# Made and Created in China: Super Processors and Two-way Heterogeneity*

Zhiyuan Chen† Aksel Erbahar‡ Yuan Zi§

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**Abstract**

This paper uses China's processing trade regime to examine firm performance and specialization within a production network. We show that there exists a special breed of firms that are active in both ordinary and processing exports, and are superior to other firms in multiple dimensions. Motivated by these "super processors," we document novel stylized facts on the interplay among exporters' performance, export mode, and brand ownership. We find that productivity and branding ability jointly shape firms' exporting activities. Based on these facts, we provide a general equilibrium model with endogenous production networks where firms are heterogeneous in both manufacturing and branding abilities. Testing our model's central prediction, we find that facilitating processing exports induces productive domestic downstream firms to establish their own trademarks. Our results highlight that processing trade not only leads goods to be "Made in China," but also "Created in China."

*JEL codes:* F1, F12, F13, F14, L11, L21

*Keywords:* heterogeneous firms, production networks, processing trade

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†Department of Economics, Pennsylvania State University, United States, *email*: zxc5109@psu.edu

‡Erasmus School of Economics (ESE), Erasmus University Rotterdam, the Netherlands, and Tinbergen Institute, *email*: erbahar@ese.eur.nl

§Department of Economics, University of Oslo, Oslo, Norway, *email*: yuanzi.economics@gmail.com (corresponding author)

## 1 Introduction

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

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

China's trade as percentage of its GDP rose from below 10% in late 1970s to over 60% just before the Great Recession (World Bank, 2018). During this period, Chinese firms supplied relatively low value-added tasks to foreign multinationals largely through processing trade, as epitomized by the "Made in China" tag. While processing trade accounted for the majority of China's total exports[1] and was the key driver of China's export boom, relatively little attention has been paid to the main participant of processing trade—the mixed firms. Mixed firms refer to firms that are active in both processing and ordinary exports. They made up about a fifth of processing exporters, and contributed to over 60% of total Chinese processing exports during 2000-2006. These firms are considered to be "perhaps the most interesting type of firm[s]" (Yu, 2015), but they were never investigated carefully in the literature.

Starting by unpacking the "black box" of mixed firms, this paper leverages China's processing trade regime to examine firm performance and specialization within a production network. We find that mixed exporters are larger and have higher revenue and physical productivity compared to firms that engage in only ordinary (i.e., pure ordinary exporters) or only processing (i.e., pure processors) activities. Importantly, unlike what is suggested in the literature, these "super processors" are 'mixed' not because they sell different products under different export modes: the majority of their exports consists of the same product being sold to the same destination under both processing and ordinary trade modes.

Even though being highly processing-oriented, mixed exporters' superior performance does not generalize to pure processing exporters. Compared to pure ordinary exporters, pure processors have significantly lower revenue productivity, but greater employment and physical productivity. We empirically rule out the conjecture that the low revenue productivity of pure processors is due to preferential processing policies or transfer pricing. Using a novel *transaction-level* customs data with detailed product and brand information, we find that (i) selling one's own branded product is positively correlated with the use of ordinary export mode, and (ii) there is a price premium associated with selling one's own branded product. This 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 stages of production (i.e., manufacturing vs. branding), which ultimately determines its measured performance at various margins.

We then develop a theoretical model to explain our stylized facts and gain a better understanding

[1] During 2000-2006, processing exports made up 54% of China's total exports on average.

of how firms' attributes determine their specialization within a value chain. Our model features an endogenous production network in which firms are heterogeneous in both manufacturing and branding abilities. Firms compete monopolistically in the final goods market and à la Bertrand in the tasks market, and thus charge positive markups in both stages of production. In equilibrium, firms with good blueprints charge higher markups and self-select into the final goods market, firms with high manufacturing ability self-select into the tasks market, and firms that have high attributes in both participate in both markets. With international trade, only 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.

Since we endogenise firms' specialization within a production network, the mass of potential suppliers is no longer exogenous. Thus, our framework differs from the existing workhorse sourcing models (see, for instance, Antràs et al. (2017) and Bernard et al. (2019)) and generates a new positive externality of processing trade policy: facilitating processing trade raises the *ex-ante* expected profits from task production and thus encourages entry, leading to a greater mass of potential suppliers in equilibrium. This improves final good producers' sourcing capacity, which in turn lowers their marginal costs. Thus, the model predicts that facilitating processing exports stimulates downstream firms' branding activity. Furthermore, conditional on employment, firms with higher measured revenue productivity benefit more from the policy, as they source a greater share of tasks from suppliers.

To empirically examine the model's prediction, we use China's pilot "paperless" processing supervision program implemented in 2000-2006 as a quasi-natural experiment. The paperless program made the supervision of processing trade more efficient by eliminating paperwork through connecting firms' computer management systems to the customs' online administration system. This policy change is highly suitable for our identification strategy as it affects *only* the cost of processing exports, and not the cost of ordinary exports. Moreover, the pilot program is experimental in nature, targets a subsample of firms, and is adopted only by a few regional customs authorities at different times, limiting the scope of anticipation effects. We document that the paperless processing program caused the processing exports of firms to increase by 28%. Consistent with the model's central prediction, we 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 4% on average. These 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 potential task suppliers for firms with good ideas.

This paper is related to several strands of the trade literature. First, 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).[2] Different from these studies which focus more on pure processing firms, we document

[2]Fernandes and Tang (2015) find that processing firms are less diversified in products and destinations when

the dominant role of mixed exporters that engage in both ordinary and processing exports.[3] By exploring the characteristics of different types of exporters but focusing on mixed exporters in a comprehensive way, and relating for the first time exporters' brand ownership with their choice of trade modes, we provide novel empirical facts. These facts suggest that firms are heterogenous in multiple dimensions, which motivates the key assumption in our model.

Our model contributes to the literature on firms' sourcing decisions in international and regional trade (Antràs et al., 2017; Tintelnot et al., 2018; Bernard et al., 2019; Kikkawa et al., 2019, among others),[4] by considering a setting where firms are characterized by their upstream and downstream productivities, and they self-select into different, and possibly multiple, stages of the production network. Unlike existing theoretical frameworks of processing trade (Defever and Riaño, 2017; Deng, 2017; Brandt et al., 2019, among others), our model is able to generate the coexistence of the three types of exporters (pure ordinary, pure processing, and mixed) alongside the performance ranks we observe in the data. The model also yields a new source of gains from processing trade through facilitating the branding activities of downstream firms that rely on task suppliers.

In the context of international trade, Antràs and Helpman (2004), Hallak and Sivadasan (2013), Harrigan and Reshef (2015), and Bernard et al. (2018) also study firms with multiple heterogeneities. The closest work to ours is Bernard et al. (2018), who develop a model of heterogeneous firms and network formation, where firms vary in their productivity and relationship capability, while we emphasize firm heterogeneity in different stages of production. To the best of our knowledge, our paper is the first to do so in the context of firm-to-firm trade.

Lastly, our empirical examination of the impact of "paperless" processing supervision program is broadly related to the literature on trade facilitation (Freund and Rocha, 2011; Hoekman and Nicita, 2011; Beverelli et al., 2015; Umana-Dajud, 2019),[5] in particular the recent literature on the impact of the internet on international trade (Kneller and Timmis, 2016; Fernandes et al., 2019; Malgouyres et al., 2019).[6] We contribute to this literature by providing the first look at the effect of digitization on processing trade, alongside its downstream spillovers on firms' branding activities.

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

[3] Yu (2015), Dai et al. (2016), and Li et al. (2018) do include mixed firms (referred to as "hybrid" firms) in their analysis but do not focus on them.

[4] Chaney (2016), Bernard and Moxnes (2018), and Johnson (2018) provide excellent reviews of the network models in international trade.

[5] Freund and Rocha (2011) and Hoekman and Nicita (2011) find that transit delays and behind-the-border measures such as logistics performance are important determinants for developing country exports; Beverelli et al. (2015) find that the WTO's trade facilitation agreement has induced developing countries to diversify their export portfolio; and Umana-Dajud (2019) shows that visa-requirements reduce bilateral flows.

[6] Kneller and Timmis (2016) find that broadband use increases business service exports of UK firms; Fernandes et al. (2019) show that the expansion of internet in China caused firm-level exports to rise; and Malgouyres et al. (2019) find that the roll-out of broadband in France has increased firm-level imports and thus reduced the consumer price index.

The rest of the paper is organized as follows. Section 2 presents the data and stylized facts. Section 3 develops the model in a closed economy setting. Section 4 introduces international trade and discusses how the model can match the stylized facts. Section 5 empirically tests the model's prediction by exploiting the pilot "paperless" supervision program. Section 6 concludes.

## 2 Data and Stylized Facts

We use four main datasets in this paper. The first is China's 2000-2006 customs data that shows firms' monthly transactions of exports and imports at the product-country level, where products are defined at the 8-digit Harmonized Schedule (HS8) level. Since our analysis is focused on manufacturing firms, we remove intermediaries and wholesalers from the dataset.[7] The dataset allows us to observe each firm's ordinary and processing exports at the product-country level. Thus, we are able to divide firms into three mutually exclusive groups: pure processing exporters, pure ordinary exporters, and mixed exporters who are engaged in both processing and ordinary exports.

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

The fourth dataset we use is a rich sample of confidential *transaction-level* customs data for 2018. This unique dataset contains highly detailed product and brand information for each export transaction, as the Chinese government began to require firms to report the brand information in customs declaration forms in 2018.[11] 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

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

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

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

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

[11] This policy change was issued in the No. 69 General Administration of Customs Announcement on Amending the "Regulations on the Customs Declaration of Imports and Exports of the People's Republic of China" in 2017, and became effective on January 1, 2018.

group into three categories: no brand, domestic brands (domestically created or purchased), and foreign brands (including original equipment manufacturers). The dataset consists of 862,567 daily transactions which make up around $38 billion worth of exports in 34 HS8 products by 29,138 firms, covering product categories from 13 out of 68 HS2 manufacturing sectors. Of the 34 products, 30 are from March and the rest are from January and April 2018. The wide variety of products, which are listed in Table A.1, includes goods that make up a large share of exports such as car tires, refrigerators, and mobile phones.

## 2.1 Mixed Exporters in China

We begin by unpacking the "black box" of mixed exporters in this section. Mixed exporters are defined as firms that engage in both processing and ordinary exports. The customs data shows that even though the number of mixed exporters was only 21% of the total number of exporters, they made up 54% of exports in 2005. Pure processors and pure ordinary exporters, on the other hand, made up 24% and 19% of exports in 2005 respectively.[12]

We present firm-level statistics for mixed exporters in Table 1, in which we have all 50,952 mixed exporters in panel (a), and 24,470 merged (with the AIS data) mixed exporters in panel (b). The figures in both panels are similar, indicating that the merged sample of exporters is representative, and thus we refer to statistics in panel (b) from here on. Row 1 shows that the median (mean) share of processing exports in a mixed firm's total exports is 66% (58%). Corresponding shares at the firm-HS8 and firm-HS8-country levels are similarly high, suggesting that mixed exporters' main activity is processing trade (hence we label them as "super processors"). Nevertheless, mixed exporters contribute substantially to China's ordinary trade as well—in 2005, they made up 63% and 42% of China's processing and ordinary exports, respectively. Moreover, mixed firms are prevalent in almost all sectors; 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. This result indicates that many "superstar" firms are mixed exporters.

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. Even though most mixed firms do export multiple products, they tend to sell their *core product*(s) under both trade regimes. Consistent with Dai et al. (2016), Table 1 panel (b) rows 4 and 5 show that the *number* of products exported under both trade regimes, on average, accounts for only 37% and 24% of mixed firms' total number of products and product-destinations respectively. However, the median (mean) *value* share of HS8 products that are exported through both ordinary and

[12] The rest is made by firms that did not fit into one of the three groups as they engaged in other export modes such as re-exporting, and made up about 3% of exports. Note that we exclude intermediaires and wholesalers, which made up 18% of exports in 2005. These figures are similar to those reported by Dai et al. (2016).

processing modes (mixed HS8) in a mixed firm's exports is 89% (71%), as reported in row 6 of panel (b). Row 7 analyzes the most disaggregate HS8-country level and finds a median (mean) share of 62% (55%).[13] This suggests that the majority of mixed exporters' exports are due to selling the same product to the same destination via both export modes.[14]

The non-trivial existence of mixed exporters is intriguing. The theoretical literature typically assumes either that processing is a different sector (Deng, 2017; Brandt et al., 2019) or that Melitz-type firms 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, if mentioned, are generated by bringing in some product- or destination-specific shock to fixed costs. However, in that case, mixed exporters would never sell the same product to a given destination via both export modes, which is in contrast to our *Fact 1.* Moreover, both types of models would predict that mixed firm attributes lie between that of processing and ordinary firms. However, as shown in the next subsection, this is not what we find in the data.

## 2.2 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. Our exercise in this section is similar to Dai et al. (2016), but while they mainly focus on comparing exporters to non-exporters, we focus on differences *between* exporters. From here on, we use the merged exporters database, and use the two-digit Chinese Industry Classification (CIC) reported in the AIS data for our definition of sectors (except for *Fact 3*, for which we use the 2018 customs sample). We run the following regression:

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

where $Y_{it}$ is an outcome variable (e.g., $\ln(empl.)_{it}$, where *empl.* is for employment) for firm $i$ in year $t$, $PP_{it}$ and $Mix_{it}$ are dummies for pure processing and mixed exporters respectively (pure ordinary exporters is the omitted group), $\delta_{ht}$ are sector-year fixed effects, and $\epsilon_{it}$ is the error term which we cluster at the sector level (29 clusters). Each row of Table 2 shows results from a separate regression, and coefficients can be interpreted as relative to pure ordinary exporters. All regressions except for row 1 include $\ln(empl.)$ as a control variable for firm size. Panel (b) excludes firms with foreign ownership.

Table 2 panel (a) row 1 shows that compared to pure ordinary firms, pure processors and mixed

[13]Also, the median (mean) share of exports to the same destination within products that are sold under both trade regimes (mixed HS8-country) is 98% (78%) for the merged mixed exporters.

[14]One can argue that there might still be different kinds of products within an HS8 code. This is less of a concern since China's product classification at the HS8 level is highly detailed: for example, there are seven different HS8 under the internationally-standardized HS6 code 520811 *Plain weave, unbleached, weighing not more than 100g/*$m^2$, that specify the type of cotton used (e.g., medical gauze). This level of detail mitigates the concern that an exporter is mixed due to its multi-product nature.

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

*Fact 1: Mixed exporters are larger than pure processors, who are larger than pure ordinary exporters in terms of employment.*

The existing empirical research, including Mayer and Ottaviano (2008) and Bernard et al. (2012) for European and US firms respectively, finds that larger firms tend to have higher labor productivity and revenue TFP ($TFPR$). Does this result hold for mixed exporters? Table 2 panel (a) row 2 shows that mixed firms have 14% higher labor productivity than pure ordinary firms, whereas pure processors have 22% lower labor productivity than pure ordinary firms.[15] Row 3 shows that the ranking we obtained based on labor productivity remains when we consider $TFPR$ calculated using the Olley-Pakes (1996) methodology.[16] The results are similar when we exclude foreign firms in panel (b) row 2.

As is well documented in the literature, $TFPR$ reflects not only firms' technical (or manufacturing) efficiency (quantity-based TFP, or $TFPQ$), but also their prices. In particular, focusing on the Chinese leather shoes industry, Li et al. (2018) find that exporters' $TFPQ$ is *higher* than non-exporters', while their $TFPR$ is *lower* than non-exporters'. They argue that processing exporters' low $TFPR$ can be explained by their relatively lower average export prices. Does this empirical regularity hold for other sectors? What is the rank of mixed firms' $TFPQ$ among exporters? With these two questions in mind, we replicate their exercise focusing on the 36 of the 693 manufacturing 5-digit products in the dataset for which we can obtain reliable estimates based on data availability. The estimation methodology and the list of products can be found in Appendix Section B and Table B.1 respectively.[17] Consistent with Li et al. (2018), we find that compared to pure ordinary exporters, pure processors have higher $TFPQ$ on average (row 4 of Table 2 panel (a)). In addition, mixed exporters have the highest physical productivity on average (though not statistically significantly different from that of pure processors). We summarize these findings in the following stylized fact:

*Fact 2: 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.*

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

[16] Our results are robust to using the Levinsohn-Petrin (2003) methodology.

[17] Our methodology is similar to the one used by Li et al. (2018) but differs slightly since instead of following De Loecker et al. (2016) and use a translog production function, we use the Olley-Pakes (1996) methodology with a Cobb-Douglas production function to control for selection. This difference, and our larger coverage of sectors, can explain the discrepancy that while we find mixed exporters and pure processors to have the highest $TFPQ$, they find that pure processors' $TFPQ$ is higher than that of "hybrid" firms.

Existing theoretical frameworks would predict that mixed firm characteristics lie between that of pure processing and pure ordinary firms, which stands in contrast with what we find in the data. One obvious rationalization would be that processing transactions have lower prices due to, for example, input tariff exemptions or transfer pricing (Li et al., 2018), which would disproportionately distort the average export price of pure processors, and hence render the lowest $TFPR$. Nevertheless, the fact that the production efficiency ($TFPQ$) ranking follows a (weakly) decreasing order of mixed exporters, pure processors, and pure ordinary exporters remains unexplained.

An alternative hypothesis is that processing firms contribute to relatively less value-added stages of production (e.g., manufacturing), and thus get a lower share of profits when compared to their foreign buyers (Feenstra and Hanson, 2005; Dai et al., 2016; Manova and Yu, 2016). Given that most value-added comes from firms' non-manufacturing activities such as innovation and marketing, processing firms can be efficient in production yet have low $TFPR$. On the contrary, ordinary producers can claim more profits thanks to their branding activities, and hence can survive even with a relatively low $TFPQ$. This view also gives a natural explanation to the existence of mixed exporters: they are simply firms that excel in both manufacturing and non-manufacturing activities. The second 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, 2017).[18]

While both explanations are plausible, which one plays a more important role is an empirical question. We investigate this by using the 2018 customs sample and reach the following stylized fact, which we explain subsequently:

*Fact 3: Ordinary transactions tend to involve firms' exports of their own branded products, whereas processing transactions tend to involve firms' exports of their customers' branded products. There is a price premium associated with selling one's own branded product.*

The 2018 customs dataset allows us to extract the brand ownership information for each export transaction, and label it as no brand, foreign brand, or domestic (own) brand. As shown in the last row of Table A.2, 12.4%, 56.4%, and 32.7% of export value are due to transactions that have no brand, foreign brand, and domestic brand respectively. Regarding export modes, the dataset reports 45 export modes which we classify into three groups: ordinary exports, processing exports, and "other" exports.[19] Based on our classification, ordinary and processing exports account for 27% and 43% of total exports in the sample.

[18]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, supplies tasks to brands such as *De'Longhi*, *General Electric*, and *Sanyo* alongside exporting its own branded microwaves and air conditioners.

[19]We treat the export mode as processing exports whenever "processing" appears in the string variable. Following this rule, we group seven export modes into processing exports. We treat the export mode named as "ordinary exports" as ordinary exports. We lump the categories that we were not able to classify into "other" exports. Our results are robust if we include other potential ordinary exports "temporary exports," "foreign contracted exports," "goods for exhibition," and "samples for advertisement" in the ordinary exports category. This group of exports make up 0.01% of total exports in the sample.

While processing transactions are typically viewed as local manufacturers supplying customized tasks to their "branded" buyers (Manova and Yu, 2016), our data enables us to confirm this conjecture empirically: Table A.2 shows that 52% of ordinary exports in the customs sample consists of goods with Chinese domestic brands, while 84% of processing exports consists of foreign branded products. More formally, we run the following transaction-level regression:

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

where $D_{ifhc}$ is a dummy indicating whether firm $f$'s export transaction $i$ of product $h$ (at the HS10 level) to country $c$ is for its own Chinese domestic brand (as opposed to foreign or no brand), $P_{ifhc}$ is a dummy for processing trade (as opposed to ordinary trade), $\delta_{hc}$ are HS10-country fixed effects to control for product-destination determinants of processing trade policy and brand ownership (e.g., FDI policy), and $\epsilon_{ifhc}$ is the error term which we cluster at the firm level. Table 3 column 1 shows that processing transactions are 13 percentage points less likely to involve products with domestic brands when compared to ordinary transactions (significant at the 1% level). 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 (mixed) firm.[20] Column 2 shows that the coefficient remains negative and significant at the 10% level, albeit with a lower magnitude (-0.032).

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

Now let us turn to the first explanation that emphasized input price differences among exporters. 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, the above conjecture would imply that within a firm-product-destination, processing exports should have a *lower* unit value, which contradicts our finding in Table 3. If transfer pricing is driving the results (i.e., processing exporters artificially lowering the price of export transactions between enterprises under common ownership or control),

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

then we would expect to see a less stark difference in $TFPQ$ between processing and ordinary firms once we exclude foreign firms—the results in Table 2 suggest the opposite. Therefore, we conclude that the higher average price of exporters' own products is more likely due to brand premium instead of input tariff exemptions or transfer pricing.

Finally, we provide some suggestive evidence that a firm's choice on export mode is indeed associated with its branding activities. Table 2 panel (a) rows 5 and 6 reveal that R&D and advertisement expenditures across firms are in the following decreasing order: pure ordinary exporters, mixed exporters, and pure processors. In fact, 85% of pure processors did not have any R&D or advertising expenses in 2005. This is in line with anecdotal evidence that pure processors tend to specialize in providing specific tasks for other firms, and thus do not need to invest in R&D or spend on advertisement, which are ultimately done by their customers. In panel (b) rows 5 and 6, we exclude foreign firms since the majority of their R&D and advertising expenses are likely to be done in their headquarter-countries, and thus are not perfectly observed in our data—the results stay qualitatively the same.[21]

To sum up, the stylized facts presented above lead us to view mixed exporters as "super processors," and motivate our investigation of how firms' efficiency in manufacturing versus branding activities jointly determine their specialization inside a production network. In the next section, we develop a theoretical model that is able to explain these stylized facts. Moreover, in our framework, processing polices can have different welfare implications compared to frameworks where firms are heterogeneous in only one dimension.

# 3 Theoretical Framework

In this section, we develop a model to allow firms to self-select into different, and possibly multiple, stages of the production network. In the model, firms differ in two dimensions, and endogenously determine the set of tasks they produce for other firms, the optimal production of their own final good, and the related sourcing strategy. Note that there is nothing intrinsically international about our model—a non-exporting manufacturer could also produce its own branded product and at the same time serve other firms. Thus, we start from a closed economy setting and focus on firms' choice between *making* and *branding*. Then, we turn to an open economy setting to discuss how our model fits the stylized facts and explore the implications of processing trade policy.

## 3.1 Basic Environment

Preferences of a representative consumer are Cobb-Douglas over two sectors. The numeraire sector produces a homogeneous product with one unit of labor, while the other sector produces differentiated products and is the focus of our analysis. An exogenous fraction $\beta$ of income is spent on

[21]A closer look at the AIS data confirms that foreign-owned firms' China operations are significantly less R&D- and advertising-intensive when compared to Chinese exporters.

differentiated products. Preferences across differentiated products exhibit CES, with the elasticity of substitution given by $\sigma > 1$.

There is a continuum of firms, and each owns a blueprint to produce a single differentiated variety. Production of a variety requires the assembly of a bundle of tasks $t \in [0, 1]$ under a CES production function with an elasticity of substitution $\rho > 1$. The quality of the blueprint owned by firm $j$ is denoted by $z_j$, which governs the mapping between the task bundle and final good production: a higher $z_j$ indicates that firm $j$ is more productive in producing the final good.

Task production requires only labor, which is inelastically supplied at the country level. All tasks are *blueprint-specific*, and firm $j$'s efficiency in producing a task is drawn from a Fréchet distribution with a firm-specific level parameter $t_j$ and a shape parameter $\theta$, with $\theta > \sigma - 1$. Here, $t_j$ governs the firm's average manufacturing ability in producing tasks, and $\theta$ the (inverse) dispersion of its manufacturing efficiency across tasks.

As holders of blueprints, firms can produce some tasks in-house and source some from other firms. Analogously, as task suppliers, firms can produce both for their own and other firms' final goods. A firm observes the average manufacturing ability of a supplier, but needs to pay a fixed cost $f$ to establish a production relationship and discover the supplier's actual efficiency in producing tasks tailored for its blueprint.

We assume Bertrand competition in task production following Bernard et al. (2003) (BEJK hereafter). As a result, even firms that do not bring their blueprint to production can earn positive profits by supplying tasks for other firms. Allowing for positive profits in task production is crucial for our analysis on processing policy, but the rest of our results hold if we assume perfect competition in the tasks market instead. Under Bertrand competition, conditional on the set of suppliers that firm $j$ has established relationships with, each tailored task is supplied by the lowest-cost supplier. This supplier is constrained to charge not more than the second-lowest cost supplier of that task. In order for prices and markups to be analytically tractable at the aggregate level, we impose an additional constraint: if supplier $i$ produces task $\kappa$ for firm $j$ at an efficiency level $\phi_{1i}(\kappa)$, then this same supplied task can be 'mimicked' by $j$ with $\phi_{2i}(\kappa) \leq \phi_{1i}(\kappa)$, with the joint distribution of $\phi_{1ij}(\kappa)$ and $\phi_{2ij}(\kappa)$ given by: $F_i(\phi_1, \phi_2) \equiv Pr[\phi_{1ij}(\kappa) \leq \phi_1, \phi_{2ij}(\kappa) \leq \phi_2] = [1 + t_i(\phi_2^{-\theta} - \phi_1^{-\theta})]e^{-t_i\phi_2^{-\theta}}$.[22]

There is an unbounded pool of prospective entrants. Firms learn about their blueprint quality and manufacturing ability after incurring a fixed entry cost $f_E$, measured in homogeneous inputs. We let $z$ and $t$ be drawn independently from two distributions $g_z(z)$ and $g_t(t)$ with support in $(0, \bar{z}]$ and $(0, \bar{t}]$, respectively.[23] Once firms make their draws, they decide to (i) exit, (ii) engage in blueprint production, (iii) engage in task production, or (iv) do both (ii) and (iii). Being active in blueprint production requires an additional fixed cost $f_B$. An active firm faces a constant probability

[22] For tractability, we allow for positive markups for both in-house and outsourced production. One can view in-house production as firms sourcing tasks from their quasi-independent manufacturing subsidiaries.

[23] Additionally, we assume that $g_t'(t) < 0$, $\lim_{t \to \bar{t}} g(t) = 0$, and $-tg_t'(t) < g_t(t)$. The latter assumption can also be written as $-\frac{\partial \ln g(t)}{\partial \ln(t)} < 1$, which guarantees that the marginal reduction in firms' marginal cost decreases as they reach less efficient suppliers.

$\delta$ of an adverse shock that would force it to exit every period.

In our model, firms differ in their blueprint quality $z$, which indicates how good their *brand* is, and manufacturing ability $t$, which determines how good they are in *production*. In the rest of the paper, we refer to firms with high $z$ as *firms with good blueprints*, and firms with high $t$ as *firms with high manufacturing ability*. Also, we refer to firms that bring their blueprints to production as *blueprint (or final good) producers*, and firms that only supply tasks to others as *task producers*.

### 3.2 Optimal Sourcing

Note that manufacturing ability $t$ varies across firms while the relationship-specific investment $f$ does not. This simplifies a firm's optimal sourcing decision to choosing the least productive supplier it reaches. As there is no fixed cost of task production, all firms are potential suppliers. Conditional on firm $j$ being connected with $i$, the probability that $i$ is the lowest-cost supplier to $j$ for a particular task is:

$$\lambda_{ij} \equiv \lambda(z_j, t_j, t_i) = \frac{t_i}{\Theta(z_j, t_j)}, \tag{3}$$

where $\Theta(z_j, t_j)$ measures firm $j$'s "sourcing capacity." Specifically:

$$\Theta(z_j, t_j) = t_j + N \int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota), \tag{4}$$

where $\underline{t}_j$ is the least productive supplier that firm $j$ sources from, and $N$ is the endogenously determined mass of entrants.[24] As in BEJK, firm $j$'s share of total purchases from firm $i$ equals $\lambda_{ij}$. The price of the task bundle used by firm $j$, $P_j^T$, is given by $P_j^T = \Theta_j^{\frac{-1}{\theta}} \gamma$, where $\gamma$ is a constant.[25] Thus, a firm's marginal cost of producing its own final good, $c_j$, is simply $\frac{P_j^T}{z_j}$. Conditional on firm $j$'s own manufacturing ability $t_j$, sourcing from a larger number of suppliers leads to a lower marginal cost. Conditional on the number of suppliers, a higher manufacturing ability also enables the firm to produce at a lower marginal cost.

Conditional on its pricing strategy, the final good producer with blueprint $z_j$ and manufacturing ability $t_j$ chooses the set of suppliers to maximize its profits from final good production:

$$\max_{\underline{t}_j} \pi^B(z_j, t_j) - fn(z_j, t_j) - f_B, \tag{5}$$

where $\pi^B(z_j, t_j) = Ak_1\Theta^{\frac{\sigma-1}{\theta}} z_j^{\sigma-1}$ is the operating profits, with $A = \beta L P^{\sigma-1}$ being the demand shifter, $L$ the country's labor endowment, $P$ the aggregate price index, and $k_1$ a constant.[26] The number of suppliers, $n(z_j, t_j)$, is given by $N \int_{\underline{t}_j}^{\bar{t}} dG_t(\iota)$. Solving this maximization problem yields

[24] Including a fixed cost for in-house production would create an additional set of "factoryless" firms that do not engage in manufacturing as identified by Bernard and Fort (2015). Since our analysis does not include these firms, we refrain from adding such a fixed cost.

[25] $\gamma^{1-\rho} = \frac{1+\theta-\rho+(\rho-1)(\frac{\rho}{\rho-1})^{-\theta}}{1+\theta-\rho}\Gamma(\frac{2\theta-\rho+1}{\theta})$, and $\Gamma$ is the gamma function.

[26] $k_1 = \frac{\gamma^{1-\sigma}}{\sigma}(1-\frac{1}{\sigma})^{\sigma-1}$.

the optimal $\underline{t}_j$, which satisfies:

$$\underline{t}(z_j, t_j) = f\left(Ak_1 z_j^{\sigma-1}\right)^{-1} \Theta(z_j, t_j)^{1-\frac{\sigma-1}{\theta}} \frac{\theta}{\sigma-1}. \tag{6}$$

With a slight abuse of notation, we also use $\underline{t}_j$ to refer to the least efficient supplier that firm $j$ matches with *in equilibrium*. It is easy to show that $\underline{t}_j \equiv \underline{t}(z_j, t_j)$ increases in $z_j$ and decreases in $t_j$. Intuitively, firms who have good ideas reach a greater number of suppliers, while firms who are efficient in producing tasks themselves reach fewer suppliers.

The blueprint-owner receives the profits generated by selling the final product. For firm $j$ with marginal cost $c_j \equiv c(z_j, t_j)$, its price, quantity, revenues, and operating profits of blueprint production can be derived à la Melitz (2003) respectively:

$$p_j^B = \frac{\sigma}{\sigma-1}c_j, \qquad q_j^B = A(\frac{\sigma}{\sigma-1})^{-\sigma}c_j^{-\sigma}, \qquad r_j^B = A(\frac{\sigma}{\sigma-1})^{1-\sigma}c_j^{1-\sigma}, \qquad \pi_j^B = \frac{r_j^B}{\sigma}.$$

Firms also receive profits by producing tasks. From BEJK, these profits are given by:

$$\pi^T(t_i) = \frac{1}{1+\theta}\sum_{j\in\Omega_i} x_{ij}(z_j, t_j, t_i), \tag{7}$$

where $x_{ij} = \frac{\sigma-1}{\sigma}\lambda_{ij}r_j^B$ is firm $j$'s purchases from firm $i$, and $\Omega_i$ is the set of buyers from $i$.

### 3.3 Equilibrium in the Closed Economy

In equilibrium, the zero-profit condition for final good production is given by:

$$\pi^B(z,t) - fn(z,t) = f_B, \tag{8}$$

where $\pi^B$ and $n$ now stand for the optimal operating profits and the number of suppliers of a firm with blueprint $z$ and manufacturing ability $t$, respectively. Rewriting $t$ as a function of $z$, equation (8) gives the cutoff *curve* above which firms choose to bring their blueprint to production, which we denote as:

$$t = \Xi(z). \tag{9}$$

It is easy to verify that $\Xi(z)$ is decreasing in $z$. Intuitively, if a firm is competitive in the final goods market despite having a low manufacturing ability, it must possess a good blueprint. Denoting the 'worst' blueprint brought to production as $\underline{z}$, we have:

$$\underline{z} = \Xi^{-1}(\bar{t}). \tag{10}$$

As the number of task suppliers that firm $j$ matches with increases in $z_j$ and decreases in $t_j$, the active task supplier with the least manufacturing ability can only be reached by the active blueprintholder $j$ who has the best blueprint but the lowest manufacturing ability, i.e., $z_j = \bar{z}, t_j = \Xi(\bar{z})$. Plugging this into equation (6), we obtain the cutoff $\underline{\mathrm{T}}$, above which firms are active in supplying tasks:

$$\underline{\mathrm{T}} = \underline{\mathrm{T}}(\bar{z}, \Xi(\bar{z})) = [Ak_1 \bar{z}^{\sigma-1}]^{-1} \Theta(\bar{z}, \Xi(\bar{z}))^{1-\frac{\sigma-1}{\theta}}. \tag{11}$$

Therefore, the mass of active task suppliers and final good producers are respectively given by:

$$N^T = N \int_{\underline{\mathrm{T}}}^{\bar{t}} dG_t(\iota). \tag{12}$$

$$N^B = \int_{\underline{\mathrm{Z}}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta). \tag{13}$$

The aggregate price index equals:

$$P = N^{\frac{1}{1-\sigma}} \left[ \int_{\underline{\mathrm{Z}}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} p^B(c(\zeta, \iota))^{1-\sigma} dG_t(\iota) dG_z(\zeta) \right]^{\frac{1}{1-\sigma}}. \tag{14}$$

Lastly, free entry implies that in equilibrium the expected profits must equal the sunk entry cost. Letting $v^B$ be the profits generated from blueprint production, i.e., $v^B \equiv \pi^B(\zeta, \iota) - fn(\zeta, \iota) - f_B$, the free entry condition can be written as:

$$\int_{\underline{\mathrm{Z}}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} (\pi^B(\zeta, \iota) - fn(\zeta, \iota) - f_B) dG_t(\iota) dG_z(\zeta) + \int_{\underline{\mathrm{T}}}^{\bar{t}} \pi^T(\iota) dG_t(\iota) = \delta f_E. \tag{15}$$

Given optimal sourcing strategies, cutoff conditions (9), (10), and (11), firm mass equations (12) and (13), the price index (14), and the free entry condition (15) give us seven equations and seven unknowns: $P$, $N$, $N^B$, $N^T$, $\Xi(z)$, $\underline{z}$, and $\underline{\mathrm{T}}$. We now formally define the equilibrium of the model:

**DEFINITION 1.** *The closed economy equilibrium consists of an aggregate price index $P$, the number of firms $N$, $N^B$, $N^T$, and the cutoffs $\Xi(z)$, $\underline{z}$, and $\underline{T}$ that satisfy the equilibrium conditions (9)-(15).*

### 3.4 Analysis of the Equilibrium

*Comparative Statics*

To facilitate our equilibrium analysis, we present four sets of comparative statics regarding firms' sourcing choices, marginal costs, and profits. We relegate proofs to Appendix C.1 and C.2. First, blueprint producers with better blueprints have lower marginal costs, source a larger share of tasks from a larger number of suppliers, and also incur more fixed costs and reach less efficient suppliers. Second, blueprint producers that are more efficient in task production have lower marginal costs, source a lower share of tasks from fewer suppliers, and are less likely to incur fixed costs to reach less efficient suppliers. Third, when the number of potential suppliers increases, firms source more tasks and their marginal costs decrease. Moreover, when $N$ increases, the mass of productive suppliers increases and thus the cutoff manufacturing ability rises. As more productive suppliers tend to supply more tasks, the number of total suppliers a firm has might increase or decrease. Finally, task producers with better manufacturing ability supply tasks to more firms, and also supply a larger number of tasks to a given firm. Since the expected profit margin for each connection is $\frac{1}{1+\theta}$, a firm with higher manufacturing ability also earns more profits for each business connection, and thus in total earns more profits from task production.

*Selection into Operating Status*

In equilibrium, equation (9) determines the zero-profit curve (ZPC), which gives the $\{z, t\}$ combinations above which firms are active in final good production; similarly, equation (11) determines the cutoff $\underline{T}$ above which firms are active in task production. As such, we can visualize firms' selection into four different activities in Figure 1: (i) firms with both low $z$ and $t$ exit, (ii) firms with high $z$ but low $t$ engage in final good production and become *pure ordinary* firms, (iii) firms with low $z$ but high $t$ engage in task production and become *pure processing* firms, and (iv) firms with both high $z$ and $t$ are active in both and become *mixed* firms.

*Uniqueness*

Because of Cobb-Douglas preferences and the constant markups on both task and final good production, total profits from task production is exogenously given by $\Pi^T = \frac{(\sigma-1)\beta L}{\sigma(\theta+1)}$. Denoting the average net profits of active blueprint producers as $\tilde{v}^B$, the free entry condition can be rewritten as:

$$\tilde{v}^B(P, N) = \frac{N\delta f_E - \frac{(\sigma-1)\beta L}{\sigma(\theta+1)}}{N^B(P, N)}. \tag{16}$$

The increase in $N$ is associated with a decrease in $N^B/N$. The intuition is that when $N$ increases, competition in the final goods market intensifies. This forces the least productive firms to exit, and therefore lowers the share of active final good producers.

In equilibrium, given $P$ and $N$, firms' operating decisions are uniquely determined. Hence the system of equations that characterize the equilibrium can be simplified to two equations linking $P$ and $N$—the free entry ($FE$) condition (16) and the aggregate price ($AP$) equation (14). When $N$ increases, the marginal cost of blueprint production decreases, competition in the final goods market intensifies, and thus the $AP$ curve is downward sloping. In contrast, a higher $N$ implies a decrease in expected profits from task production, and a lower $N^B/N$ implies that a smaller fraction of entrants will be active in blueprint production—both require $P$ to rise to make firms indifferent to enter, and thus the $FE$ curve is increasing and cut by the $AP$ curve only once from above in the $(P, N)$ space. This ensures the uniqueness of the equilibrium, which we present graphically in Figure 2 and formally prove in Appendix Section C.3.

# 4 Open Economy

We now turn to the open economy case with two countries: Home and Foreign (denoted with asterisk). The differentiated sector is subject to iceberg trade costs such that $\tau_B, \tau_T > 1$ units are required to be shipped for one unit of final goods and tasks to reach the destination, respectively. Exporting final goods also requires a fixed cost $f_X$, and the homogeneous sector is assumed to be freely traded.

The equilibrium can be solved similarly to the closed economy case. Consider first the final goods market. Note that introducing iceberg trade costs is equivalent to increasing the average production cost of foreign task suppliers by ${\tau_T^*}^{\theta}$. Therefore, the blueprint producers at Home de facto face $N+N^*$ potential task suppliers, whose manufacturing abilities are distributed as $\hat{G}_t(\iota) = \frac{N}{N+N^*}G_t(\iota) + \frac{N^*}{N+N^*}G_t^*(\iota {\tau_T^*}^{\theta})$. Here, we use subscripts $D$ and $X$ to denote firms' export decisions: $D$ stands for selling domestically and $X$ stands for exporting. Then, a blueprint producer's optimization problem can be written as:

$$v^B(z_j, t_j) = \max_{\{D,X,Exit\}} \left\{ v_D^B(z_j, t_j), v_X^B(z_j, t_j), 0 \right\}, \tag{17}$$

where:

$$v_D^B(z_j, t_j) = \max_{\underline{\mathrm{t}}} \left\{ \pi_D^B(z_j, t_j) - fn(z_j, t_j) - f_B \right\},$$

$$v_X^B(z_j, t_j) = \max_{\underline{\mathrm{t}}} \left\{ \pi_D^B(z_j, t_j)(1 + \frac{A_F}{A}\tau_B^{1-\sigma}) - fn(z_j, t_j) - f_B - f_X \right\}.$$

It is easy to verify that $v_D^B$ and $v_X^B$ are both upward sloping in $z$, with $v_X^B$ being steeper since: (i) market access is greater, and (ii) improved market access leads to a lower marginal cost of production via increased optimal sourcing. Therefore, for two firms with the same manufacturing ability, the one with the better blueprint is more likely to export.

Firms are indifferent between selling domestically and exporting when $v_D^B = v_X^B$. This yields the export cutoff curve $t_X = \Xi_X(z)$. Expressions for the zero-profit curve and the domestic task production cutoff remain the same as in the closed economy equilibrium. The only change is that the sourcing capacity of a given firm becomes $\Theta(z_j, t_j) = t_j + (N+N^*)\int_{\underline{\mathrm{t}}(z_j,t_j)}^{\bar{t}} \iota d\hat{G}_t(\iota)$ as now it can reach task suppliers in both countries. The number of active final good producers and exporters in Home can then be expressed as:

$$N^B = \int_{\underline{\mathrm{z}}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta), \qquad N_X^B = \int_{\underline{\mathrm{z}}_X}^{\bar{z}} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta),$$

where $\underline{\mathrm{z}} = \Xi^{-1}(\bar{t})$ and $\underline{\mathrm{z}}_X = \Xi_X^{-1}(\bar{t})$. The aggregate price index therefore satisfies:

$$P^{1-\sigma} = N \int_{\underline{\mathrm{z}}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} p^B(\zeta, \iota)^{1-\sigma} dG_t(\iota) dG_z(\zeta) + {N_X}^* \int_{\underline{\mathrm{z}}_X^*}^{\bar{z}} \int_{\Xi_X^*(\zeta)}^{\bar{t}} \left(\tau_B^* p^{B*}(\zeta, \iota)\right)^{1-\sigma} dG_t^*(\iota) dG_z^*(\zeta). \tag{18}$$

The supply of tasks mirrors the demand from the final goods market. With the presence of export costs, the task supplier with the lowest manufacturing ability in Home that exports to Foreign satisfies: $\underline{\mathrm{T}}_X = \tau_T^{\theta} \underline{\mathrm{T}}^*$. The free entry condition becomes:

$$\int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} v^B(\zeta, \iota) dG_t(\iota) dG_z(\zeta) + \int_{\underline{\mathrm{T}}}^{\bar{t}} \pi^T(\iota) dG_t(\iota) = \delta f_E. \tag{19}$$

Given the mass of entrants and the aggregate price indices in both countries, firms' optimal sourcing and operating decisions can be determined; equations (18) and (19) provide four equations, from which we can uniquely identify $N$, $N^*$, $P$, and $P^*$, and hence solve the equilibrium.

### 4.1 Selection into Export Mode

Introducing international trade yields two additional cutoffs compared to the closed economy equilibrium. As presented graphically in Figure 3, a subset of entrants survive in each country and a smaller subset of those export. On the task production margin, active task producers have higher manufacturing ability than firms who exit, while task exporters have even higher manufacturing ability. Similarly, firms with the 'worst' blueprint quality exit, the better ones operate only in the domestic market, and the ones with the highest blueprint quality export. If a firm has both high manufacturing ability and blueprint quality, it becomes a mixed exporter. The following proposition summarizes this result:

**PROPOSITION 1.** *In equilibrium, firms with both low $z$ and $t$ exit, and firms with intermediate $z$ or $t$ operate solely domestically. Firms with high $z$ but low $t$ become pure ordinary exporters; firms with low $z$ but high $t$ become pure processing exporters; and firms with both high $t$ and $z$ engage in both activities and become* mixed *exporters.*

### 4.2 Linking the Model to Data

We now examine how the model can help us explain the stylized facts in Section 2. In the model, we implicitly let the choice of export mode to determine firms' specialization, motivated by *Fact 3*. Hence we aim to explain *Fact 1* and *Fact 2*, as well as firms' R&D and advertisement expenditure ranks. For the remainder of this section, we refer to pure processing exporters ($PP$) as processing exporters, pure ordinary exporters ($PO$) as ordinary exporters, and exporters that engage in both activities ($Mix$) as mixed exporters. To facilitate the analysis, we first introduce the ranking theorem which is used repetitively in this subsection:

**Ranking Theorem.** *For any increasing and piecewise differentiable function $u(x)$, if cumulative $G$ first-order stochastically dominates (FSD) cumulative $G'$, then:*

$$E_G[u(x)] > E_{G'}[u(x)].$$

**Physical TFP** Physical TFP measures the efficiency of a firm in transforming inputs into outputs in terms of quantities. In our model this is best captured by $t_j$, which reflects the average efficiency of a firm in task production. We first compare the $t$ of mixed exporters with that of processing exporters. We use $G_t^s$ to denote the cumulative distribution function (*cdf*) of $t$ in equilibrium for $s \in \{PP, PO, Mix\}$. As the export cutoff curve is downward sloping, and $z$ and $t$ are distributed independently, there are relatively more firms with lower $t$ among processing exporters. This implies that $G_t^{Mix}$ FSD $G_t^{PP}$, a result we formally prove in Appendix Section C.4. Next, we compare processing exporters to ordinary exporters. The export selection cutoff ensures that $t_{PO}$ is always lower than $t_{PP}$. Therefore $G_t^{PP}$ FSD $G_t^{PO}$. Then, by applying the ranking theorem, we immediately have that $E_{Mix}[t] > E_{PP}[t] > E_{PO}[t]$.[27]

**R&D and advertisement expenses** Similarly, we use $G_z^s$ to denote the *cdf* of $z$ for $s \in \{PP, PO, Mix\}$. We first prove that $G_z^{PO}$ FSD $G_z^{Mix}$ and $G_z^{Mix}$ FSD $G_z^{PP}$ in Appendix Section C.4. As Figure 3 intuitively suggests, there are relatively more firms with lower $z$ among processing exporters compared to mixed exporters, and more firms with lower $z$ among mixed exporters compared to ordinary exporters.

In the data, we find that pure ordinary exporters spend more on R&D and advertising than mixed exporters, who spend more than pure processing exporters. A simple twist in our model can rationalize this finding. Suppose that firms draw their blueprint quality and manufacturing ability sequentially. After observing its $z$, a firm can choose whether to incur an additional cost $f_{RD}(a)$ to improve its blueprint quality to $za^{\frac{1}{\sigma-1}}$ before observing its manufacturing ability $t$.[28] Note that 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. However, $f_{RD}(a)$ is increasing in $z$ in equilibrium; thus by the ranking theorem, we immediately have that $E_{PO}[f_{RD}] > E_{Mix}[f_{RD}] > E_{PP}[f_{RD}]$.

**Employment** We first compare the employment of mixed and processing exporters. As labor is the only input, the associated employment increases in $t$. We assume that $f$ is sufficiently small such that $\underline{t}_j < t_j$ always holds for exporters. As a result, we have that $E_{Mix}[l \mid t] = E_{PP}[l \mid t]$.[29] From the comparative statics, we know that the employment of a firm is increasing in $t$. Applying the ranking theorem, it is immediate that $E_{Mix}[l] > E_{PP}[l]$.

Now we compare the employment of processing and ordinary exporters. Consider a processing exporter $j$ and an ordinary exporter $j'$. As $t_j > t_{j'}$, for any final good producer that both $j$ and $j'$ supply tasks to, firm $j$ has higher sales. Firm $j$ also reaches a larger number of final good producers. Therefore, $x_j > x'_j$, which in turn implies that $l_j > l'_j$. As this inequality holds for any processing

[27] Moreover, the comparative statics result suggests that sales to each customer, the number of customers, and the total profits from task production are increasing in $t$. The ranking theorem therefore implies that, on average, mixed firms have greater processing exports, reach more customers, and earn higher total profits from processing when compared to processing exporters.

[28] We assume that $f'_{RD} > 0$ and $f''_{RD} > 0$.

[29] This assumption greatly simplifies our analysis, resulting in no 'additional' labor for in-house production, as exporter $j$ sources from all suppliers (including itself) with manufacturing ability $t_j$ anyways.

exporter $j$ and ordinary exporter $j'$, $E_{PP}[l] > E_{PO}[l]$ holds as well.

**Labor productivity** The log labor productivity of firm $j$ is measured as $LP(z_j, t_j) = ln\left(\frac{v^B(z_j,t_j)+\pi^T(z_j,t_j)+l(z_j,t_j)}{l(z_j,t_j)}\right)$, where $v^B$ and $\pi^T$ are net profits from blueprint and task production respectively. Given $\pi^T = \frac{1}{\theta}l$, the above equation can be simplified to:

$$LP(z_j, t_j) = ln\left(\frac{v^B(z_j, t_j)}{l(z_j, t_j)} + \frac{\theta + 1}{\theta}\right).$$

We first compare processing and ordinary exporters. The export cutoff ensures that $v^B_{PO} > v^B_{PP}$ for any pair of firms. We also showed that $l_{PP} > l_{PO}$ always holds. Therefore, for any processing exporter $j'$ and ordinary exporter $j$, $LP_j > LP_{j'}$, and thus $E_{PO}(LP) > E_{PP}(LP)$. The comparison between ordinary and mixed exporters is less obvious; in Appendix Section C.4, we show that $\frac{v^B_j}{l_j}$ is an increasing function of $z_j$, and *can* be an increasing function of $t_j$. If the latter holds, firms with the highest labor productivity will be mixed. When their share is sufficiently large, we have that $E_{Mix}(LP) > E_{PO}(LP)$.

**Revenue TFP** To be consistent with the Olley-Pakes estimation of TFP, we can instead assume that tasks are produced using labor and capital with a Cobb-Douglas technology. The share parameter on labor is $\alpha$, and thus the revenue TFP of firm $j$ is given by:

$$TFPR(z_j, t_j) = ln\left(\frac{v^B_j + \pi^T_j + l_j}{{l_j}^{\alpha}{k_j}^{1-\alpha}}\right) \propto ln\left(\frac{v^B_j + \pi^T_j + l_j}{l_j}\right) = LP_j.$$ [30]

The ranking is therefore the same as that of labor productivity.

## 4.3 Processing Trade Policy

There is widespread belief among policymakers that exporting is beneficial for a country's economic development. As a result, many emerging countries, most notably China, adopted policies that encourage exporting such as input tariff exemptions. Another processing trade policy championed mostly by East and Southeast Asian economies is the establishment of export processing zones that provide various incentives to processing exporters (Radelet and Sachs, 1997).[31] However, existing work typically suggests that promoting processing trade crowds out ordinary firms and thus reduce welfare (Defever and Riaño, 2017; Deng, 2017).[32] Does our framework provide any new insights regarding processing trade policy?

To highlight the model's novel prediction, we focus on a small open economy setting such that changes at Home does not affect any aggregate variables of Foreign. Our model predicts that when

[30] This is because ${l_j}^{\alpha}{k_j}^{1-\alpha} = {l_j}^{\alpha}(\frac{w}{w_K}l_j)^{1-\alpha} \propto l_j$ in equilibrium, where $w_K$ is the rental price of capital.

[31] Nevertheless, the Chinese customs data shows that 86% of processing exporters in 2000-2006 were located outside of special economic zones, which include export processing zones.

[32] One exception is Brandt et al. (2019), where tariff exemptions on imported inputs for processing has a positive welfare impact.

Home introduces a processing policy that lowers $\tau_T$, firms' task exporting opportunities increase. These opportunities raise the *ex-ante* expected value from task production, and thus firms' expected profits from final good production must decrease for the free entry condition to hold. Therefore, the $FE$ curve shifts downwards. On the other hand, the small open economy assumption ensures that the change in $\tau_T$ casts no direct impact on the final goods market, and therefore for a given $N$, the aggregate price index remains unchanged. As illustrated in Figure 4, these together imply that the equilibrium $N$ increases while $P$ decreases.

With the increase in both the mass of potential suppliers and the final goods market competition, firm heterogeneity remains an important determinant of profitability. In Appendix Section C.5, we show that in this case, the rise in net profits from final good production, $v^B$, is an increasing function of $z$ but a decreasing function of $t$, which we summarize in the following proposition:

**PROPOSITION 2.** *When $\tau_T$ decreases, the rise in net profits from final good production for a given firm $j$ increases in $z_j$ and decreases in $t_j$.*

Intuitively, firms with high blueprint quality but low manufacturing ability rely more on task suppliers, and thus they benefit more from the increase in $N$. Promoting processing trade not only directly benefits task suppliers with high manufacturing abilities ("Made in China"), but also helps firms with good ideas ("Created in China") by increasing the pool of suppliers they could source from. Another implication is that when the number of potential suppliers increase in equilibrium, firms will be more specialized in what they are relatively good at. Firms with good blueprints are less constrained by their manufacturing ability, and thus are more likely to thrive in the final goods market. Analogously, firms with good manufacturing ability but low blueprint quality are less likely to produce their own branded products and more likely to specialize in processing.[33]

An obvious difficulty in testing Proposition 2 is that we do not observe $z$ and $t$. However, we do observe firm-level outcomes that are functions of $z$ and $t$, such as employment and labor productivity. Therefore, given aggregate variables and parameters, we can back out a firm's blueprint quality and manufacturing ability using information on observables. This means that we can translate Proposition 2 to ask: how does the reaction of net profits from blueprint production to trade costs ($\partial v^B/\partial \tau_T$) change with respect to firm-level characteristics that are directly measurable? Following this line of thought, we prove in Appendix Section C.6 that when $\tau_T$ decreases, the rise of net profits from final good production for a given firm $j$ increases in labor productivity, conditional on employment. At the extensive margin, this implies that when $\tau_T$ decreases, firms with higher labor productivity are more likely to enter the final goods market. This gives the testable prediction of the model:

[33] Our model's insight is consistent with the observation that 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. For example, Shenzhen's fast turnover of supply chains, the proximity of its factories to the city center, and the wide availability of competitively priced parts and components in its famous electronics market Huaqiangbei has made the city a boon for startups (Wang, 2019). Our model is one of the few that can provide a formal characterization of this phenomenon.

**PREDICTION.** *When the cost of processing exports ($\tau_T$) decreases, conditional on employment, firms with higher labor productivity are more likely to bring their blueprints to production.*

We formally test the above prediction in Section 5. We do not observe the time when a firm starts to produce its own branded product, and thus we use a close proxy: firms' registration of trademarks. Trademarks are often symbols that 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 brands. If we simply extend our model by allowing firms to register their brands via costly trademark applications to avoid potential piracy, we reach the prediction that when $\tau_T$ decreases, firms with higher labor productivity would be more likely to register their trademarks.

# 5 Empirical Analysis

In this section, we start by examining the direct effect of China's "paperless" processing trade policy in 2000-2006 on its processing exporters. We then test the model's central prediction by focusing on the policy's downstream spillovers. Note that China's total exports made only 4% of world exports in 2000; its processing exports, even if we focus on the top five destinations, made up 3% of those countries' total imports on average. In contrast, China's total exports was 21% of its GDP in 2000, of which 55% was done by processing firms. Hence for a given policy shock on processing trade, its direct impact on Chinese firms, in relative terms, should be much larger than its impact on the foreign market. Our choice of policy shock, the "paperless" processing supervision program, is highly suitable for our identification strategy as it affects *only* the cost of processing exports, leaving other exporting costs as well as inherent marginal costs unchanged.

We utilize two additional datasets. The first is the yearly firm-level effective trademarks collected by the State Administration for Industry and Commerce in China, which we merge with the AIS data using unique firm IDs provided by Deng et al. (2019).[34] 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 official customs notices. We discuss the policy in more detail in the following subsection.

## 5.1 China's "Paperless" Processing Trade

China's customs authorities closely monitor the supply chain for processing trade because of special duty drawbacks granted to processing exporters. Thus, to organize processing trade, firms have to fill in grueling paperwork that details their financial condition and upstream and downstream connections for each contract, and then wait to get approved by the customs authority. In order to make processing trade less costly for firms, China began to experiment with an online supervi-

[34] We are grateful to Ran Jing for sharing the data. See Deng et al. (2019) for a detailed description of the trademarks dataset.

sion system in 2000. By connecting firms' computer management systems to the customs' online administration system, it made the processing trade application paperless, and thus significantly reduced the burden of red-tape on processing firms. 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%, and the clearance speed is greatly improved."*[35]

The pilot program for paperless processing trade targeted Class A firms: firms that had at least \$10 million worth of exports. Favorable to our setting, this threshold of \$10 million was set by the Chinese authorities in 1999 as a way to classify firms for administrative purposes and is unrelated to the paperless processing trade program.[36] This policy experiment was gradually introduced to different prefectures: between 2000 and 2006, customs authorities of 50 (out of 334) prefectures in 18 (out of 34) provinces of China adopted the pilot program, as illustrated in Figure 5. By the end of 2006, inspired by the success of the pilot program, the policy rolled over nation-wide and was made available to *all* processing firms, regardless of size.

To test the effect of the paperless program, we use a difference-in-differences (DD) methodology. Note that the \$10m threshold is a high bar: around 90% of processing firms export less than \$10m in a given year, and more than half of processing firms in the sample export less than \$1m worth of goods annually. As shown in Table A.3 panel (a) columns 1-3, compared to the rest of firms in our data, firms that are above the \$10m threshold are more likely to be mixed, more likely to be importers, less likely to be exiters or entrants, less likely to be foreign-owned, and more likely to be SOEs. They are also more processing-oriented and grow faster on average. The last two rows use variables from the merged AIS-customs data and reveal, expectedly, that the above-threshold firms are significantly larger both in terms of employment and capital. Moreover, Figure A.1 panel (a) suggests that the processing export pre-trends of the two groups are not parallel, which would threaten the identification strategy in a simple DD framework.

To address this, we compare firms that exported between \$10-11m worth of processing goods with firms that exported between \$9-10m before the policy was introduced. By incorporating this bandwidth, our approach resembles a regression discontinuity (RD) design with difference-in-differences (DD-RD). As emphasized by Lemieux and Milligan (2008), selecting an appropriate

[35]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.

[36]As paperless supervision requires firms to have an Enterprise Resource Planning (ERP) system (a computer software for business management), customs authorities naturally targeted large firms for the pilot since most of them had already installed an ERP system. Hence, the threshold of \$10m provides a simple yet established selection criteria. See `http://www.people.com.cn/zixun/flfgk/item/dwjjf/falv/6/6-1-50.html` (Chinese) for the official firm classification notice, and `http://www.fdi.gov.cn/1800000121_39_1919_0_7.html` (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 since firms in this industry had a lower threshold (\$5m) to qualify for the pilot program.

control group in DD and thus have a DD-RD type of estimation is crucial to get 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 full 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 to a simple RD.

The balancing checks in Table A.3 panel (b) reveal that our selected treatment and control group of firms are similar in almost all key aspects. There are two statistically significant discrepancies between the two groups: \$10-11m firms are slightly more processing oriented (89% vs. 84%) and they are less likely to be foreign-owned (45% vs. 51%). With firm fixed effects, we control for ownership and partially for the difference in processing shares, but we do two further robustness checks: we restrict the sample to non-foreign firms, and include lagged processing share as a control. Most importantly, Figure A.1 panel (b) shows that the pre-trends between the chosen treatment and control groups are similar, with the \$10-11m firms increasing their processing exports sharply in $t + 1$. Note that even though our choice of bandwidth is a relevant and restrictive bandwidth for processing exports that still allows some variation for our independent variable, our results are qualitatively insensitive to alternative bandwidths as shown in our robustness checks.

We start by running the following DD-RD specification at the firm-level to test the direct effect of the policy:

$$\ln(\text{proc. exp.})_{icst} = \alpha + \beta \ OS_{ict-1} + \gamma_i + \delta_{st} + \phi_{ct} + \epsilon_{icst}, \tag{20}$$

where $\ln(\text{proc. exp.})_{icst}$ is the processing exports of firm $i$ that resides in prefecture $c$, with its core HS2 sector $s$, in year $t$.[37] $OS_{ict-1}$ is a dummy variable that indicates the adoption of the pilot paperless processing trade program in prefecture $c$ in year $t-1$ that targeted firm $i$, $\gamma_i$ are firm fixed effects, $\delta_{st}$ are sector-year fixed effects to control for overall supply and demand shocks, $\phi_{ct}$ are prefecture-year fixed effects to capture aggregate prefecture shocks, and $\epsilon_{icst}$ is the error term which we cluster two-way at the prefecture and sector level to allow for correlated shocks. Our main independent variable $OS_{ict-1}$ is lagged by one year to allow some time for firms to adapt to the new declaration system. Since we do not observe whether the firm is actually using the paperless system, the estimate of $\beta$ in (20) should be interpreted as an intention-to-treat effect.

We report the estimation results of (20) in Table 4. The first column shows the benchmark result: firms that are in the treatment group in year $t-1$ increase their processing exports by 28% in year $t$, relative to the control group of firms with \$9-10m of exports in the year prior to policy adoption. An important identification concern is that the exact implementation time of the pilot program may be known to firms beforehand, making the timing of the policy adoption correlated to firms' strategic decisions. In column 2, we use a leads and lags strategy to rule out anticipation effects, and find that the lead variable $OS_{ict+1}$ is not statistically different from

[37]We assign a core HS2 sector to each exporter based on the ranked value of exports in its initial export year.

zero, while the coefficient of $OS_{ict-1}$ barely changes when compared to column 1. In column 3, we control for lagged processing share since our balancing checks in Table A.3 indicate that the $10-11m firms are slightly more processing-oriented than the $9-10m firms—the coefficient remains identical. Similarly, In column 4, we exclude foreign firms since our balancing checks show that there were more foreign-owned firms in the $9-10m sample when compared to the $10-11m sample. This results in a larger and more precisely estimated coefficient.

In Table A.4, we show that our results are not sensitive to controlling for entry and exit in column 1, using a first-difference specification in column 2, using alternative bandwidths of $9.5-10.5m and $8.5-11.5m respectively in columns 3 and 4, or restricting the sample to always exporters or non-SOEs respectively in columns 5 and 6. Column 7 does a falsification analysis by focusing on the ordinary exports of mixed exporters, which shows a coefficient that is not statistically different than zero. On the contrary, column 8 shows that mixed exporters do increase their processing exports as expected. In columns 9 and 10, we do falsification analyses by setting the threshold to $9m and $11m, and the bandwidth to $8-10m and $10-12m respectively—coefficients in both columns are not statistically different than zero. These robustness checks support our finding that the pilot program increased firm-level processing exports.

## 5.2 Downstream Spillovers and Trademarks

We now turn to the downstream spillovers of the pilot "paperless" processing trade program. The model predicts that *productive* downstream firms would be more likely to establish their own brands/trademarks thanks to the larger mass of potential suppliers when processing cost $\tau_T$ falls. Existing empirical research suggests that supplier-buyer relationships are highly localized (Bernard et al., 2019), and thus we hypothesize that downstream firms that are in the same prefecture as the affected suppliers would be more likely to benefit from the spillover and thus apply for new trademarks.

To examine the effect of the pilot program on firm-level branding activity, we focus on the sample of *non-processing domestic* firms. We exclude pure processing exporters as this allows us to examine the spillover to firms that already engage in ordinary activities; we also exclude foreign-owned firms since their trademark applications more likely reflect protecting their existing brands rather than bringing in new blueprints to production. Finally, we exclude firms that have more than 25 trademarks (outliers at the 99$^{\text{th}}$ percentile) in a given year since these firms are already experienced trademark applicants and thus are unlikely to be affected by the policy change.[38] We then run the following specification:

$$Y_{icst} = \alpha + \beta OS_{ct-1} \times \text{Productive}_i + \lambda \ln (empl.)_{it} + \psi \ln (capital)_{it} + \gamma_i + \delta_{st} + \phi_{ct} + \epsilon_{icst}, \quad (21)$$

[38]Including these outlier firms leads to a coefficient of similar magnitude to our benchmark case, significant at the 10% level.

where $Y_{icst}$ is the number of effective trademarks a firm has,[39] $OS_{ct-1}$ is the policy adoption indicator as before, and $\text{Productive}_i$ indicates whether the firm's initial log labor productivity is above the median value. We focus on the interaction coefficient as our model predicts that productive firms will be more likely to bring their blueprint to production when faced with a positive upstream shock. We include $\ln(empl.)_{it}$ and $\ln(capital)_{it}$ to control for firm-level employment and capital stock, firm fixed effects $\gamma_i$ to control for unobserved firm-level characteristics, sector-year fixed effects $\delta_{st}$ to control for sector-specific supply and demand shocks (sectors are at the 4-digit CIC level), and prefecture-year fixed effects $\phi_{ct}$ to control province-wide policy changes that might affect trademark applications.[40] We cluster the errors $\epsilon_{icst}$ two-way at the prefecture and sector level as before. Due to the count nature of our dependent variable, we estimate specification (21) using a Poisson pseudo-maximum likelihood (PPML) model.[41] We provide various robustness checks with alternative measures.

Our identification relies on the plausible assumption that the timing of introducing the pilot paperless *processing* program by a prefecture's customs is exogenous to the branding activities of the *non-processing* firms in the same region. We also rely on the fact that processing exporters can sell domestically. The literature has largely ignored this possibility, but processing firms do sell domestically if they pay the required taxes.[42] The matched customs-AIS data indicates that 76% of processing exporters in 2005 also sold domestically.[43]

Table 5 presents our main results. In column 1, in order to focus on the main effect, we use a less restrictive specification with province-year (instead of prefecture-year) fixed effects, and find that the pilot program does not have a significant effect on the number of trademarks for the average firm. This is not surprising given that the model predicts the effect to be more significant for productive firms, and the average firm might not be productive enough to take advantage of the spillover. Thus, in column 2, we interact $OS_{ct-1}$ with $\text{Productive}_i$, and in our preferred specification in column 3 we add prefecture-year fixed effects and find that the pilot paperless processing trade program increased the number of trademarks of a productive firm by about 4%. In column 4, to allow for a more flexible effect, instead of the $\text{Productive}_i$ indicator, we interact $OS_{ct-1}$ with the firm's demeaned initial labor productivity, $\ln(labor\ prod.)_i$, and the result stays robust.

Column 5 of Table 5 excludes SOEs from the sample as these firms' trademark activities might be subject to government controls. Column 6 uses a linear probability model (LPM) instead of PPML. Neither of these robustness checks change the qualitative result. In column 7, the dependent

[39] As mentioned before, trademarks are the legal basis for brands and thus we are using the number of effective trademarks as a proxy for firms' branding activity. The discussion on how to link trademarks to brands under our theoretical framework is provided at the end of Section 4.3.

[40] 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 standard deviation 9.6.

[41] For our PPML estimations, we use Correia et al.'s (2019) Stata package *ppmlhdfe*, which is robust to convergence issues inherent in maximum-likelihood estimation with multiple high-dimensional fixed effects.

[42] The official customs regulatory document that explains how processing exporters can sell domestically can be found in `http://www.customs.gov.cn/customs/302249/302266/302267/356603/index.html`.

[43] The median (mean) exports share (exports/sales) for these processing firms was 81% (63%).

variable is a dummy that indicates whether the firm has at least one effective trademark. In column 8, we focus on the log number of trademarks, which results in a smaller sample size due to dropping firms with no trademarks. The coefficients show that the processing trade shock has positive effects on both the extensive and the intensive margins of trademark activity. 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. Finally, in column 9, we use a mixed-firm interaction and find a positive and significant interaction term, indicating that these firms were more likely to increase their trademark activity due to the paperless processing trade program.

One might be concerned that the above result does not specifically identify the *downstream* firms that are affected by the processing trade shock. In order to dispel this concern, we use an alternative strategy that uses China's official 2002 Input-Output (IO) table. Since our shock is based on the customs data which is in HS classification, we concord the shock to the industry classification used in China's IO table, which we then concord to the 4-digit CIC level used in the AIS firm-level data. For this, we use crosswalks from the HS8-IO industry concordance to the CIC-IO industry concordance to create 74 tradable industries.[44] Once we redefine our shock at this new sector level, we aggregate the IO table to the level of the 74 IO industries, labeling the unmatched non-tradable industries as "other." We also assign each firm an IO industry based on the CIC-IO industry concordance table.

We define the "treated processing share" for each prefecture-sector-year ($cst$) in the following way:

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

where $i \in A$ are processing firms that are above the \$10m threshold, and sector $s$ is defined at the IO level. For prefecture-sector-years with no processing exports, we set the treated processing share to zero. This share, which proxies for the intensity of the processing cost shock for each prefecture-sector-year, ranges from 0% to 100% with a mean of 8% (standard deviation: 23%).[45] Then, we create a time-varying input shock using the treated processing share for each output sector $n$ and prefecture $c$ as follows:

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

where $\omega_{ns}$ are cost shares from the redefined IO table. We then run the following specification:

$$Y_{icnt} = \alpha + \beta\, \text{Input shock}_{cnt} \times \text{Productive}_i + \lambda \ln{(empl.)}_{it} + \psi \ln{(capital)}_{it} + \gamma_i + \delta_{nt} + \phi_{ct} + \epsilon_{icnt}, \quad (22)$$

[44]We thank Yu Shi for providing the HS8-IO industry correspondance table. There are 7,428 HS8 matched to 85 distinct IO industries. We adjust for the one-to-many and many-to-many matches using the aggregation algorithm provided by Van Beveren et al. (2012). The CIC-IO industry concordance table is from Zi (2019). Since the CIC codes changed after 2002, we first adjust the CIC industries overtime to create uniform CIC industry codes using pre- to post-2002 CIC concordance tables.

[45]Our results are qualitatively similar if we define the shock to be simply the level of affected processing exports (the numerator of the Treated processing share$_{cst}$). These results are available on request.

where $Y_{icnt}$ is the number of trademarks as before, $\delta_{nt}$ are sector-year fixed effects, now at the IO level, $\phi_{ct}$ are prefecture-year fixed effects, and $\epsilon_{icnt}$ is the error term which we cluster two-way at the prefecture and sector level. Compared to (21), specification (22) allows us to focus directly on downstream firms at the cost of some measurement error created by sector aggregation.

Table A.5 column 1 shows that the input shock does not have a significant effect on the number of trademarks for the average firm. In column 2, we interact the input shock variable with the Productive$_i$ dummy, and find an interaction coefficient of 0.428, significant at the 1% level. This result indicates that a one standard deviation (0.033) increase in Input shock$_{cnt}$ raises the number of trademarks of a productive firm by 0.035 ($(2.222 - 1.167) \times 0.033$), which is 1.5% of the average number of trademarks (2.34) for firms with above-median productivity. In column 3, we directly control for the treated processing share as well as its interaction with Productive$_i$ (i.e., control for Output shock$_{cnt}$ = Treated processing share$_{cnt}$). We include this control since promoting processing policy might crowd out ordinary firms and hence directly affect their branding activities. The estimated coefficient in column 3 barely changes when compared to column 2. Finally, in column 4, we use a mixed-firm interaction and continue to find a positive and significant interaction term. Overall, results in Table A.5 confirm the findings in Table 5 that the pilot paperless processing trade program has induced downstream firms to increase their branding activity as predicted by our model.

## 6 Conclusion

In this paper, we unpacked the "black box" of mixed exporters that engage in both ordinary and processing exports. Contrary to the existing literature that describes processing firms as inferior, we showed that mixed firms, who engage predominantly in processing, are superior to other firms in multiple dimensions. We revisited some of the earlier findings in the literature but focused on these "super processors," and provided novel stylized facts on firms' performance, brand ownership, and choice of export modes.

We formalized a parsimonious general equilibrium model based on the frameworks of Antràs et al. (2017) and Bernard et al. (2019). We allowed for markups in both stages of production and introduced two dimensions of firm heterogeneity: manufacturing ability, which determines how efficient a firm is in producing tasks, and blueprint quality, which determines how good a firm is in selling its own branded products. Our framework rationalized the ranking among the different types of exporters that we observe in the data, and provided a new source of gains: facilitating processing trade raises the *ex-ante* expected profits from task production and hence encourages entry, leading to a greater mass of potential suppliers, which eventually benefits downstream ordinary firms.

In the last part of the paper, we tested our model's prediction using China's pilot "paperless" processing supervision program in 2000-2006 as a quasi-natural experiment. Consistent with the model's prediction, we found that promoting processing trade not only increased the processing exports of firms, but also induced productive domestic downstream firms to establish their own trademarks. Overall, our theoretical and empirical analyses in this paper highlighted that processing trade led goods to be not only “Made in China,” but also “Created in China” by providing a breeding ground of potential task suppliers for firms with good ideas.

## References


Ahn, J., Khandelwal, A. K., and Wei, S.-J. (2011). The role of intermediaries in facilitating trade. *Journal of International Economics*, 84(1):73–85.

Antràs, P., Fort, T. C., and Tintelnot, F. (2017). The margins of global sourcing: Theory and evidence from US firms. *American Economic Review*, 107(9):2514–64.

Antràs, P. and Helpman, E. (2004). Global sourcing. *Journal of Political Economy*, 112(3):552–580.

Baroncelli, E., Fink, C., and Javorcik, B. S. (2005). The global distribution of trademarks: Some stylised facts. *The World Economy*, 28(6):765–782.

Bernard, A. B., Eaton, J., Jensen, J. B., and Kortum, S. (2003). Plants and productivity in international trade. *American Economic Review*, 93(4):1268–1290.

Bernard, A. B. and Jensen, J. B. (1995). Exporters, jobs, and wages in US manufacturing: 1976-1987. *Brookings Papers on Economic Activity. Microeconomics*, 26(1995):67–119.

Bernard, A. B. and Jensen, J. B. (1999). Exceptional exporter performance: Cause, effect, or both? *Journal of International Economics*, 47(1):1–25.

Bernard, A. B. and Jensen, J. B. (2004). Why some firms export. *Review of Economics and Statistics*, 86(2):561–569.

Bernard, A. B., Jensen, J. B., Redding, S. J., and Schott, P. K. (2012). The empirics of firm heterogeneity and international trade. *Annual Review of Economics*, 4(1):283–313.

Bernard, A. B. and Moxnes, A. (2018). Networks and trade. *Annual Review of Economics*, 10:65–85.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy*, 127(2):639–688.

Bernard, A. B., Moxnes, A., and Ulltveit-Moe, K. H. (2018). Two-sided heterogeneity and trade. *Review of Economics and Statistics*, 100(3):424–439.

Beverelli, C., Neumueller, S., and Teh, R. (2015). Export diversification effects of the WTO trade facilitation agreement. *World Development*, 76(C):293–310.

Brandt, L., Biesebroeck, J. V., and Zhang, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics*, 97(2):339–351.

Brandt, L., Li, B., and Morrow, P. M. (2019). Is processing good?: Theory and evidence from China. *mimeo.*

Brandt, L. and Morrow, P. M. (2017). Tariffs and the organization of trade in China. *Journal of International Economics*, 104(C):85–103.

Chaney, T. (2016). Networks in international trade. In Bramoulle, Y., Galleoti, A., and Rogers, B., editors, *The Oxford Handbook of the Economics of Networks*, pages 754–75. Oxford University Press.

Chen, Z., Zhang, J., and Zheng, W. (2017). Import and innovation: Evidence from Chinese firms. *European Economic Review*, 94(C):205–220.

Correia, S., Guimarães, P., and Zylkin, T. (2019). Ppmlhdfe: Fast Poisson estimation with high-dimensional fixed effects. *arXiv preprint arXiv:1903.01690*.

Dai, M., Maitra, M., and Yu, M. (2016). Unexceptional exporter performance in China? The role of processing trade. *Journal of Development Economics*, 121(C):177–189.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.

Defever, F. and Riaño, A. (2017). Subsidies with export share requirements in China. *Journal of Development Economics*, 126(C):33–51.

Deng, J. (2017). Processing trade and global idea diffusion. *mimeo*.

Deng, X., Jing, R., and Liang, Z. (2019). Trade liberalization and domestic brands: Evidence from China's accession to the WTO. *The World Economy*.

Feenstra, R. C. and Hanson, G. H. (2005). Ownership and control in outsourcing to China: Estimating the property-rights theory of the firm. *The Quarterly Journal of Economics*, 120(2):729–761.

Fernandes, A. M., Mattoo, A., Nguyen, H., and Schiffbauer, M. (2019). The internet and Chinese exports in the pre-ali baba era. *Journal of Development Economics*, 138(C):57–76.

Fernandes, A. P. and Tang, H. (2015). Scale, scope, and trade dynamics of export processing plants. *Economics Letters*, 133(C):68–72.

Foster, L., Haltiwanger, J., and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1):394–425.

Freund, C. and Rocha, N. (2011). What constrains Africa's exports? *The World Bank Economic Review*, 25(3):361–386.

Hallak, J. C. and Sivadasan, J. (2013). Product and process productivity: Implications for quality choice and conditional exporter premia. *Journal of International Economics*, 91(1):53–67.

Harrigan, J. and Reshef, A. (2015). Skill-biased heterogeneous firms, trade liberalization and the skill premium. *Canadian Journal of Economics*, 48(3):1024–1066.

Hoekman, B. and Nicita, A. (2011). Trade policy, trade costs, and developing country trade. *World Development*, 39(12):2069–2079.

Johnson, R. C. (2018). Measuring global value chains. *Annual Review of Economics*, 10(1):207–236.

Kee, H. L. and Tang, H. (2016). Domestic value added in exports: Theory and firm evidence from China. *American Economic Review*, 106(6):1402–36.

Kikkawa, A. K., Magerman, G., and Dhyne, E. (2019). Imperfect competition in firm-to-firm trade. *ECARES Working Papers*, 2019-05.

Kneller, R. and Timmis, J. (2016). ICT and exporting: The effects of broadband on the extensive margin of business service exports. *Review of International Economics*, 24(4):757–796.

Lemieux, T. and Milligan, K. (2008). Incentive effects of social assistance: A regression discontinuity approach. *Journal of Econometrics*, 142(2):807–828.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2):317–341.

Li, Y. A., Smeets, V., and Warzynski, F. (2018). Processing trade, productivity and prices: Evidence from a Chinese production survey. *HKUST IEMS Working Paper*, 2018-58.

Malgouyres, C., Mayer, T., and Mazet-Sonilhac, C. (2019). Technology-induced trade shocks? Evidence from broadband expansion in France. *mimeo*.

Manova, K. and Yu, Z. (2016). How firms export: Processing vs. ordinary trade with financial frictions. *Journal of International Economics*, 100(C):120–137.

Mayer, T. and Ottaviano, G. I. P. (2008). The happy few: The internationalisation of European firms. *Intereconomics*, 43(3):135–148.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):263–97.

Ornaghi, C. (2006). Assessing the effects of measurement errors on the estimation of production functions. *Journal of Applied Econometrics*, 21(6):879–891.

Radelet, S. and Sachs, J. (1997). Asia's reemergence. *Foreign Affairs*, 76(6):44–59.

Tintelnot, F., Kikkawa, A. K., Mogstad, M., and Dhyne, E. (2018). Trade and domestic production networks. *NBER Working Paper Series*, 25120.

Umana-Dajud, C. (2019). Do visas hinder international trade in goods? *Journal of Development Economics*, 140(C):106–126.

Van Beveren, I., Bernard, A. B., and Vandenbussche, H. (2012). Concording EU trade and production data over time. *NBER Working Paper Series*, 18604.

Wang, A. (2019). Team LEWIS ASIA: Shenzen's potential as the next global hub of innovation [available at: `https://www.teamlewis.com/asia/magazine/shenzhen-the-next-global-innovation-hub/`].

World Bank (2018). World Bank Open Data [available at: `https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS?locations=CN`].

Yu, M. (2015). Processing trade, tariff reductions and firm productivity: Evidence from Chinese firms. *The Economic Journal*, 125(585):943–988.

Zi, Y. (2019). Trade liberalization and the great labor reallocation. *mimeo*.

# Tables and Figures

Table 1: Mixed Exporters

| | (a) All mixed exp. | | | (b) Merged mixed exp. | | |
|---|---|---|---|---|---|---|
| | Median | Mean | Sd. | Median | Mean | Sd. |
| (1) Processing share | 0.64 | 0.58 | 0.36 | 0.66 | 0.58 | 0.36 |
| (2) Processing share, mixed HS8 | 0.71 | 0.62 | 0.34 | 0.74 | 0.63 | 0.34 |
| (3) Processing share, mixed HS8-country | 0.68 | 0.62 | 0.32 | 0.70 | 0.63 | 0.32 |
| (4) Share of mixed HS8 | 0.29 | 0.37 | 0.31 | 0.31 | 0.37 | 0.30 |
| (5) Share of mixed HS8-country | 0.19 | 0.25 | 0.24 | 0.20 | 0.24 | 0.23 |
| (6) Value share of mixed HS8 | 0.87 | 0.68 | 0.37 | 0.89 | 0.71 | 0.35 |
| (7) 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, and their composition of exports (mixed exports/total exports) in rows 4-7, 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.

Table 2: Mixed Exporter Premia

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

*Notes:* This table reports the results of running specification (1). Each row is a separate OLS regression of the dependent variable shown in column 1 on dummy variables $PP_{it}$ and $Mix_{it}$ that indicate whether the firm $i$ is a pure processor or a mixed exporter in year $t$ respectively (pure ordinary is the omitted group). $\ln(R\&D\ exp.)_{it}$ and $\ln(advert.\ exp.)_{it}$ are calculated by $\ln(x+1)$ to avoid dropping zeros. $TFPR_{it}$ and $TFPQ_{it}$ refer to TFP calculated using revenue and quantity data respectively (see the text for details). Rows 1-2 and 5-6 include sector-year fixed effects, and all except those in the first row control for firm size. Rows 3-4 focus on single-product producers only and thus include product-year fixed effects. Coefficients for the two dummy variables are significantly different from each other in all rows except for row 4 in both panels. Standard errors clustered by 2-digit CIC industries (29 clusters) are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Table 3: Export Mode and Brand Ownership

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

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

Table 4: Paperless Trade and Processing Exports

| Dep. var.: ln(proc. exp.)$_{icst}$ | (1) Benchmark | (2) Leads & lags | (3) Proc. share | (4) No foreign firms |
|---|---|---|---|---|
| $OS_{ict-1}$ | 0.277** | 0.281** | 0.277** | 0.454*** |
| | (0.126) | (0.119) | (0.112) | (0.101) |
| $OS_{ict+1}$ | | 0.033 | | |
| | | (0.161) | | |
| Proc. share$_{ict-1}$ | | | 1.168*** | |
| | | | (0.192) | |
| Firm FE | Yes | Yes | Yes | Yes |
| Sector-year FE | Yes | Yes | Yes | Yes |
| Prefecture-year FE | Yes | Yes | Yes | Yes |
| Obs. | 1,718 | 1,452 | 1,418 | 779 |
| $R^2$ | 0.62 | 0.65 | 0.68 | 0.65 |

*Notes:* This table reports the results of running specification (20). $OS_{ict-1}$ indicates the implementation of the pilot paperless processing trade programme in prefecture $c$ in year $t-1$ for firm $i$ (i.e., Class A firms). Sector $s$ refers to the top (core) HS2 of each firm. Standard errors clustered at the prefecture and sector level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Table 5: Trademarks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dep. var.: $Y_{icst}$ | Overall effect | Median | +CT FE | Demeaned | No SOEs | LPM | Extensive margin | Intensive margin | Mixed interaction |
| $OS_{ct-1}$ | -0.012 | -0.033*** | | | | | | | |
| | (0.010) | (0.011) | | | | | | | |
| $\times$ Productive$_i$ | | 0.040*** | 0.040*** | | 0.029** | 0.143*** | 0.019*** | 0.026*** | |
| | | (0.012) | (0.012) | | (0.012) | (0.049) | (0.007) | (0.009) | |
| $\times \ln{(labor\ prod.)}_i$ | | | | 0.019*** | | | | | |
| | | | | (0.006) | | | | | |
| $\times$ Mixed$_{it}$ | | | | | | | | | 0.028*** |
| | | | | | | | | | (0.010) |
| $\ln{(empl.)}_{it}$ | 0.102*** | 0.101*** | 0.100*** | 0.100*** | 0.097*** | 0.279*** | 0.041*** | 0.058*** | 0.100*** |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.006) | (0.017) | (0.003) | (0.003) | (0.005) |
| $\ln{(capital)}_{it}$ | 0.054*** | 0.054*** | 0.053*** | 0.053*** | 0.052*** | 0.131*** | 0.025*** | 0.029*** | 0.053*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.010) | (0.002) | (0.002) | (0.003) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector-year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-year FE | Yes | Yes | No | No | No | No | No | No | No |
| Prefecture-year FE | No | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 408,998 | 408,998 | 408,998 | 408,998 | 366,848 | 408,998 | 408,998 | 371,269 | 408,998 |
| pseudo-$R^2$ | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 | 0.90 ($R^2$) | 0.03 | 0.93 ($R^2$) | 0.48 |

*Notes:* This table reports the results of running specification (21) using a PPML model. $Y_{icst}$ is the number of trademarks of firm $i$ in sector $s$ residing in prefecture $c$ in year $t$. Sectors refer to 425 4-digit CIC industries. Productive$_i$ indicates firms whose initial log labor productivity is larger than the median. $\ln{(labor\ prod.)}_i$ is demeaned so that the main effect corresponds to the effect for the average firm. Mixed$_{it}$ indicates whether the firm engages in both ordinary and processing exports. Column 6 uses the linear probability model (LPM) instead of PPML. In column 7, $Y_{icst}$ is a dummy variable that indicates whether the firm has a trademark, whereas in column 8, $Y_{icst}$ is the log number of trademarks (estimated linearly). Standard errors clustered at the prefecture and sector level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Figure 1: Selection into Operating Status

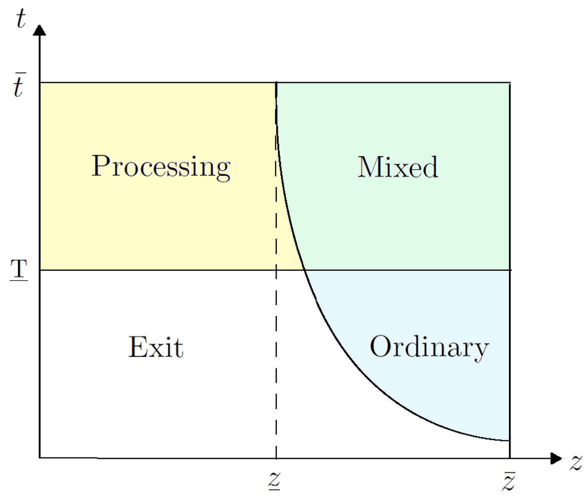



Figure 2: Determination of the Equilibrium

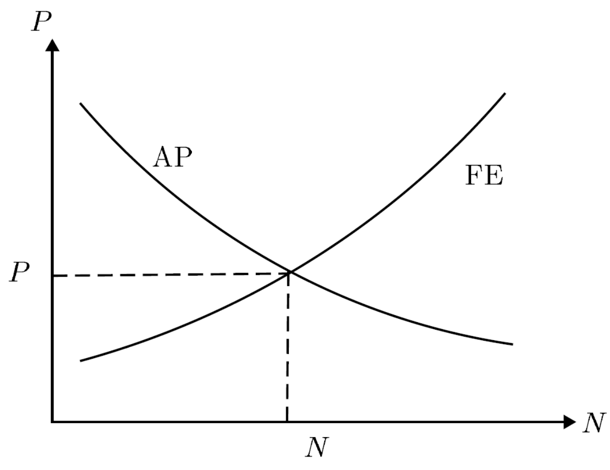


Figure 3: Selection with International Trade

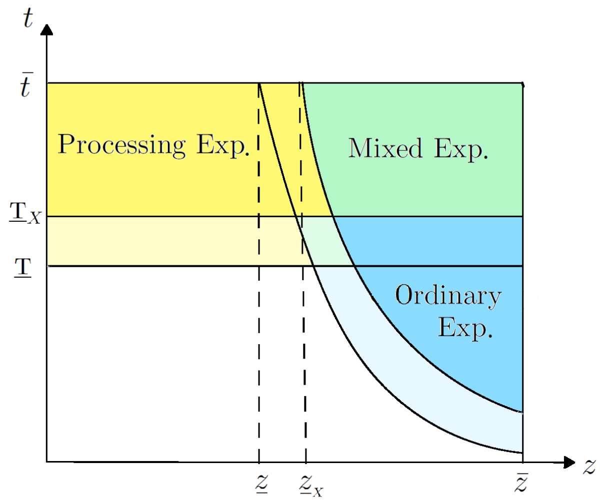



Figure 4: Impact of Processing-promoting Policy

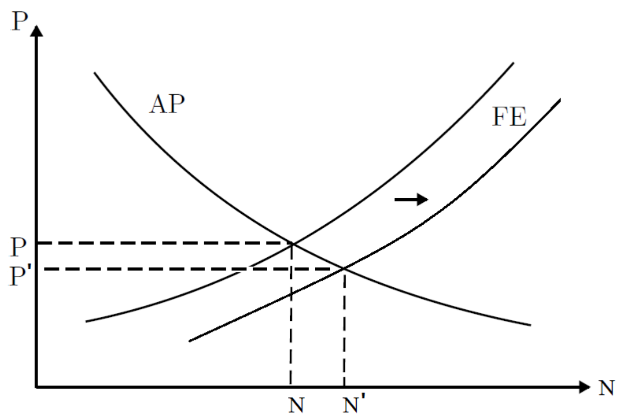
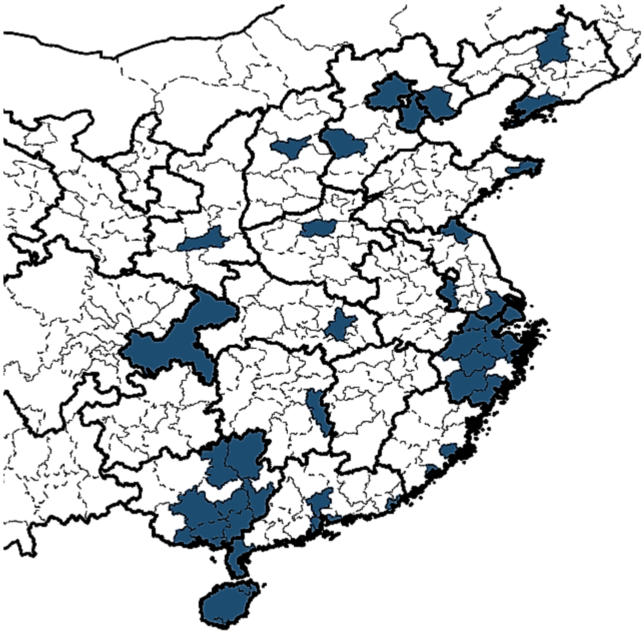


Figure 5: Adoption of the Pilot Paperless Processing Trade Program



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

# A Appendix Tables and Figures

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

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

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

Table A.2: Export Mode and Brand Ownership: Summary Statistics

| | (1) No brand | (2) Foreign brand | (3) Domestic brand |
|---|---|---|---|
| Ordinary exports | 14.3% | 33.5% | 52.2% |
| Processing exports | 7.0% | 83.9% | 9.1% |
| Other exports | 3.2% | 92.8% | 4.0% |
| Total | 12.4% | 56.4% | 32.7% |

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

Table A.3: Comparisons of Firms

| Sample | (1) All <$10m processors | (2) All >$10m processors | (3) Difference | (4) $9-10m processors | (5) $10-11m processors | (6) Difference |
|---|---|---|---|---|---|---|
| Mixed | 0.63 | 0.67 | -0.04*** | 0.62 | 0.62 | -0.00 |
| Importer | 0.73 | 0.76 | -0.03*** | 0.75 | 0.78 | -0.03 |
| Exiter | 0.07 | 0.02 | 0.05*** | 0.02 | 0.02 | -0.00 |
| Entrant | 0.11 | 0.04 | 0.07*** | 0.04 | 0.05 | -0.01 |
| Foreign | 0.49 | 0.47 | 0.02*** | 0.51 | 0.45 | 0.06** |
| SOE | 0.12 | 0.20 | -0.08*** | 0.16 | 0.13 | 0.02 |
| Proc. share of exports | 0.70 | 0.86 | -0.17*** | 0.84 | 0.89 | -0.05*** |
| Avg. log annual growth | 0.05 | 0.14 | -0.09*** | 0.12 | 0.18 | -0.06 |
| $\ln(empl.)$ | 5.43 | 6.82 | -1.38*** | 6.17 | 6.22 | -0.06 |
| $\ln(capital)$ | 8.83 | 10.57 | -1.74*** | 9.92 | 9.83 | 0.09 |
| Obs. | 189,195 | 8,818 | | 1,019 | 736 | |

*Notes:* This table reports balancing checks between the treatment and control groups. Columns 1 and 2 represent the means of the variables for exporters that are below and above the $10m threshold respectively (entire sample). Columns 4 and 5 represent the means of the variables for exporters that have $9-10m and $10-11m processing exports respectively (restricted sample). Columns 3 and 6 show the differences in the means across the groups. The number of observations reported in the last row corresponds to the variable in the first row, and might deviate across variables depending on data availability. The electronics sector is excluded due to its lower $5m threshold. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Table A.4: Paperless Trade and Processing Exports - Robustness Checks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dep. var.: ln(proc. exp.)$_{icst}$ | Entry & exit | *FD* | bw: \$9.5-10.5m | bw: \$8.5-11.5m | Always exporters | No SOEs | Mixed only (ordinary) | Mixed only (proc.) | False threshold (\$9m) | False threshold (\$11m) |
| $OS_{ict-1}$ | 0.238* | 0.140*** | 0.207* | 0.179** | 0.239** | 0.241** | -0.256 | 0.354* | 0.019 | -0.056 |
| | (0.117) | (0.045) | (0.117) | (0.072) | (0.101) | (0.114) | (0.313) | (0.197) | (0.072) | (0.092) |
| Entrant$_{it}$ | -1.341*** | | | | | | | | | |
| | (0.172) | | | | | | | | | |
| Exiter$_{it}$ | -1.125*** | | | | | | | | | |
| | (0.212) | | | | | | | | | |
| Firm FE | Yes | No | 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 |
| Observations | 1,254 | 1,417 | 716 | 2,690 | 1,120 | 1,414 | 936 | 936 | 2,223 | 1,379 |
| $R^2$ | 0.74 | 0.37 | 0.75 | 0.58 | 0.64 | 0.64 | 0.87 | 0.67 | 0.59 | 0.62 |

*Notes:* This table reports further robustness checks for the results in Table 4. $OS_{ict-1}$ indicates the implementation of the pilot paperless processing trade programme in prefecture $c$ in year $t-1$ for firm $i$ (i.e., Class A firms). Sector $s$ refers to the top (core) HS2 of each firm. In column 2, we use a first-difference ($FD$) specification. In columns 3 and 4, we change the bandwidth to \$9.5-10.5m and \$8.5-11.5m respectively. In columns 9 and 10, we do falsification analyses by setting the threshold to \$9m and \$11m, and the bandwidth (bw) to \$8-10m and \$10-12m respectively. Standard errors clustered at the prefecture and sector level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

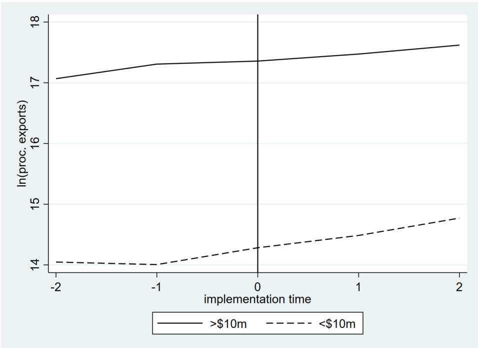
Table A.5: Trademarks, with IO Linkages

| Dep. var.: $Y_{icnt}$ | (1) Overall effect | (2) Median | (3) Output control | (4) Mixed interaction |
|---|---|---|---|---|
| Input shock$_{cnt-1}$ | 0.084 | -0.152** | -0.164** | 0.053 |
| | (0.084) | (0.073) | (0.072) | (0.084) |
| $\times$ Productive$_i$ | | 0.428*** | 0.437*** | |
| | | (0.087) | (0.084) | |
| $\times$ Mixed$_{it}$ | | | | 0.194** |
| | | | | (0.084) |
| Output shock$_{cnt-1}$ | | | -0.010 | -0.010 |
| | | | (0.009) | (0.007) |
| $\times$ Productive$_i$ | | | 0.007 | |
| | | | (0.012) | |
| $\times$ Mixed$_{it}$ | | | | 0.032** |
| | | | | (0.012) |
| $\ln(empl.)_{it}$ | 0.102*** | 0.101*** | 0.101*** | 0.102*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $\ln(capital)_{it}$ | 0.054*** | 0.054*** | 0.054*** | 0.054*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Firm FE | Yes | Yes | Yes | Yes |
| Sector-year FE | Yes | Yes | Yes | Yes |
| Prefecture-year FE | Yes | Yes | Yes | Yes |
| Obs. | 480,051 | 480,051 | 480,051 | 480,051 |
| pseudo-$R^2$ | 0.48 | 0.48 | 0.48 | 0.48 |

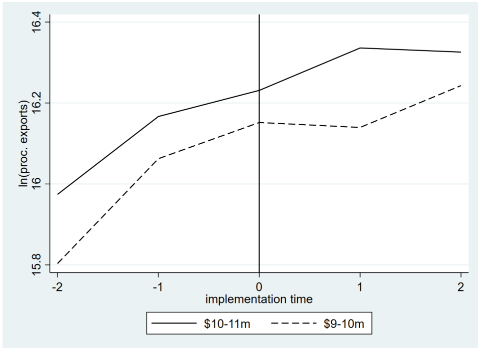
*Notes:* This table reports the results of running specification (22) using a PPML model. $Y_{icnt}$ is the number of trademarks of firm $i$ in downstream sector $n$ residing in prefecture $c$ in year $t$. Sectors refer to 57 downstream IO industries. Productive$_i$ indicates firms whose initial log labor productivity is larger than the median. Mixed$_{it}$ indicates whether the firm engages in both ordinary and processing exports. Standard errors clustered at the prefecture and sector level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Figure A.1: Processing Export Trends

(a) All firms




(b) $9-11m firms




*Notes:* The figure plots the level of processing exports for all exporters in panel (a) and exporters that had $9-11m worth of processing exports in the year prior to policy adoption in panel (b). Implementation time 0 indicates the year the prefecture's customs authority adopted the pilot paperless processing trade program.

# B Calculating Physical TFP

To calculate physical TFP, we use the firm-product level production survey conducted by the NBS in China. This survey records information on products produced by all SOEs and private firms that have annual sales of at least five million RMB in 2000-2006.[46] To be able to assign an export mode for each firm, we merge this database with the merged Chinese customs-AIS dataset using unique firm IDs. Then, to obtain reliable productivity estimates at the firm level, we focus on single-product firms. Counting by the number of firm-product-year observations, single-product firms account for 56% of observations. Considering the relatively large amount of single-product observations, we expect that focusing on these observations will not severely bias our results. To ensure that the sample size is large enough to perform the estimation, we keep product categories with at least 2,000 firm-year observations and at least four years of existence.[47] Moreover, for each product category we require that there are at least 50 yearly observations. This results in a sample of 36 products (out of 693 manufacturing products) and 145,832 firm-year observations. Table B.1 lists the 36 products with their brief descriptions.

## B.1 Methodology and Estimation

Our goal is to compare the production efficiency of exporters with different export modes. Following Foster et al. (2008), we use quantity data to get rid of the estimation bias caused by the heterogeneity in output pricing. Because we do not have information on firms' inputs, the input price dispersion may also bias our productivity estimates. To deal with this concern, we follow De Loecker et al. (2016) and use output prices to control for the input price dispersion. Note that for the final sample with single-product firms, 19% of firms exit before the end of sample period. This attrition rate can potentially cause a selection bias as first pointed out by Olley and Pakes (1996). To deal with this concern, we also control for firm exit.[48] We outline the estimation framework below.

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

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma m_{it} + \omega_{it} + \varepsilon_{it}, \tag{23}$$

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

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

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

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

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

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

$$m_{it} = \tilde{m}_{it} - p_{Mit}. \tag{24}$$

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

$$\bar{m}_{it} = \tilde{m}_{it} - p_{Mjt}. \tag{25}$$

Plugging (25) into (24), we can express the quantity of materials as:

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

Therefore, we can rewrite the production function as:

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma \bar{m}_{it} + \omega^*_{it} + \varepsilon_{it}, \tag{26}$$

where:

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

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

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

$$p_{Mit} = f(p_{it}, \mathbf{X}_{it}). \tag{27}$$

This allows us to express physical material input as:

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

Thus, the production function we estimate is given by:

$$q_{it} = \alpha k_{it} + \beta l_{it} + \gamma \tilde{m}_{it} + \gamma f(p_{it}, \mathbf{X}_{it}) + \omega_{it} + \varepsilon_{it}. \tag{28}$$

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

$$p_{it} = \log\left(\frac{R_{it}}{Q_{it}}\right), \tag{29}$$

where $R_{it}$ and $Q_{it}$ are firm $i$'s sales in values and quantities respectively in year $t$. We follow the Olley-Pakes methodology except that in the first-stage estimation, in addition to $k_{it}$, $l_{it}$, and $\tilde{m}_{it}$, we add polynomials of logged output prices to control for material prices. We also control for firm exit as a function of polynomials of capital stock, investment, and year dummies. This allows us to address the potential selection bias caused by less productive firms exiting the sample. To account for heterogeneity in production technology, we perform the estimation product by product.[49] Once we estimate the production function coefficients, we then compute our physical productivity ($TFPQ$) estimates, which are used in the regressions in Table 2.

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

Table B.1: Products in the Estimation Sample

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

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

# C Theory Appendix

## C.1 Comparative Statics for Blueprint Producers

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

$$\underline{t}\left(z_j,\, t_j\right) = \frac{\theta f}{\sigma - 1}\left(Ak_1 z_j^{\sigma-1}\right)^{-1} \Theta(z_j, t_j)^{1-\frac{\sigma-1}{\theta}}. \tag{30}$$

Since $A$ and $z_j^{\sigma-1}$ enter the expression of $\underline{t}$ multiplicatively, they should affect other choice variables similarly. To save space, we only show the comparative statics for $z_j$. For clarity, we denote $\Theta_j \equiv \Theta\left(z_j,\, t_j\right)$ and $\underline{t}_j \equiv \underline{t}\left(z_j,\, t_j\right)$. Taking the derivative of $\underline{t}\left(z_j,\, t_j\right)$ with respect to $z_j$, we obtain:

$$\frac{\partial \underline{t}_j}{\partial z_j} = \frac{\theta f}{\left(\sigma - 1\right) Ak_1}\left[\left(1-\sigma\right) z_j^{-\sigma}\Theta_j^{1-\frac{\sigma-1}{\theta}} + z_j^{1-\sigma}\frac{\partial \Theta_j^{1-\frac{\sigma-1}{\theta}}}{\partial z_j}\right], \tag{31}$$

where:

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

Now suppose $\frac{\partial \underline{t}_j}{\partial z_j} > 0$, then the right-hand side of Equation (31) will be negative because $\frac{\partial \Theta_j}{\partial \underline{t}_j} < 0$ and $\theta > \sigma - 1$. This leads to a contradiction, which implies that $\frac{\partial \underline{t}_j}{\partial z_j} < 0$. Note that $n\left(z_j,\, t_j\right) = N\int_{\underline{t}_j}^{\bar{t}} dG_t\left(\iota\right)$, and thus $\frac{\partial n}{\partial \underline{t}_j} < 0$. By the chain rule, we have:

$$\frac{\partial n\left(z_j,\, t_j\right)}{\partial z_j} = \frac{\partial n\left(z_j,\, t_j\right)}{\partial \underline{t}_j}\frac{\partial \underline{t}_j}{\partial z_j} > 0. \tag{32}$$

Our model implies that the share of tasks outsourced by firm $j$, $o\left(z_j,\, t_j\right)$, is given by:

$$o\left(z_j,\, t_j\right) = 1 - \frac{t_j}{\Theta_j}. \tag{33}$$

It immediately follows that:

$$\frac{\partial o\left(z_j,\, t_j\right)}{\partial z_j} \propto \frac{\partial \Theta_j}{\partial z_j} = \frac{\partial \Theta_j}{\partial \underline{t}_j}\frac{\partial \underline{t}_j}{\partial z_j} > 0.$$

Lastly, the unit cost is expressed as:

$$c\left(z_j,\, t_j\right) = \frac{\Theta_j^{-\frac{1}{\theta}}\gamma^{\frac{1}{1-\rho}}}{z_j}. \tag{34}$$

Note that $\Theta_j^{-\frac{1}{\theta}}$ is decreasing in $z_j$ since $\frac{\partial \Theta_j^{-\frac{1}{\theta}}}{\partial z_j} \propto -\frac{\partial \Theta_j}{\partial \underline{t}_j}\frac{\partial \underline{t}_j}{\partial z_j} < 0$ and $z_j^{-1}$ is also decreasing in $z_j$. This implies that $\frac{\partial c(z_j, t_j)}{\partial z_j} < 0$.

**Comparative statics for $t_j$** Taking the derivative of Equation (30) with respect to $t_j$, we get:

$$\frac{\partial \underline{t}_j}{\partial t_j} \propto \left(1 - \frac{\sigma - 1}{\theta}\right) \frac{\partial \Theta_j}{\partial t_j}. \tag{35}$$

Recall that $\Theta_j = t_j + N \int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota)$, which implies:

$$\frac{\partial \Theta_j}{\partial t_j} = 1 - N \underline{t}_j g_t\left(\underline{t}_j\right) \frac{\partial \underline{t}_j}{\partial t_j}.$$

If $\frac{\partial \underline{t}_j}{\partial t_j} \leq 0$, we must have that $\frac{\partial \Theta_j}{\partial t_j} > 0$. By (35), this in turn implies that $\frac{\partial \underline{t}_j}{\partial t_j} > 0$, which is a contradiction. Therefore it has to be the case that $\frac{\partial \underline{t}_j}{\partial t_j} > 0$. Using the expression of $n\left(z_j, t_j\right)$ and applying the chain rule, we have:

$$\frac{\partial n\left(z_j, t_j\right)}{\partial t_j} = \frac{\partial n\left(z_j, t_j\right)}{\partial \underline{t}_j} \frac{\partial \underline{t}_j}{\partial t_j} < 0. \tag{36}$$

From (33), we know that $\frac{\partial o(z_j, t_j)}{\partial t_j} = -\frac{1}{\Theta_j} + \frac{t_j}{\Theta_j^2} \frac{\partial \Theta_j}{\partial t_j}$. Since $\frac{\partial \Theta_j}{\partial t_j} = \frac{\partial \Theta_j}{\partial \underline{t}_j} \frac{\partial \partial \underline{t}_j}{\partial t_j} < 0$, it follows that $\frac{\partial o(z_j, t_j)}{\partial t_j} < 0$. Using the expression for the unit cost as defined in (34), we know that $\frac{\partial c(z_j, t_j)}{\partial t_j} \propto -\frac{\partial \Theta_j}{\partial t_j} \propto -\frac{\partial \underline{t}_j}{\partial t_j} < 0$.

**Comparative statics for $N$** Taking the derivative of Equation (30) with respect to $N$, we obtain:

$$\frac{\partial \underline{t}_j}{\partial N} = \frac{\theta f}{\sigma - 1} \left(A k_1 z_j^{\sigma - 1}\right)^{-1} \left(1 - \frac{\sigma - 1}{\theta}\right) \Theta_j^{-\frac{\sigma - 1}{\theta}} \frac{\partial \Theta_j}{\partial N}. \tag{37}$$

From the expression of $\Theta_j$, we obtain:

$$\frac{\partial \Theta_j}{\partial N} = \left(\int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota) - N \underline{t}_j g_t\left(\underline{t}_j\right) \frac{\partial \underline{t}_j}{\partial N}\right). \tag{38}$$

Now suppose that $\partial \underline{t}_j / \partial N \leq 0$, then expression (38) implies that $\partial \Theta_j / \partial N > 0$. By (37), this in turn means that $\partial \underline{t}_j / \partial N > 0$, which is a contradiction. Therefore, $\partial \underline{t}_j / \partial N$ has to be positive. This also implies that $\partial \Theta_j / \partial N > 0$ by inspection of (37). After some algebra, one can show that:

$$\frac{\partial \underline{t}_j}{\partial N} = \frac{(1 - \frac{\sigma - 1}{\theta}) \frac{t_j}{\Theta_j} \int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota)}{1 + (1 - \frac{\sigma - 1}{\theta}) N \underline{t}_j g_t(\underline{t}_j) \frac{t_j}{\Theta_j}}.$$

Taking the derivative of $n$ with respect to $N$, we have:

$$\frac{\partial n}{\partial N} = \int_{\underline{t}_j}^{\bar{t}} dG_t(\iota) - N g_t\left(\underline{t}_j\right) \frac{\partial \underline{t}_j}{\partial N} = \frac{\int_{\underline{t}_j}^{\bar{t}} dG_t + N(1 - \frac{\sigma - 1}{\theta}) \frac{t_j}{\Theta_j} \int_{\underline{t}_j}^{\bar{t}} (\underline{t}_j - \iota) dG_t(\iota)}{1 + (1 - \frac{\sigma - 1}{\theta}) N \underline{t}_j g_t(\underline{t}_j) \frac{t_j}{\Theta_j}}. \tag{39}$$

Inspecting the right-hand side, the first term is positive and the second term is negative. As a result, $\partial n\left(z_j,\, t_j\right)/\partial N$ can either be positive or negative. By expression (33), we have:

$$\frac{\partial o}{\partial N} \propto \frac{\partial \Theta_j}{\partial N} > 0.$$

Lastly, the change in unit cost with respect to $N$ is:

$$\frac{\partial c\left(z_j,\, t_j\right)}{\partial N} \propto -\frac{\partial \Theta_j}{\partial N} < 0.$$

### C.2 Comparative Statics for Task Producers

Now we consider two task producers denoted by $i$ and $i'$. For any given blueprint producer $j$, its purchase of tasks from $i$ and $i'$ are $x_{ij}$ and $x_{i'j}$, respectively. Without loss of generality, we assume that $j$ has established business relations with both suppliers, i.e., $\min\left\{T_i,\, T_{i'}\right\} \geq \underline{t}\left(z_j,\, t_j\right)$. In this case, recall that the bilateral trade between two firms is given by:

$$x_{ij} = \lambda_{ij} x_j = \frac{T_i}{\Theta_j} x_j, \tag{40}$$

$$x_{i'j} = \lambda_{i'j} x_j = \frac{T_{i'}}{\Theta_j} x_j. \tag{41}$$

This implies that $x_{i'j} > x_{ij}$. Since $\Omega_i$ represents the set of firms that source from $i$, we can express it as:

$$\Omega_i = \left\{ j \middle|\, \underline{t}_j \leq T_i \right\}.$$

When $T_i < T_{i'}$, for any $j \in \Omega_i$, $\underline{t}_j \leq T_i < T_{i'}$, which implies that $j \in \Omega_{i'}$. This indicates that $\Omega_i \subseteq \Omega_{i'}$. Because $\underline{t}_j$ is a continuous and monotone function with respect to $z_j$ or $t_j$, and there is a continuum of firms, there exists a $j'$ such that $T_i < \underline{T}^*_{j'} < T_{i'}$. Therefore $\Omega_i \subset \Omega_{i'}$. Lastly, note that profits of the task producer is given by $\pi^T\left(T_i\right) = \frac{1}{1+\theta}\sum_{j\in\Omega_i} x_{ij}$, and thus $\pi^T\left(T_i\right) < \frac{1}{1+\theta}\sum_{j\in\Omega_i} x_{i'j} < \frac{1}{1+\theta}\sum_{j\in\Omega_{i'}} x_{i'j} = \pi^T\left(T_{i'}\right)$.

### C.3 Proof of Uniqueness

We decompose the proof of uniqueness into two parts. In the first part, we show that the aggregate price index is increasing in $N$. In the second part, we prove that $FE$ curve is increasing in $N$.

**Part I:** $P(N)$ is decreasing in $N$.

We prove that $P(N)$ is decreasing in $N$ by contradiction. Recall that the aggregate price index is:

$$P = N^{\frac{1}{1-\sigma}} \left[ \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} p^B (c(\zeta,\iota))^{1-\sigma} dG_t(\iota) dG_z(\zeta) \right]^{\frac{1}{1-\sigma}}. \tag{42}$$

Consider $N' > N$ and $P' \geq P$. As we showed in the comparative statics, $\frac{\partial c_j}{\partial N} < 0$, $\frac{\partial c_j}{\partial P} < 0$, and hence $p'_j < p_j$. As $v_j$ increases in $P$ and decreases in $p_j$, ${v'}_j > v_j \geq 0$ for any firm $j$ active in blueprint production at the old equilibrium. Therefore:

$$P' < N'^{\frac{1}{1-\sigma}} \left[ \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} p'^B (c(\zeta,\iota))^{1-\sigma} dG_t(\iota) dG_z(\zeta) \right]^{\frac{1}{1-\sigma}}$$
$$< N^{\frac{1}{1-\sigma}} \left[ \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} p^B (c(\zeta,\iota))^{1-\sigma} dG_t(\iota) dG_z(\zeta) \right]^{\frac{1}{1-\sigma}} = P,$$

which contradicts $P' \geq P$. Hence it must be that $P' < P$, which concludes the proof.

**Part II:** $FE$ curve is upward sloping.

Let $F_{FE}(P,N) = \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} v^B(\zeta,\iota) dG_t(\iota) dG_z(\zeta) + \int_{\underline{T}}^{\bar{t}} \pi^T(\iota) dG_t(\iota) - \delta f_E$. The proof proceeds in three steps.

**Step 1:** $\frac{\partial F_{FE}}{\partial P} > 0$. Note that $\int_{\underline{T}}^{\bar{t}} \pi^T(\iota) dG_t(\iota) = \frac{(\sigma-1)\beta L}{N\sigma(\theta+1)}$. Applying the Leibniz rule,

$$\frac{\partial F_{FE}}{\partial P} = \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \frac{\partial v^B(\zeta,\iota)}{\partial P} dG_t(\iota) dG_z(\zeta)$$
$$- \int_{\Xi(\underline{Z})}^{\bar{t}} g_z(\underline{z}) v^B(\underline{z},\iota) \frac{\partial \underline{Z}}{\partial P} dG_t(\iota) - \int_{\underline{Z}}^{\bar{z}} g_t(\Xi(\zeta)) v^B(\zeta, \Xi(\zeta)) \frac{\partial \Xi(\zeta)}{\partial P}(\iota) dG_z(\zeta) \ .$$

As $v^B(\zeta,\Xi(\zeta)) = 0$, $\Xi(\underline{z}) = \bar{t}$, the last two terms of above equation are zero; hence:

$$\frac{\partial F_{FE}}{\partial P} = \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \frac{\partial v^B(\zeta,\iota)}{\partial P} dG_t(\iota) dG_z(\zeta).$$

By the envelope theorem, we know that $\frac{\partial v^B}{\partial P} = (\sigma-1)\frac{v^B}{P} \geq 0$, which holds with equality when $v = 0$. Hence:

$$\frac{\partial F_{FE}}{\partial P} = \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} (\sigma-1)\frac{v^B}{P} dG_t(\iota) dG_z(\zeta) > 0.$$

**Step 2:** $\frac{\partial F_{FE}}{\partial N} < 0$. Applying the Leibniz rule, we get:

$$\frac{\partial F_{FE}}{\partial N} = \int_{\underline{Z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \frac{\partial v^B(\zeta,\iota)}{\partial N} dG_t(\iota) dG_z(\zeta) - \frac{(\sigma-1)\beta L}{N^2\sigma(\theta+1)}.$$

By the envelope theorem:

$$\frac{\partial v^B}{\partial N} = \frac{\sigma-1}{\theta}\pi^B \frac{\Theta - t}{\Theta}\frac{1}{N} - \frac{fn}{N}$$
$$= \frac{\sigma-1}{\theta}\frac{\pi^B}{\Theta}\int_{\underline{t}}^{\bar{t}} \iota dG_t(\iota) - f\int_{\underline{t}}^{\bar{t}} dG_t(\iota),$$

and thus we get:

$$\begin{aligned}\frac{\partial F_{FE}}{\partial N} &= \int_{\underline{z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \left( \frac{\sigma-1}{\theta} \pi^B \frac{\Theta - t}{\Theta} \frac{1}{N} \right) dG_t(\iota) dG_z(\zeta) \\ &- \int_{\underline{z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \frac{fn}{N} dG_t(\iota) dG_z(\zeta) - \frac{(\sigma-1)\beta L}{N^2 \sigma(\theta+1)}. \end{aligned} \tag{43}$$

Because $N \int_{\underline{z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \pi^B dG_t(\iota) dG_z(\zeta) = \frac{\beta L}{\sigma}$, equation (43) can then be simplified to:

$$\frac{\partial F_{FE}}{\partial N} = \frac{\sigma-1}{N\theta} \left( \int_{\underline{z}}^{\bar{z}} \int_{\Xi(\zeta)}^{\bar{t}} \left( \frac{1}{\theta+1} \pi^B - \frac{t\pi^B}{\Theta} - \frac{\theta}{\sigma-1} fn \right) dG_t(\iota) dG_z(\zeta) \right).$$

Given that $\underline{t}_j = f \left( Ak_1 z_j^{\sigma-1} \right)^{-1} \Theta(z_j, t_j)^{1-\frac{\sigma-1}{\theta}} \dfrac{\theta}{\sigma-1}$, we can express $f$ as a function of $\pi_j^B$ and $\underline{t}_j$:

$$f = \underline{t}_j \frac{\pi_j^B}{\Theta_j} \frac{\sigma-1}{\theta}.$$

Hence we can show that $\frac{1}{\theta+1}\pi^B - \frac{t\pi^B}{\Theta} - \frac{\theta}{\sigma-1} fn = \frac{\pi^B}{\Theta} \left( \frac{\Theta}{\theta+1} - t - n\underline{t} \right)$.

Now focus on $\frac{\Theta}{\theta+1} - t - n\underline{t}$. Taking the partial derivative with respect to $\underline{t}$, we get:

$$\frac{\partial(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}} = \frac{\theta}{\theta+1} N\underline{t} g_t(\underline{t}) - N \int_{\underline{t}}^{\bar{t}} g_t(\iota) d\iota. \tag{44}$$

Furthermore:

$$\frac{\partial^2(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}^2} = \frac{\theta}{\theta+1} N\underline{t} g'_t(\underline{t}) + \frac{\theta}{\theta+1} N g_t(\underline{t}) + N g_t(\underline{t}). \tag{45}$$

Recall that $\iota g'_t(\iota) + g_t(\iota) > 0$, and hence $\frac{\partial^2(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}^2} > 0$. Therefore, $\frac{\partial(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}}$ reaches its maximum when $\underline{t} = \bar{t}$. As $\frac{\partial(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}}$ approaches zero when $\underline{t}$ approaches $\bar{t}$, we have $\frac{\partial(\frac{\Theta}{\theta+1} - t - n\underline{t})}{\partial \underline{t}} \leq 0$. In other words, $\frac{\Theta}{\theta+1} - t - n\underline{t}$ reaches its highest value when $\underline{t}$ reaches its lowest. Recall that in equilibrium, the least productive suppliers are reached by firms with the best blueprint quality and the 'worst' manufacturing ability, i.e., $i = \{\bar{z}, \Xi(\bar{z})\}$. At the same time, $v^B(\bar{z}, \Xi(\bar{z})) = 0$, which implies that:

$$fn_i = \pi_i^B. \tag{46}$$

Optimal sourcing condition implies that:

$$f = \underline{t}_i \frac{\pi_i^B}{\Theta_i} \frac{\sigma-1}{\theta}. \tag{47}$$

Equations (46) and (47) together imply that $n_i\underline{t}_i = \Theta_i \frac{\theta}{\sigma-1}$. Therefore:

$$\frac{\Theta}{\theta+1} - t - n\underline{t} \leq \frac{\Theta_i}{\theta_i+1} - t_i - n_i\underline{t}_i < \frac{\Theta_i}{\theta_i+1} - n_i\underline{t}_i < \frac{\Theta_i}{\theta_i+1} - \frac{\Theta_i\theta}{\sigma-1} < 0. \tag{48}$$

As a result, $\frac{1}{\theta+1}\pi^B - \frac{t\pi^B}{\Theta} - \frac{\theta}{\sigma-1}fn < 0$, and hence $\frac{\partial F}{\partial N} < 0$. As $\frac{\partial F}{\partial P} > 0$ and $\frac{\partial F}{\partial N} < 0$, it is immediate that the $FE$ curve is upward sloping:

$$\frac{\partial P(N)}{\partial N} = -\frac{\partial F_{FE}/\partial N}{\partial F_{FE}/\partial P} > 0.$$

## C.4 Proofs of Ranks

**Proof of $G_{Mix}(t)$ FSD $G_{PP}(t)$.**

We first write down the cumulative distribution functions of mixed and processing exporters:

$$F_{Mix}(t < t') = \frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}, \qquad F_{PP}(t < t') = \frac{\int_{\underline{T}_X}^{t'} \int_{\underline{Z}}^{\Xi_X^{-1}(\iota)} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} \int_{\underline{Z}}^{\Xi_X^{-1}(\iota)} dG_z(\zeta)dG_t(\iota)}.$$

Proving $F_{Mix}(t < t') < F_{PP}(t < t')$ for any $t' > \underline{T}_X$ is equivalent to proving:

$$\frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)} < \frac{\int_{\underline{T}_X}^{t'} \int_{\underline{Z}}^{\Xi_X^{-1}(\iota)} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} \int_{\underline{Z}}^{\Xi_X^{-1}(\iota)} dG_z(\zeta)dG_t(\iota)},$$

which, after some algebra, is equivalent to:

$$\frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)} - \frac{\int_{\underline{T}_X}^{t'} dG_t(\iota)}{\int_{\underline{T}_X}^{\bar{t}} dG_t(\iota)} < 0.$$

The left-hand side of above expression equals zero when $t' = \bar{t}$. Hence for the inequality to hold, it is sufficient to prove that $\frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{t'} dG_t(\iota)}$ is increasing in $t$. Taking a partial derivative with respect to $t'$, we get:

$$\begin{aligned}
\frac{\partial \frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota)}{\int_{\underline{T}_X}^{t'} dG_t(\iota)}}{\partial t'} &= \frac{g_t(t')}{(\int_{\underline{T}_X}^{t'} dG_t(\iota))^2} \int_{\Xi_X^{-1}(t')}^{\bar{z}} dG_z(\zeta) \int_{\underline{T}_X}^{t'} dG_t(\iota) \\
&- \frac{g_t(t')}{(\int_{\underline{T}_X}^{t'} dG_t(\iota))^2} \int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota) \\
&\propto \int_{\Xi_X^{-1}(t')}^{\bar{z}} dG_z(\zeta) \int_{\underline{T}_X}^{t'} dG_t(\iota) - \int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)dG_t(\iota).
\end{aligned}$$

Note that as $\Xi_X^{-1}(t)$ is decreasing in $t$, $\Xi_X^{-1}(t')$ is smaller than any $\Xi_X^{-1}(\iota)$ with $\iota \in (\underline{T}_X, t')$. Hence, $\int_{\Xi_X^{-1}(t')}^{\bar{z}} dG_z(\zeta) > \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta)$ for $\iota \in (\underline{T}_X, t')$:

$$\int_{\Xi_X^{-1}(t')}^{\bar{z}} dG_z(\zeta) \int_{\underline{T}_X}^{t'} dG_t(\iota) - \int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta) dG_t(\iota)$$
$$= \int_{\underline{T}_X}^{t'} \left( \int_{\Xi_X^{-1}(t')}^{\bar{z}} dG_z(\zeta) - \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta) \right) dG_t(\iota) > 0.$$

Thus, $\partial \frac{\int_{\underline{T}_X}^{t'} \int_{\Xi_X^{-1}(\iota)}^{\bar{z}} dG_z(\zeta) dG_t(\iota)}{\int_{\underline{T}_X}^{t'} dG_t(\iota)} / \partial t' > 0$, which concludes the proof.

**Proof of $G_{Mix}(z)$ FSD $G_{PP}(z)$.**

Denote $z_1 \equiv \Xi_X^{-1}(\bar{t})$, $z_2 \equiv \Xi_X^{-1}(\underline{T}_X)$. If $z' < z_1$, then $F_{Mix}(z < z') = 0, F_{PP}(z < z') > 0$; if $z' \geq z_2$, then $F_{Mix}(z < z') < 1, F_{PP}(z < z') = 1$. In these two cases, $F_{Mix}(z < z') < F_{PP}(z < z')$ always holds. When $z' \in [z_1, z_2)$, we have:

$$F_{Mix}(z < z') = \frac{\int_{z_1}^{z'} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta) + (1 - G_t(\underline{T}_X))(1 - G_z(z_2))} < \frac{\int_{z_1}^{z'} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta)},$$

$$F_{PP}(z < z') = \frac{\int_{z_1}^{z'} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta) + (1 - G_t(\underline{T}_X)) G_z(z_1)}{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta) + (1 - G_t(\underline{T}_X)) G_z(z_1)} > \frac{\int_{z_1}^{z'} \int_{\underline{T}_X}^{\Xi_X(\zeta)} dG_t(\iota) dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\underline{T}_X}^{\Xi_X(\zeta)} dG_t(\iota) dG_z(\zeta)}.$$

As $\Xi_X(z)$ is decreasing in $z$, the proof for $G_{Mix}(t)$ FSD $G_{PP}(t)$ applies here as well. Therefore, we have:

$$F_{Mix}(z < z') < \frac{\int_{z_1}^{z'} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta)} < \frac{\int_{z_1}^{z'} \int_{\underline{T}_X}^{\Xi_X(\zeta)} dG_t(\iota) dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\underline{T}_X}^{\Xi_X(\zeta)} dG_t(\iota) dG_z(\zeta)} < F_{PP}(z < z'),$$

when $z' \in [z_1, z_2)$. This concludes the proof.

**Proof of $G_{PO}(z)$ FSD $G_{Mix}(z)$.**

When $z' \in [z_1, z_2)$, $F_{PO}(z < z') = 0, F_{Mix}(z < z') > 0$, and hence $F_{PO}(z < z') < F_{Mix}(z < z')$ holds. When $z' \geq z_2$, we have:

$$F_{Mix}(z < z') = \frac{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta) + (1 - G_t(\underline{T})) \int_{z_2}^{z'} dG_z(\zeta)}{\int_{z_1}^{z_2} \int_{\Xi_X(\zeta)}^{\bar{t}} dG_t(\iota) dG_z(\zeta) + (1 - G_t(\underline{T}_X))(1 - G_z(z_2))}$$
$$> \frac{(1 - G_t(\underline{T}_X)) \int_{z_2}^{z'} dG_z(\zeta)}{(1 - G_t(\underline{T}_X))(1 - G_z(z_2))} = \frac{\int_{z_2}^{z'} dG_z(\zeta)}{1 - G_z(z_2)}.$$

Similarly, one can show that when $z' \geq z_2$:

$$F_{PO}(z < z') = \frac{\int_{z_2}^{z'} \int_{\Xi_X(\zeta)}^{\mathrm{T}_X} dG_t(\iota) dG_z(\zeta)}{\int_{z_2}^{\bar{z}} \int_{\Xi_X(\zeta)}^{\mathrm{T}_X} dG_t(\iota) dG_z(\zeta)} < \frac{\int_{z_2}^{z'} dG_z(\zeta)}{1 - G_z(z_2)}.$$

Therefore, $F_{Mix}(z < z') > F_{PO}(z < z')$, i.e., $G_{PO}(z)$ FSD $G_{Mix}(z)$.

**Labor Productivity.** The labor productivity of firm $j$ is given by:

$$LP_j = \frac{v_j^B}{l_j} + (1 + \frac{1}{\theta}).$$

Note that:

$$\frac{\partial ln v_j^B}{\partial ln z_j} = (\sigma - 1)\frac{\pi_j^B}{v_j^B} > \sigma - 1, \tag{49}$$

$$\frac{\partial ln l_j^B}{\partial ln z_j} = \frac{(\frac{\sigma-1}{\theta} - 1)(\sigma - 1)M_j}{1 + (1 - \frac{\sigma-1}{\theta})M_j} + (\sigma - 1) = \frac{\sigma - 1}{1 + (1 - \frac{\sigma-1}{\theta})M_j} < \sigma - 1, \tag{50}$$

where $M_j \equiv N \underline{\mathrm{t}}_j g_t(\underline{\mathrm{t}}_j) \frac{\mathrm{t}_j}{\Theta}$. Hence $\frac{v_j^B}{l_j^B}$ increases in $z_j$. As the labor used for producing tasks for other firms does not change with $z$, it immediately follows that $\frac{v_j^B}{l_j}$ is increasing in $z_j$ as well. Similarly, it is easy to verify that:

$$\frac{\partial ln v_j^B}{\partial ln t_j} = \frac{(\sigma - 1)t_j \pi_j^B}{\theta v_j^B \Theta_j}, \tag{51}$$

$$\frac{\partial ln l_j^B}{\partial ln t_j} = 1 - \frac{(1 - \frac{\sigma-1}{\theta})t_j}{\Theta_j} \frac{1}{1 + (1 - \frac{\sigma-1}{\theta})M_j}. \tag{52}$$

Hence, we have:

$$\begin{aligned}
\frac{\partial ln v_j^B}{\partial ln t_j} - \frac{\partial ln(l_j^B)}{\partial ln t_j} &= \frac{(\sigma - 1)t_j \pi_j^B}{\theta v_j^B \Theta_j} + \frac{(1 - \frac{\sigma-1}{\theta})t_j}{\Theta_j} \frac{1}{1 + (1 - \frac{\sigma-1}{\theta})M_j} - 1 \\
&= \frac{t_j}{\Theta_j}\left(\frac{(\sigma - 1)\pi_j^B}{\theta v_j^B} + \frac{(1 - \frac{\sigma-1}{\theta})}{1 + (1 - \frac{\sigma-1}{\theta})M_j}\right) - 1 \\
&> \frac{t_j}{\Theta_j} \frac{(\sigma - 1)\pi_j^B}{\theta v_j^B} - 1 = \frac{(\sigma - 1)l_j^B}{\theta v_j^B} - 1.
\end{aligned}$$

Thus for $\frac{v_j^B}{l_j^B}$ to increase in $t_j$, it is necessary that $\frac{l_j^B}{v_j^B} > \frac{\theta}{\sigma-1}$. This can happen if the fixed cost of exporting is sufficiently high, so that the production employment is much larger than profits even for firms with the best manufacturing ability. If, at the same time, when $t$ increases, the increase in production workers due to the increased task supply is not high enough to completely offset the increase in $\frac{v_j^B}{l_j^B}$, then $\frac{v_j^B}{l_j}$ will increase in $t$.

## C.5 Proof of Proposition 2

Define changes due to a reduction of $\tau_T$ in $N$ and $P$ as $dN$ and $dP$, respectively. By the envelope theorem, the change in profits from final good production for firm $j$, $dv_j^B$, equals:

$$dv_j^B = \frac{\partial v_j^B}{\partial N}dN + \frac{\partial v_j^B}{\partial P}dP = \frac{\sigma-1}{\theta}\frac{\pi_j^B}{\Theta_j}\frac{\partial \Theta_j}{\partial N}dN - f\frac{\partial n_j}{\partial N}dN + (\sigma-1)\pi_j^B\frac{dP}{P}.$$

Recall that when firms optimize their sourcing decisions, we have that $f = \underline{t}_j\frac{\pi_j^B}{\Theta_j}\frac{\sigma-1}{\theta}$. Hence, we can rewrite $dv_j^B$ as:

$$\begin{aligned} dv_j^B &= \frac{\sigma-1}{\theta}\frac{\pi_j^B}{\Theta_j}\frac{\partial \Theta_j}{\partial N}dN - \underline{t}_j\frac{\pi_j^B}{\Theta_j}\frac{\sigma-1}{\theta}\frac{\partial n}{\partial N}dN + (\sigma-1)\pi_j^B\frac{dP}{P} \\ &\propto \frac{1}{\Theta_j}N\frac{\partial \Theta_j}{\partial N}N - \frac{1}{\Theta_j}\underline{t}_j\frac{\partial n}{\partial N} + \theta\frac{\partial dlnP}{\partial dlnN}. \end{aligned} \tag{53}$$

With international trade, the expression of $\Theta_j$ is the following:

$$\Theta_j = t_j + (N+N^*)\int_{\underline{t}_j}^{\bar{t}} \iota d\hat{G}_t(\iota),$$

where $\hat{G}_t(\iota) = \frac{N}{N+N^*}G_t(\iota) + \frac{N^*}{N+N^*}G_t^*(\iota\tau_T^{*\theta})$. After some algebra, one can show that:

$$\frac{\partial \Theta_j}{\partial N} = \int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota), \qquad \frac{\partial n}{\partial N} = \int_{\underline{t}_j}^{\bar{t}} dG_t(\iota).$$

Plugging the above two equations into (53), we get:

$$dv_j^B = \frac{\sigma-1}{\theta}\pi_j^B\left(\frac{N\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)}{\Theta_j} + \theta\frac{\partial dlnP}{\partial dlnN}\right). \tag{54}$$

Let $F_{dv} \equiv \frac{N\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)}{\Theta_j}$. We now have:

$$\frac{\partial F_{dv}}{\partial t_j} = \frac{N}{\Theta_j^2}\int_{\underline{t}_j}^{\bar{t}}(-1)dG_t(\iota)\frac{\partial \underline{t}_j}{\partial t_j}\Theta_j - \frac{N}{\Theta_j^2}\frac{\partial \Theta_j}{\partial t_j}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota).$$

Recall that:

$$\frac{\partial \pi_j^B}{\partial t_j} = \frac{(\sigma-1)\pi_j^B}{\theta\Theta_j}\frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}.$$

Therefore:

$$\begin{aligned}\frac{\partial dv_j^B}{\partial t_j} &\propto \frac{(\sigma-1)\pi_j^B}{\theta\Theta_j}\frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}(F_{dv}+\theta\frac{\partial dlnP}{\partial dlnN})+\pi_j^B\frac{\partial F_{dv}}{\partial t_j}\\ &< \frac{\pi_j^B}{\Theta_j}\frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}F_{dv}+\pi_j^B\frac{\partial F_{dv}}{\partial t_j} \propto \frac{1}{\Theta_j}\frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}F_{dv}+\frac{\partial F_{dv}}{\partial t_j}.\end{aligned}$$

As $\frac{\partial \underline{t}_j}{\partial t_j}>0$ and $\frac{\partial \Theta_j}{\partial t_j}>0$, the following inequality holds:

$$\begin{aligned}\frac{1}{\Theta_j}\frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}F_{dv}+\frac{\partial F_{dv}}{\partial t_j} &= \frac{N}{\Theta_j^2}\frac{\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)}{1+(1-\frac{\sigma-1}{\theta})M_j}+\frac{\partial F_{dv}}{\partial t_j}\\ &< \frac{N}{\Theta_j^2}\frac{\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)}{1+(1-\frac{\sigma-1}{\theta})M_j}-\frac{N}{\Theta_j^2}\frac{\partial\Theta_j}{\partial t_j}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)\\ &\propto \frac{1}{1+(1-\frac{\sigma-1}{\theta})M_j}-\frac{\partial\Theta_j}{\partial t_j}=0. \end{aligned}\tag{55}$$

This concludes the proof that $\frac{\partial dv_j^B}{\partial t_j}<0$. Similarly, taking the partial derivative of $F_{dv}$ with respect to $z_j$ yields:

$$\frac{\partial F_{dv}}{\partial z_j}=\frac{N}{\Theta_j^2}\int_{\underline{t}_j}^{\bar{t}}(-1)dG_t(\iota)\frac{\partial \underline{t}_j}{\partial z_j}\Theta_j-\frac{N}{\Theta_j^2}\frac{\partial\Theta_j}{\partial z_j}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota).$$

Note that $\frac{\partial\Theta_j}{\partial z_j}=\frac{\partial\Theta_j}{\partial\underline{t}_j}\frac{\partial\underline{t}_j}{\partial z_j}$. As $\frac{\partial\underline{t}_j}{\partial z_j}<0$, we have:

$$\begin{aligned}\frac{\partial dv_j^B}{\partial z_j} &\propto \frac{(\sigma-1)\pi_j^B}{\theta\Theta_j}(-\frac{\partial\Theta_j}{\partial\underline{t}_j})(F_{dv}+\theta\frac{\partial dlnP}{\partial dlnN})+\frac{\pi_j^B N}{\Theta_j^2}\left(\int_{\underline{t}_j}^{\bar{t}}dG_t(\iota)\Theta_j+\frac{\partial\Theta_j}{\partial\underline{t}_j}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)\right)\\ &\propto (1-\frac{(\sigma-1)}{\theta})\frac{\partial\Theta_j}{\partial\underline{t}_j}F_{dv}+\frac{\partial\Theta_j}{\partial\underline{t}_j}\left(-\frac{(\sigma-1)\partial dlnP}{\partial dlnN}\right)+N\int_{\underline{t}_j}^{\bar{t}}dG_t(\iota).\end{aligned}$$

Denoting $1-\frac{(\sigma-1)}{\theta}\equiv\Delta_1\in(0,1)$, $\left(-\frac{(\sigma-1)\partial dlnP}{\partial dlnN}\right)\equiv\Delta_2>0$, we simplify the above expression to:

$$\frac{\partial dv_j^B}{\partial z_j}\propto\int_{\underline{t}_j}^{\bar{t}}dG_t(\iota)+\Delta_1\frac{\partial\Theta_j}{\Theta_j\partial\underline{t}_j}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)+\frac{\Delta_2\partial\Theta_j}{N\partial\underline{t}_j}\equiv f_{dv}.$$

Note that given $-tg_t'(t)<g_t(t)$, we have $\frac{\partial^2\Theta_j}{\partial\underline{t}_j^2}<0$. Thus:

$$\begin{aligned}\frac{\partial f_{dv}}{\partial\underline{t}_j} &= -g_t(\underline{t}_j)+\Delta_1\frac{\partial^2\Theta_j}{\Theta_j\partial\underline{t}_j^2}\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota)+\Delta_1\frac{\partial\Theta_j}{\Theta_j\partial\underline{t}_j}\int_{\underline{t}_j}^{\bar{t}}(-1)dG_t(\iota)\\ &\quad+\frac{\Delta_2\partial^2\Theta_j}{N\partial\underline{t}_j^2}-\Delta_1\frac{1}{\Theta_j^2}(\frac{\partial\Theta_j}{\partial\underline{t}_j})^2\int_{\underline{t}_j}^{\bar{t}}(\iota-\underline{t}_j)dG_t(\iota).\end{aligned}\tag{56}$$

Note that:

$$-g_t(\underline{t}_j) + \Delta_1 \frac{\partial \Theta_j}{\Theta_j \partial \underline{t}_j} \int_{\underline{t}_j}^{\bar{t}} (-1) dG_t(\iota) < -g_t(\underline{t}_j) + \Delta_1 \frac{\underline{t}_j g_t(\underline{t}_j)}{\int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota)} \int_{\underline{t}_j}^{\bar{t}} (1) dG_t(\iota)$$

$$= -g_t(\underline{t}_j) + \Delta_1 g_t(\underline{t}_j) \frac{\int_{\underline{t}_j}^{\bar{t}} \underline{t}_j dG_t(\iota) g_t(\underline{t}_j)}{\int_{\underline{t}_j}^{\bar{t}} \iota dG_t(\iota)} < 0,$$

while the rest of the terms on the right-hand side of (56) are all negative, and thus we have $\frac{\partial f_{dv}}{\partial \underline{t}_j} < 0$. As $\lim_{\underline{t} = \bar{t}} f_{dv}(\underline{t}) = 0$, we know that $\frac{\partial dv_j^B}{\partial z_j} > 0$ when $\underline{t}_j \neq \bar{t}$. Hence $dv_j$ is increasing in $z_j$.

## C.6 Proof of Prediction

We decompose the proof of our model's testable prediction into two parts. In the first part, we show that conditional on employment, firms' labor productivity increases as $z$ increases. In the second part, we prove that conditional on employment, we get $\frac{\partial^2 v_j^B}{\partial \tau_T \partial LP_j} > 0$.

**Part I:** Conditional on employment, firms' labor productivity increases as $z$ increases.

Given (49), (50), (51), and (52), we calculate how $z$ and $t$ change along the iso-$l^B$ and iso-$v^B$ curves. Along the iso-$l^B$ curve, we have:

$$\frac{\partial lnt_j}{\partial lnz_j} \mid l^B = -\frac{\sigma - 1}{1 + \Delta_1 M_j - \frac{\Delta_1 t_j}{\Theta_j}} < 0.$$

Along the iso-$v^B$ curve, we have:

$$\frac{\partial lnt_j}{\partial lnz_j} \mid v^B = -\frac{\theta_1 \Theta_j}{t_j} < 0.$$

Therefore:

$$\frac{\partial lnt_j}{\partial lnz_j} \mid v_B - \frac{\partial lnt_j}{\partial lnz_j} \mid l^B = -\frac{1 + \Delta_1 M_j - \Delta_1(\sigma - 1) + (\sigma - 1)}{1 + \Delta_1 M_j - \frac{\Delta_1 t_j}{\Theta_j}}. \quad (57)$$

Recall that $\Delta_1 \equiv 1 - \frac{(\sigma-1)}{\theta}$, hence (57) can be reduced to:

$$\frac{\partial lnt_j}{\partial lnz_j} \mid v_B - \frac{\partial lnt_j}{\partial lnz_j} \mid l^B = -\frac{1 + \Delta_1 M_j + \frac{(\sigma-1)^2}{\theta}}{1 + \Delta_1 M_j - \frac{\Delta_1 t_j}{\Theta_j}} < 0.$$

Denoting the number of production workers employed to produce tasks for other firms as $l_j^T$, we know that $\frac{\partial \pi_j^T}{\partial t_j} > 0$ from the comparative statics proof in Section C.2. Because of constant markups, this in turn implies that $\frac{\partial l_j^T}{\partial t_j} > 0$. Hence:

$$\frac{\partial lnt_j}{\partial lnz_j} \mid l = -\frac{z_j}{t_j}\frac{\frac{\partial l_j^B}{\partial z}}{\frac{\partial l_j^B}{\partial t_j}+\frac{\partial l_j^T}{\partial t_j}} > -\frac{t_j}{z_j}\frac{\frac{\partial l_j^B}{\partial t_j}}{\frac{\partial l_j^B}{\partial z}} \equiv \frac{\partial lnz_j}{\partial lnt_j} \mid l_B. \tag{58}$$

Therefore, $\frac{\partial lnt_j}{\partial lnz_j} \mid v_B - \frac{\partial lnt_j}{\partial lnz_j} \mid l < 0$ holds as well. This in turn implies that holding employment constant, with the increase in $z$, $v^B$ must increase, since:

$$\frac{\partial v_j^B}{\partial z_j} \mid l = \frac{\partial v_j^B}{\partial z_j} + \frac{\partial v_j^B}{\partial t_j}\frac{\partial t_j}{\partial z_j} \mid l \propto -\frac{\partial lnt_j}{\partial lnz_j} \mid v_B + \frac{\partial lnt_j}{\partial lnz_j} \mid l > 0.$$

Recall that the labor productivity of firm $j$ is given by:

$$LP_j = \frac{v_j^B}{l_j} + (1+\frac{1}{\theta}).$$

Holding $l_j$ constant, $LP_j$ is positively associated with $v_j^B$. Therefore, conditional on employment, firms' labor productivity increases as $z$ increases.

**Part II:** $\frac{\partial^2 v_j^B}{\partial \tau_T \partial LP_j} \mid l > 0$. Consider two firms $j$ and $j'$ with the same employment, but $LP_j > LP_{j'}$. From Part I, we know that $z_j > z_{j'}$ must hold. Moreover, given (58), it is easy to verify that $\frac{\partial lnt_j}{\partial lnz_j} \mid l < 0$. Therefore, we have $t_j < t_{j'}$. Recall that in Section C.5 we proved Proposition 2 and showed that $\frac{\partial^2 v_j^B}{\partial \tau_T \partial z_j} > 0$ and $\frac{\partial^2 v_j^B}{\partial \tau_T \partial t_j} < 0$. Hence, it immediately follows that $\frac{\partial v_j^B}{\partial \tau_T} > \frac{\partial v_{j'}^B}{\partial \tau_T}$. This concludes the proof that $\frac{\partial^2 v_j^B}{\partial \tau_T \partial LP_j} \mid l > 0$.