})_i$, and the result stays robust. In Column 4, we use a normalized input shock variable by dividing treated processing exports by total processing exports for each cst, and continue to find a positive and statistically significant coefficient for the Productive_i interaction.

In Column 5 of Table 6, we directly control for $\text{Treated processing exports}_{cnt-1}$ of the firm's own industry and its upstream industry $\text{Output shock}_{cnt-1}$, which we compute analogously to $\text{Input shock}_{cnt-1}$ but with usage shares instead of cost shares. Because promoting processing policy might crowd out ordinary firms and hence directly affect their branding activities, we include $\text{Treated processing exports}_{cnt-1}$; we also include $\text{Output shock}_{cnt-1}$ as affected downstream buyers could potentially induce their suppliers to innovate. The estimated interaction coefficient remains the same, and we see that the own industry and upstream effects are not significantly different than zero. One might be concerned that $\ln(empl.)_{it}$ and $\ln(capital)_{it}$ are potentially endogenous controls. Thus, in Column 6, we use initial $\ln(empl.)_i$ and $\ln(capital)_i$ interacted with year dummies, and find very similar results (coefficients not reported in the table for brevity).

Column 7 excludes SOEs from the sample as these firms' trademark activities might be subject to government controls. In Column 8, we estimate our specification using OLS instead of PPML. Neither of these robustness checks change the qualitative result. In Column 9, the dependent variable is a dummy that indicates whether the firm has at least one effective trademark. In

Table 6. Trademarks with IO linkages

Dep. var.: Y_{icnt}	Overall effect (1)	Median (2)	Demeaned (3)	Shares (4)	Other linkages (5)	Fixed empl. and capital (6)	No SOEs (7)	OLS (8)	Extensive margin (9)	Intensive margin (10)
$\ln(\text{Input shock})_{cnt-1}$	0.001	−0.001	0.001		−0.002	−0.000	−0.000	−0.008	−0.000	−0.001
	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.001)
$\times$ Productive$_i$		0.003***		0.428***	0.003***	0.004***	0.002***	0.010***	0.001**	0.002***
		(0.001)		(0.087)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)
$\times \ln(\textit{labor prod.})_i$			0.001***							
			(0.000)							
$Inputshock_{cnt-1}$ (normalized)				−0.152**						
				(0.073)						
$\ln(\text{Treated processing exports})_{cnt-1}$					−0.000					
					(0.000)					
$\ln(\text{Output shock})_{cnt-1}$					0.003					
					(0.002)					
$\ln(empl.)_{it}$	0.102***	0.100***	0.100***	0.101***	0.100***		0.097***	0.274***	0.042***	0.057***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)		(0.006)	(0.016)	(0.004)	(0.003)
$\ln(capital)_{it}$	0.054***	0.054***	0.054***	0.054***	0.054***		0.053***	0.135***	0.025***	0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.004)	(0.012)	(0.002)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector–year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture–year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	408,051	408,051	408,051	408,051	408,051	408,051	366,052	408,051	408,051	370,409
Pseudo-R^2	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.90 (R^2)	0.03	0.93 (R^2)

Notes: This table reports the results of running specification (3) using a PPML model. Y_{icnt} is the number of trademarks of firm i in downstream sector n residing in prefecture c in year t. Sectors refer to 57 downstream IO industries. Productive$_i$ indicates firms whose initial log labor productivity is larger than the median. Column 6 uses initial $\ln(empl.)_i$ and $\ln(capital)_i$ interacted with year dummies (coefficients not reported for brevity). Column 8 uses OLS instead of PPML. In column 9, Y_{icnt} is a dummy variable that indicates whether the firm has a trademark, whereas in Column 10, Y_{icnt} is the log number of trademarks (estimated linearly). Standard errors clustered at the prefecture and sector level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Column 10, we use the log number of trademarks, which results in a smaller sample size due to dropping firms with no trademarks. The coefficients show that the input shock has positive effects on trademarks at both the extensive and the intensive margins. We also find that the number of employees and the capital stock have a positive and significant effect on trademarks in all regressions, as expected. Overall, results in Table 6 suggest that the pilot paperless processing trade program has induced more productive downstream firms to increase their branding activity.

Regarding the mechanism, our model proposes that the positive spillover on downstream firms is due to their access to a larger mass of potential suppliers as a result of the processing-promoting policy. However, because we do not observe firm-to-firm linkages, we cannot pinpoint the exact mechanism. As a result, alternative mechanisms, such as technology transfers, learning about more efficient production and management techniques, and/or process upgrading, can also explain our findings.

6. Conclusion

In this paper, we unpacked the "black box" of mixed exporters that were the driving force behind China's export boom in 2000–2006 by engaging in both processing and ordinary exports. Importantly, we showed that 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 mixed exporters 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 in various margins.

To rationalize our empirical findings, we provided a simple theoretical framework where multi-attributes firms endogenously determine their specialization. In particular, the model predicts a novel positive impact of processing trade policy: facilitating processing trade leads to a greater mass of potential suppliers, which eventually benefits downstream firms with good ideas. Using China's pilot paperless processing supervision program in 2000–2006 as a quasi-natural experiment, we found that promoting processing trade induced domestic downstream firms to establish their own trademarks as predicted by our model.

Overall, our analysis 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. Finally, we showed that processing trade can lead goods to be not only "Made in China", but also "Created in China". Our proposed mechanism suggests that this is due to firms with good ideas having access to a larger mass of potential suppliers. Future research could test this hypothesis using detailed buyer–seller data with price information. Additionally, exploring the impact of traditional processing trade centers such as Huaqiangbei in Shenzhen and others in the Yangtze River Delta and Shandong regions on China's export quality and downstream firm benefits would be valuable. Moreover, investigating alternative mechanisms such as technology transfers is essential for a comprehensive understanding of how Chinese firms transition from manufacturing to innovation.

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Supporting information

Additional supporting information can be found online in the supporting information section at the end of the article.

Online appendix
Replication files

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