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# ACCOUNTING FOR THE EVOLUTION OF CHINA'S PRODUCTION AND TRADE PATTERNS

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**ABSTRACT**

This paper studies the evolution of China's production and trade patterns during its integration into the global economy. We document and explain new facts concerning changes in production and exports at the industry and firm levels using microdata and a quantitative Ricardian and Heckscher–Ohlin model with heterogeneous firms. Counterfactual simulations reveal that capital deepening made China's production and exports more capital-intensive, although labor-biased productivity growth acted as a counterforce. Consistent with the data, our model demonstrates that China's trade openness peaked around the mid-2000s and fell until the 2020s, while the world's exposure to Chinese exports rose continuously.

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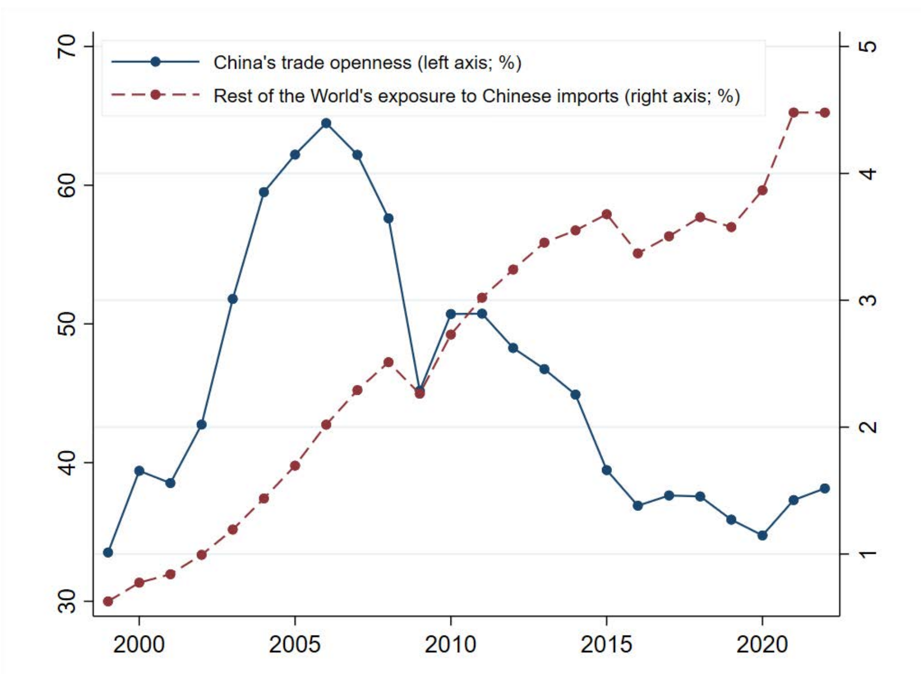
# 1 Introduction

Since its accession to the World Trade Organization (WTO) in 2001, China has become a manufacturing powerhouse and champion of international trade. After initially focusing on labor-intensive products like textiles and apparel, China rapidly expanded its manufacturing capabilities and is now competing head-to-head with capital-abundant countries in the manufacturing of products like machinery, electronics, and transportation vehicles. This transformation is evident in the substantial growth of the Rest of the World's (RoW) exposure to Chinese imports, which increased more than seven-fold from 1999 to 2022, as shown in Figure 1. This substantial increase in imports from China, often referred to as the "China shock," has generated wide-ranging repercussions worldwide.[1] Paradoxically, China's trade openness peaked around the mid-2000s at about 64% and has been on a declining trend for almost two decades, currently standing at a level similar to that of before its WTO accession.




**Notes**: Trade openness is measured by the sum of exports and imports divided by GDP. The RoW's exposure to Chinese imports is measured by total Chinese exports divided by the RoW's GDP (data source: World Bank).

Figure 1: China's Trade Openness and Rest of the World's Exposure to Chinese Exports

In this paper, we demonstrate that changes in factor endowments, technology, and trade costs jointly

[1]A growing body of research shows that the "China shock" has had far-reaching impacts on the labor market, technological change, and elections in other countries (Autor et al., 2013; Autor et al., 2020; Bloom et al., 2016; Pierce and Schott, 2016).

account for the underlying evolution of China's production and trade patterns at the industry and firm levels, as well as the secular trends in its integration into the global economy. Leveraging micro firm-level data, we document changes in the distribution of production and exports across industries and within industries across firms. Through a quantitative model that incorporates comparative advantage and heterogeneous firms, we demonstrate that, in addition to trade liberalization, changes in technologies and endowments have played a significant role in reshaping China's comparative advantage and driving the observed micro and macro evolution. Our study not only enhances the understanding of the "China shock" but also contributes to the broader understanding of China's integration into the global economy. In addition, this study offers lessons and insights for other emerging and developing economies seeking to interpret and learn from China's experience.

The standard view of the evolution of China's production and trade patterns is a typical Heckscher–Ohlin (HO) story: China first specialized in labor-intensive activities when China was labor-abundant, and, as the country accumulated capital, it shifted to capital-intensive activities. Consistent with this conventional view, we find that the accumulation of capital endowments made Chinese production more capital-intensive. Unlike the standard HO story (and consistent with the Ricardian story), however, we find that sector-biased productivity growth favored labor-intensive industries and provided a counter-balancing force to maintain China's comparative advantage in labor-intensive industries. The labor-biased productivity growth boosted firms' export participation in labor-intensive industries more than it did in capital-intensive industries. However, as capital deepening and productivity growth continued, China became more similar to the RoW in terms of endowments and technology. Therefore, there was less scope for comparative advantage to be exploited. Firms' export participation began to decline, and China's trade openness consequentially dropped. These forces drove the rise and fall of China's trade openness. Nevertheless, the RoW's exposure to Chinese imports continued to rise as the Chinese economy grew relatively faster than the RoW, which dominated the effect of declining trade openness.

We begin by presenting three newly discovered stylized facts regarding the evolution of Chinese production and exports between 1999 and 2007 using firm-level data. 1) In 2007, manufacturing production exhibited a lower degree of labor intensity than it did in 1999. 2) In contrast, the labor intensity of the export sector remained almost unchanged and, if anything, increased slightly. Notably, labor-intensive industries experienced a rise in export intensity, and the proportion of firms engaged in exporting increased, while capital-intensive industries witnessed a decline in both aspects. 3) Total factor productivity growth was more pronounced in labor-intensive industries than in capital-intensive industries.

These facts serve as the impetus for the development of a comprehensive framework that integrates the continuous HO and Ricardian models while incorporating firm heterogeneity, as proposed by Melitz (2003). This unified framework aims to quantitatively explain the observed evolution of production and trade patterns. Notably, the increased abundance of capital in China in 2007 aligns with the predictions of HO theory, suggesting a greater production and export focus on capital-intensive goods. However, Fact 2) indicates that China has gained comparative advantages in labor-intensive sectors, partially driven by productivity growth (as Fact 3 suggests). These findings collectively emphasize the insufficiency of considering either HO or Ricardian theory in isolation and underscore the need for a unified model.[2]

Our model is constructed within the frameworks of the HO and Ricardian theories of comparative advantage, drawing on the seminal work of Dornbusch, Fischer, and Samuelson (1977, 1980), hereafter referred to as DFS. In line with Romalis (2004), our model posits that countries produce and export more in industries with comparative advantages than in industries with comparative disadvantages. While all firms export in Romalis's model, export propensity, measured by the conditional probability of exporting, is higher in industries with a stronger comparative advantage in our model. Bernard et al. (2007a) also explore a two-sector HO model with heterogeneous firms. However, their analysis is limited to scenarios in which factor endowments fall within the "diversification cone," allowing countries to engage in production across both sectors. In our model, specialization occurs when countries exhibit sufficient dissimilarity in their technologies or factor endowments.

The unified model enables us to assess the relative importance of changes in factor endowments, technology, and trade costs in explaining the observed evolution in production and trade patterns across various industries and in shaping China's integration into the global economy. We first conducted separate estimations of the model's underlying parameters by fitting the model to the economies of China and the RoW for 1999 and 2007. The estimation results reveal that noteworthy changes occurred between 1999 and 2007. Specifically, the capital-to-labor ratio in Chinese manufacturing production more than

[2]This echoes earlier studies by Trefler (1993, 1995), Harrigan (1997), and Davis and Weinstein (2001), which all emphasize the importance of considering the combined effects of endowments and technology when studying countries' production and trade patterns. We extend their analyses to the case of heterogeneous firms.

doubled, technology experienced significant improvements that favored labor-intensive industries, and trade liberalization led to a reduction of about 25% in variable trade costs.[3]

Using the estimated model, we next disentangled the evolution of production and trade patterns from 1999 to 2007 through counterfactual simulations. The simulations indicate that changes in factor endowments played a primary role in driving the shift of Chinese production toward capital-intensive industries. The process of capital deepening, in particular, led to a larger increase in production in capital-intensive industries than in labor-intensive industries. Additionally, sector-biased technological advancements that favored labor-intensive industries emerged as the primary driver of export adjustments. Consistent with the observed higher productivity growth in labor-intensive industries, our estimations suggest that China's Ricardian comparative advantages in these industries grew over time. The technological advancements prompted a greater number of firms to engage in exporting in labor-intensive industries than in capital-intensive industries. Finally, changes in trade costs increased export propensity in all industries, which significantly increased the trade openness of China and the RoW's exposure to Chinese imports.

We then extended the analysis to 2017, the year before the start of the U.S.–China trade war. Due to a lack of high-quality, firm-level data during this later period, instead of re-estimating the model, we conducted counterfactual analyses by replacing the technology and endowment parameters of the 2007 economy with those calibrated for the 2017 economy.[4] We calibrated the endowment parameters using the Penn World Table (Feenstra et al., 2015). For the technology parameters, we developed a sufficient statistics approach to estimate the relative productivity between China and the RoW in 2013 and extrapolated it to 2017. Applying these parameters to the 2007 economy, we find that China's continued capital deepening increased the capital intensity of Chinese production and exports. As the capital-labor ratio and the level of technology between China and the RoW became more similar, firms' export intensity declined substantially, even without changes in trade costs, which reduced China's trade openness by 16% from 2007 to 2017. Nevertheless, the RoW's exposure to Chinese imports increased by about 50% due to the expansion of production spurred by increased capital endowments and technological advancements in China.

[3]The sector-biased productivity growth we observe is consistent with the findings of Di Giovanni et al. (2014). In this paper, we provide further discussion and collaborative evidence.

[4]The latest firm-level data we have are for 2013. The National Bureau of Statistics of China stopped reporting key variables from the firm-level survey, including value-added and intermediate inputs, after 2008. See Brandt et al. (2014) for a detailed discussion of the data.

Our study highlights the important implications of firm heterogeneity on production and trade patterns. By employing our estimated model, we are able to separate and evaluate the impact of export selection on Ricardian comparative advantage and productivity growth. We find that variation in export selection across industries contributes to Ricardian productivity differences, as theorized by Bernard et al. (2007a). The effect of export selection proves to be non-trivial, with a stronger influence observed in labor-intensive industries than in capital-intensive industries. Specifically, for 1999, the effect of export selection increased China's productivity relative to the RoW by 6.1% in the most capital-intensive industries and by 10.7% in the most labor-intensive industries. For 2007, the corresponding figures are 7.3% and 26.2%, respectively. Consequently, export selection reinforced China's sector-biased technological change relative to the RoW, intensifying over time. When considering the aggregate impact, export selection generated overall productivity gains (Melitz, 2003). We find that export selection contributed to an annual increase of 0.49% in China's aggregate productivity and accounted for 11.2% of the country's overall manufacturing productivity growth from 1999 to 2007. These findings deepen our understanding of the role of international trade in explaining China's productivity growth.

Our paper contributes to multiple strands of the literature. First, it contributes to the extensive body of research on production and trade patterns (Davis and Weinstein, 2001; Harrigan, 1997; Trefler, 1993, 1995). Our study provides a quantitative assessment of the joint effects of Ricardian and HO forces. In a similar vein, Chor (2010), Morrow (2010), and Morrow and Trefler (2022) conduct quantitative analyses to explore the joint role of endowments and technology. Relative to these studies, our study is the first to consider the interplay between the comparative advantages of the Ricardian and HO models in conjunction with heterogeneous firms within a quantitative model. By focusing on supply-side forces, our model enables us to assess the relative importance of changes in factor endowments, technology, and trade costs in elucidating the observed transformations in production and trade patterns across various industries.[5] By considering firm heterogeneity, our model effectively accounts for adjustments occurring within industries, particularly changes in export propensity and intensity.

[5] Similarly, recent research on structural transformation, such as Uy et al. (2013) and Fajgelbaum and Redding (2022), underscores the role of trade in elucidating the long-term shifts in the relative importance of the agriculture, manufacturing, and service sectors. Matsuyama (2019) examines the impact of non-homothetic demand on the process of structural transformation. As per his analysis, an increasing inclination of Chinese consumers toward capital-intensive goods may have propelled the shift toward a more capital-intensive production structure. He suggests that this shift in demand also entails heightened levels of innovation and enhanced productivity growth in capital-intensive sectors. Nevertheless, our findings diverge from this perspective, which we explore further in subsequent discussions.

Our contribution extends to the literature on firm heterogeneity and comparative advantage. Bernard et al. (2007a) make a groundbreaking contribution by incorporating Melitz (2003) into a two-country, two-sector HO model.[6] They demonstrate that export selection gives rise to an endogenous Ricardian comparative advantage, which reinforces the pre-existing comparative advantage. Subsequently, researchers such as Okubo (2009), Lu (2010), Fan et al. (2011), Burstein and Vogel (2017), and Gaubert and Itskhoki (2021) explore firm heterogeneity within either a Ricardian or HO framework. In our study, we integrate both Ricardian and HO comparative advantages into our model.[7] Notably, our paper is the first to quantitatively examine the endogenous Ricardian comparative advantage stemming from firm heterogeneity, a mechanism initially identified by Bernard et al. (2007a). Our findings reveal that export selection gives rise to noteworthy variations in productivity across industries. Consequently, adjustments within and between industries are interdependent and not mutually exclusive.

In addition, we make a methodological contribution by developing a sufficient statistics approach to estimate relative industry productivity, hence Ricardian comparative advantage, based on the observed export propensity of firms and other parameters, including factor costs, trade costs, and trade elasticity. Although we are not the first to identify technological parameters from trade data (see, for example, Costinot et al., 2012; Levchenko and Zhang, 2016; Waugh, 2010), we deviate from the existing approach that relies on the gravity equation and the Ricardian model of Eaton and Kortum (2002), which assumes perfect competition. We show that technological parameters can be derived from a few variables and reduced-formed elasticities in an environment of imperfect competition and endogenous selection of heterogeneous firms.

Finally, our contribution extends to the literature that investigates China's integration into the global economy and the implications for the RoW. It has been observed that Chinese exports have grown in sophistication (Schott, 2008; Wang and Wei, 2010) and that Chinese production has expanded stages in the global production line (Chor et al., 2021). As mentioned, substantial evidence suggests that the "China shock" has had a global impact. A growing number of studies explore the welfare implications of the "China shock" (Di Giovanni et al., 2014; Hsieh and Ossa, 2016) and its origins (Amiti and Freund,

[6] As previously mentioned, their focus revolves around scenarios in which endowments fall within the "diversification cone," while we allow for specialization.

[7] Huang and Ottaviano (2024) also integrate firm heterogeneity into a model with Ricardian and HO comparative advantages, albeit in an environment with variable markups.

2010; Brandt and Lim, 2024). Although we also account for the rise of the RoW's exposure to Chinese imports (Brandt and Lim, 2024), we focus on the evolution of production and trade patterns over time, i.e., the distribution of outputs and exports across and within industries.[8] Our analysis further enables us to study the associated income distribution between capital and labor. We show that the "China shock" increases, rather than decreases, the global wage-to-rental ratio and therefore creates relative benefits for labor factors in the RoW.[9]

The remainder of the paper is organized as follows. Section 2 presents the observed data patterns based on Chinese firm-level data. Section 3 develops the model and is followed by our equilibrium analysis in Section 4. Section 5 discusses the estimation of the model and presents our quantitative results, including counterfactual experiments and robustness checks. Section 6 concludes the paper.

# 2 Motivating Evidence

In this section, we document stylized facts about the evolution of production and trade patterns over time from 1999 to 2007. This sample period is chosen for two reasons. First, it covers the episode of China's trade liberalization since its WTO accession in 2001 and the rest of the world started to feel the "China shock" (Autor et al., 2013) during this period. Second, this is also the period when high-quality Chinese micro firm-level data are available to researchers. Later, we will use more recent data and our model to extend the quantitative analysis to the year 2017.

## 2.1 Data

The data we use is the Chinese Annual Industrial Survey, which covers all state-owned enterprises (SOE) and non-SOEs with annual sales higher than 5 million RMB Yuan. The dataset provides information on balance sheets, income statements, cash flow statements, and firms' identification, ownership, exports, employment, etc. We focus on manufacturing firms and exclude utility and mining firms. We follow Brandt et al. (2012) to drop firms with missing, zero, or negative capital stock, exports, or value-added

[8]In accounting for China's export growth, Brandt and Lim (2024) further consider changes in foreign demand and access to foreign intermediate inputs.

[9]There are two forces that worked together with the distribution effect from trade liberalization. First, capital accumulation in China increased the global supply of capital, which reduced the capital rental rate. Second, productivity growth that favored labor-intensive industries raised the wage rate.

and exclude firms with less than eight employees. Panel (a) of appendix Table A.1 provides a summary of the cleaned data. We can see that both Chinese production and exports have expanded dramatically during the sample period: firms' average output and exports more than doubled from 1999 to 2007.

## 2.2 Definition of Industry

Our first goal is to measure the industrial distribution of production and exports to their evolution. However, conventional industry classification potentially fails to group firms and products appropriately. As Schott (2003, page 687) argues, "testing the key insight of Heckscher-Olin theory... requires grouping together products that are both close substitutes and manufactured with identical techniques. Traditional aggregates can fail on both counts."[10] Indeed, under traditional industry classification, firms within the same industry can use quite different production technologies. In appendix Table A.2, we show that there are substantial variations of labor share across firms within each two-digit industry under the Chinese Industry Classification (CIC), while labor share is measured as $\frac{labor\ cost}{value\ added}$.[11] Firms' average labor share is 29.3%, but its standard deviations fluctuate around 20% across industries.

In addition, the labor share between exporters and non-exporters differs systematically under conventional industry classifications. As also shown in appendix Table A.2, Chinese exporters are 11.7% more labor-intensive than non-exporters on average. Such differences persist even when we use the 4-digit CIC industry classification, which includes more than 400 industries.[12]

To overcome these problems, we follow Schott's idea to define the industry as "HO aggregate" and regroup firms according to their labor share. For example, firms with labor shares from 0 to 0.01 are lumped together and defined as Industry 1. In total, we have 100 industries.[13] Industries with higher indexes are of higher labor intensity. Following the Heckscher-Ohlin capital and labor paradigm, we call

[10] Similarly, Lind and Ramondo (2023) argue that observed sectoral classifications may not correspond to actual technology classes employed in each sector in a Ricardian framework.

[11] Labor cost is the sum of payable wage, labor and employment insurance fee, and total employee benefits payable. We drop firms with labor shares larger than one or less than zero. Hsieh and Klenow (2009) and Bradt et al. (2014) pointed out that the labor share from the firm survey is significantly less than the numbers reported in the Chinese national accounts. They argued that it could be explained by non-wage compensation. Aggregate capital share has been increasing globally, as documented by Karabarbounis and Neiman (2014), and in China, as documented by Chang et al. (2015).

[12] Similarly, Bernard et al. (2007b) find US exporters are more capital-intensive than non-exporters. Using capital-labor ratios as the indicator of factor intensity, Ma et al. (2014) find that Chinese exporters are less capital-intensive than non-exporters.

[13] Such an industry definition has also been used by Ju, Lin, and Wang (2015) to study industry dynamics.

the non-labor factors "*capital*" in the rest of the paper.

Before examining changes in industrial distribution from 1999 to 2007, we look at changes in aggregate factor allocation and export participation in panel (b) of Table A.1. There were significant changes in aggregate factor allocation and export participation. The average capital share of manufacturing firms increased by $4.0\%$. So overall manufacturing production was more capital-intensive in 2007 than in 1999. In contrast, exporters became slightly more labor-intensive. The average capital share of exporters decreased by $0.40\%$. The fraction of exporting firms remained around 25.0%. The share of goods exported increased by about $2.4\%$, from 18.4% to 20.8%.

Table 1: Evolution of Production and Trade Patterns

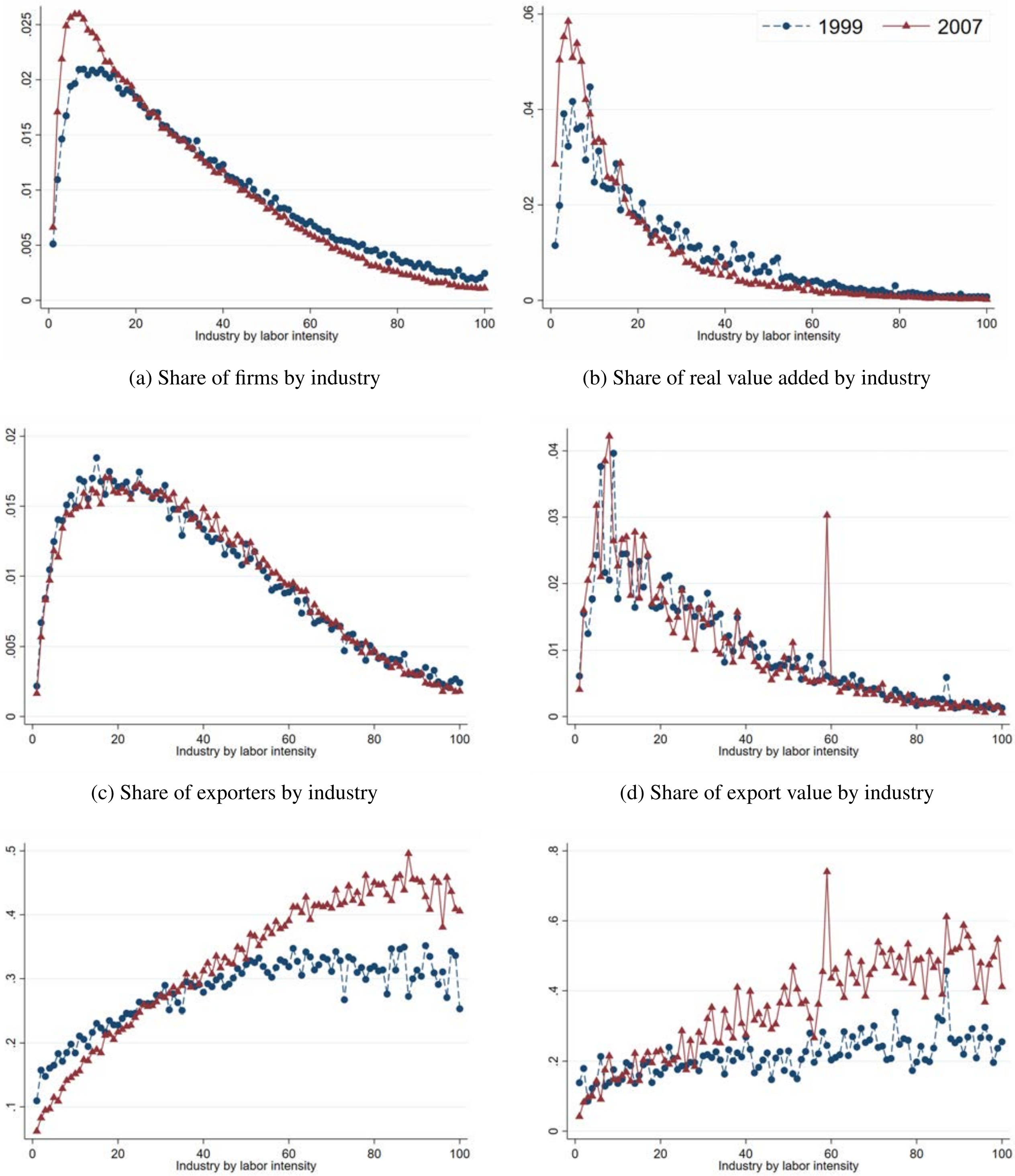
| | (1) | (2) | (3) |
|---|---|---|---|
| | Year 1999 | Year 2007 | Difference |
| Panel **(a)**: Capital-intensive Industries' Production | | | |
| share in total firm number | 76.6% | 81.8% | 5.2% |
| share in total employment | 67.3% | 76.2% | 8.9% |
| share in total value-added | 87.7% | 93.8% | 6.1% |
| Panel **(b)**: Capital-intensive Industries' Exports | | | |
| share in total exporter number | 70.8% | 70.3% | -0.5% |
| share in total export value | 81.1% | 81.0% | -0.1% |
| average export propensity | 23.7% | 21.4% | -2.3% |

**Notes:** Capital-intensive industries are industries with labor shares less than 0.5. Column (3) is the difference between column (2) and column (1).

## 2.3 Stylized Facts

**Fact 1**: *The Chinese manufacturing production became more capital-intensive over time.*

We first examine China's production pattern. Figure 2 (a) plots the distribution of production across "industries." Each data point on the figure represents the share of firms operating in an industry. The share of firms producing in capital-intensive industries increases over time as the whole distribution in 2007 shifts to the left of the distribution in 1999. Figure 2 (b) plots the distribution of outputs in terms of the real value added. Again, firms in capital-intensive industries accounted for larger fractions in 2007 than in 1999. These can also be seen in panel (a) of Table 1, which compares the production of capital-intensive industries (industries with labor intensity less than 0.5) across years. Column (3) indicates that the share




(a) Share of firms by industry

(b) Share of real value added by industry

(c) Share of exporters by industry

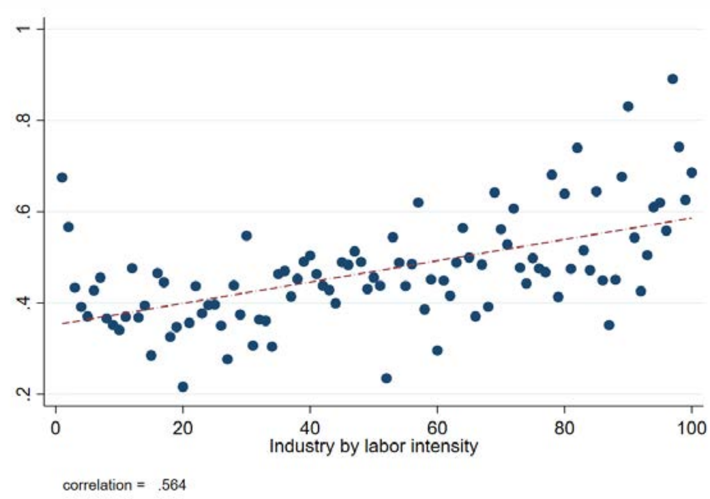
(d) Share of export value by industry

(e) Export propensity by industry

(f) Export intensity by industry

**Notes**: Figures (a) - (d) plot each industry's share in the total number of firms, total value added, total number of exporters, and total exports, respectively. Figures (e) and (f) plot the share of firms that export and sales exported within each industry, respectively.

Figure 2: Evolution of Chinese Production and Exports from 1999-2007




**Notes**: This figure plots the growth rate of the average total factor productivity across firms for each industry.

Figure 3: TFP Growth 1999 - 2007

of capital-intensive firms increased by 5.2 percentage points from 1999-2007. Their employment and value-added shares increased by 8.9 and 6.1 percentage points, respectively.

**Fact 2**: *The labor intensity of Chinese exports stays almost unchanged over time. Export participation increased in labor-intensive industries and decreased in capital-intensive industries.*

Next, we examine China's trade pattern. Figure 2 (c) plots the distribution of exporters in 1999 and 2007. The distribution shifted slightly toward labor-intensive industries over time. Figure 2 (d) plots the distribution of export value. We can see that the distributions are almost indistinguishable between the two years. At the same time, we find substantial adjustments within industries over time. Figure 2 (e) plots the export propensity for each industry, defined as the number of exporters divided by the total number of firms. We find that export propensity increased over time in labor-intensive industries but decreased in capital-intensive industries. Figure 2 (f) plots export intensity, i.e., exports divided by total sales. Its pattern is similar to export propensity.

These adjustments are also shown in Panel (b) of Table 1. Column (3) indicates that the share of capital-intensive exporters decreased by 0.5% from 1999-2007. Their contribution to total exports stayed around 81.0%. But their average export propensity decreased by 2.3% from 23.7% in 1999 to 21.4% in 2007. We summarize these findings as follows.

**Fact 3**: *Total factor productivity growth was faster among labor-intensive industries than capital-intensive* *industries*.

As Trefler (1993, 1995), Harrigan (1997), and Davis and Weinstein (2001) all point out, we cannot ignore the importance of technology when examining the HO theory. Therefore, we next examine productivity growth from 1999 to 2007. Following Brandt et al. (2012) and Brandt et al. (2017), we assembled a panel of firms from 1999-2007 to estimate the total factor productivity (TFP) of firms using the Levinsohn and Petrin (2003) method. Figure 3 plots each industry's estimated TFP growth rates and its (unweighted) best-fitted linear line against the labor intensity.[14] There are two basic observations. First, all industries witnessed growth in TFP. Second, TFP grew faster in labor-intensive industries. In other words, productivity growth is biased toward labor-intensive industries.

## 2.4 Robustness Checks

We conduct a few checks on the robustness of the stylized facts. The first concern might be that our findings are driven purely by the "HO aggregate." We used a four-digit CIC industry classification to regenerate all facts and show that this is not the case. As evident in appendix Figure A.1, the facts continue to hold. Nevertheless, the patterns are noisier than using the "HO aggregate."

The facts we have uncovered are not limited to the long difference between 1999 and 2007. We examine the annual adjustments during the same period using the following specification:

$$\Delta Y_{it} = \alpha Z_i + \epsilon_{it},$$

where $\Delta Y_{it}$ is the change of industry $i$ outcome $Y$ from period t-1 to t: $\Delta Y_{it} = Y_{it} - Y_{it-1}$, $t = 2000$, 2001, ..., 2007, and $Z_i$ is the average labor intensity of industry $i$ across years. This specification allows us to study how annual changes in industry outcomes are systematically related to labor intensity. Table 2 presents the results. From columns (1) to (3), we find that production becomes capital-intensive over time as changes in the share of firms, value-added, and sales all decrease with labor intensity. Columns (4) and (5) indicate that the correlations between changes in the share of exporters and export volume and labor intensity are not statistically significant. In contrast, within-industry reallocation across exporters and

[14] Appendix Figure A.5 (a) plots the estimated average TFP for each industry for both years. We find that industry TFP tends to be lower among labor-intensive industries in both years.

non-exporters systematically correlates with labor intensity, as shown in columns (6) and (7). Changes in export propensity and export intensity tend to rise with labor intensity. Finally, column (8) confirms that TFP growth was faster among labor-intensive industries.

Table 2: Annual Adjustments in Production and Trade

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Firm # | Value added | Sales | Exporter # | Export volume | Export propensity | Export intensity | TFP |
| labor intensity | -0.000618$^a$ | -0.00104$^a$ | -0.00105$^a$ | 0.0000581 | -0.000226 | 0.0271$^a$ | 0.0382$^a$ | 0.0292$^a$ |
| | (0.0000874) | (0.000348) | (0.000300) | (0.0000385) | (0.000264) | (0.00138) | (0.00307) | (0.00525) |
| Constant | 0.000315$^a$ | 0.000523$^b$ | 0.000528$^b$ | -0.0000267 | 0.000114 | -0.00779$^a$ | -0.00222 | 0.0442$^a$ |
| | (0.0000582) | (0.000237) | (0.000205) | (0.0000245) | (0.000185) | (0.000481) | (0.00150) | (0.00269) |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.0718 | 0.0123 | 0.0141 | 0.000375 | 0.000182 | 0.265 | 0.0339 | 0.448 |
| No. of observations | 800 | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

**Notes**: The dependent variables are the first difference of the corresponding variable in each column. The estimation method is OLS. Robust standard errors clustered at the industry level are reported in parentheses. Significance levels are indicated by $a$, $b$, and $c$ at 0.01, 0.05, and 0.1, respectively.

We next checked whether any particular economic institution in China drives our results. We regenerated the three stylized facts using various sub-samples in appendix Figure A.2. To address the concern of the expiration of the Multi Fibre Arrangement in 2005 and rising exports in the labor-intensive textile and garment industries, we excluded the corresponding two-digit CIC industry categories per Khandelwal et al. (2013). We excluded all SOEs from our sample to deal with the SOE reform that started in the 1990s, which might favor specific industries over others. Finally, to address the effects of processing trade and export subsidies, we excluded all pure exporters who are predominantly processing exporters and thus benefit from export subsidies.[15] In these various sub-samples, our basic findings are qualitatively preserved.

The next concerns are about the quality of Chinese firm-level data and how we classify industries. Researchers have uncovered certain anomalies in the Chinese data (Huang et al., 2020). To deal with outliers that report extreme capital intensities, we dropped firms among the top and bottom five percentiles in terms of capital intensity. In addition, rather than casting the firms into 100 bins with varying numbers of firms, we followed Lu (2010) to rank firms by capital intensity and divide them into bins with equal numbers of firms. The results are in appendix Figure A.3. Again, we find the baseline facts continue to hold.

[15] Pure exporters are exporters with export intensity greater than 70% following Defever and Riaño (2017).

## 2.5 Discussions

Putting stylized facts 1 and 2, we have a seemingly puzzling observation. Production became more capital-intensive in 2007 than in 1999, while exports did not. Stylized fact 2 is at odds with the Rybczynski theorem that a country's production and exports become more capital-intensive when the country becomes more capital-abundant. It even suggests China gained a comparative advantage in labor-intensive industries over time. These adjustments are unlikely to be driven by the force of non-homothetic demand. Chinese production could have become more capital-intensive if Chinese consumers' demand for capital-intensive goods increased disproportionally when they became more affluent. Then, there will be more innovation and faster productivity growth in capital-intensive industries due to the *"Schmookler effect"* (Matsuyama, 2019). But this is inconsistent with stylized fact 3 that productivity growth was faster in labor-intensive industries, and the higher innovation intensity among labor-intensive industries documented in Appendix Figure A.4.[16] The remaining paper aims to develop a quantitative supply-side model that simultaneously explains facts 1 and 2 and is consistent with fact 3.

# 3 Model Setup

To account for the empirical features of the data, we built a model that incorporates Ricardian comparative advantage, HO comparative advantage, and firm heterogeneity. The model embeds heterogeneous firms (Melitz, 2003) into a Ricardian and HO theory within a continuum of industries (DFS 1977, 1980). Suppose there are two countries, Home and Foreign, which differ in technology and factor endowments. Without loss of generality, we assume that the Home is labor abundant, that is: $L/K > L^*/K^*$, and has a Ricardian comparative advantage in labor-intensive industries.[17] There is a continuum of industries indexed by $z \in [0, 1]$. A higher $z$ stands for higher capital intensity. Each industry is inhabited by heterogeneous and atomistic firms that produce differentiated varieties of goods sold in markets with monopolistic competition.

[16] The firm survey data report firms' expenditure on R&D from 2005-2007. Innovation intensity is measured by the ratio of R&D expenditure to output for each industry.

[17] Variables with "*" are for Foreign. When quantifying the model, we allow HO and Ricardian comparative advantages to favor different industries.

## 3.1 Demand Side

There is a continuum of identical and infinitely lived households that can be aggregated into a representative household. The following utility function gives the representative household's preference over the continuum of differentiated goods:

$$U = \int_0^1 b(z) \ln Q(z) dz,$$

where $b(z)$ is the expenditure share on industry $z$ and satisfies $\int_0^1 b(z)dz = 1$, and $Q(z)$ is the sub-utility function with Constant Elasticity of Substitution (CES) over the consumption of industry $z$ varieties: $Q(z) = (\int_{\omega \in \Omega_z} q_z(\omega)^\rho d\omega)^{1/\rho}$, where $q_z(\omega)$ is the consumption of variety $\omega$ and $\Omega_z$ is the varieties available for industry $z$. We assume $0 < \rho \leq 1$ so that the elasticity of substitution $\sigma = \frac{1}{1-\rho} > 1$. The demand function for individual varieties is given by:

$$q_z(\omega) = Q(z)(\frac{p_z(\omega)}{P(z)})^{-\sigma}, \tag{1}$$

where $P(z) = (\int_{\omega \in \Omega_z} p_z(\omega)^{1-\sigma} d\omega)^{\frac{1}{1-\sigma}}$ is the dual price index defined over price of varieties $p_z(\omega)$.

## 3.2 Production

Following Melitz (2003), we assume that production incurs a fixed cost common across firms in the same industry, but the variable cost varies with firm productivity. Firm productivity $A(z)\varphi$ has two components: $A(z)$ is the industry-specific productivity, and $\varphi$ is an idiosyncratic firm-level component drawn from a common distribution $G(\varphi)$. Following Romalis (2004) and Bernard et al. (2007a), we assume that fixed costs are paid using capital and labor with a factor proportion that matches that of production, and the total cost function is Cobb-Douglas in both factors:

$$\Gamma(z, \varphi) = \left( f_z + \frac{q(z, \varphi)}{A(z)\varphi} \right) r^z w^{1-z}, \tag{2}$$

where $q(z,\varphi)$ is the output quantity, $r$ and $w$ are rents for capital and labor, respectively, and $z$ is capital intensity. We assume that the industry-specific productivity of Home relative to Foreign, $\Psi(z)$, is:

$$\Psi(z) \equiv \frac{A(z)}{A^*(z)} = \lambda A^z,\ \lambda > 0,\ A > 0, \tag{3}$$

where $\lambda$ captures the *absolute advantage* and $A$ captures the *comparative advantage*. An increase in $\lambda$ raises Home's relative productivity in all industries. If $A > 1$, Home is relatively more productive in capital-intensive industries and has Ricardian comparative advantages in those industries. If $A = 1$, $\Psi(z)$ does not vary with $z$, and there is no role for Ricardian comparative advantage. Under the assumption that Home has a Ricardian comparative advantage in labor-intensive industries, we have $0 < A < 1$.

Trade is costly. Firms that export need to pay a per-period fixed cost $f_{zx}r^z w^{1-z}$, which requires both labor and capital. In addition, there are variable iceberg trade costs. Firms need to ship $\tau$ units of goods for 1 unit of goods to arrive in the foreign market. Given the CES demand, profit maximization implies that the equilibrium price is a constant markup over the marginal cost. Hence, the exports and domestic prices satisfy:

$$p_{zx}(\varphi) = \tau p_{zd}(\varphi) = \tau \frac{r^z w^{1-z}}{\rho A(z)\varphi}, \tag{4}$$

where $p_{zx}(\varphi)$ and $p_{zd}(\varphi)$ are the export and domestic price, respectively. Given the pricing rule, firms' revenues from domestic and foreign markets $r_{zd}(\varphi)$ and $r_{zx}(\varphi)$ are:

$$r_{zd}(\varphi) = b(z)R\left(\frac{\rho A(z)\varphi P(z)}{r^z w^{1-z}}\right)^{\sigma-1}, \tag{5}$$

$$r_{zx}(\varphi) = \tau^{1-\sigma}\left(\frac{P(z)^*}{P(z)}\right)^{\sigma-1}\frac{R^*}{R} r_{zd}(\varphi), \tag{6}$$

where $R$ and $R^*$ are aggregate revenues for Home and Foreign, respectively. Firms have two sources of profit: profit earned from domestic markets and profit earned from foreign markets, which are given by

$$\begin{aligned} \pi_{zd}(\varphi) &= \frac{r_{zd}}{\sigma} - f_z r^z w^{1-z}, \\ \pi_{zx}(\varphi) &= \frac{r_{zx}}{\sigma} - f_{zx} r^z w^{1-z}. \end{aligned} \tag{7}$$

and the total firm profit $\pi_z(\varphi)$ is:

$$\pi_z(\varphi) = \pi_{zd}(\varphi) + \max\{0, \pi_{zx}(\varphi)\}. \tag{8}$$

A firm produces if its revenue at least covers the fixed cost, that is $\pi_{zd}(\varphi) \geq 0$. Similarly, it exports if $\pi_{zx}(\varphi) \geq 0$. The productivity cut-offs for zero-profit $\bar{\varphi}_z$ and for zero export profit $\bar{\varphi}_{zx}$ satisfy

$$\begin{aligned} r_{zd}(\bar{\varphi}_z) &= \sigma f_z r^z w^{1-z}, \\ r_{zx}(\bar{\varphi}_{zx}) &= \sigma f_{zx} r^z w^{1-z}. \end{aligned} \tag{9}$$

Using the zero-profit conditions above, we find that the productivity cut-offs satisfy

$$\bar{\varphi}_{zx} = \Lambda_z \bar{\varphi}_z, \tag{10}$$

where $\Lambda_z = \frac{\tau P(z)}{P(z)^*} \left[\frac{f_{zx} R}{f_z R^*}\right]^{\frac{1}{\sigma-1}} > 1$ implies selection into the export market: exporters are more productive than non-exporters. Since the empirical literature strongly supports selections into export, we focus on parameters where exporters are always more productive.[18] Each period, $G(\bar{\varphi}_z)$ fraction of firms exit upon entry. And $1 - G(\bar{\varphi}_{zx})$ fraction of firms export because they have sufficiently high productivity and earn positive profit from both domestic and foreign sales. Firms whose productivity is between $\bar{\varphi}_{zx}$ and $\bar{\varphi}_z$ sell only in the domestic market. So the ex-ante probability of exporting conditional on successful entry $\chi(z)$, or the export propensity, is given by

$$\chi(z) = \frac{1 - G(\bar{\varphi}_{zx})}{1 - G(\bar{\varphi}_z)}. \tag{11}$$

## 3.3 Free entry

As in Melitz (2003), firms face a constant probability $\delta$ of bad shock per period, forcing them to exit. The steady-state equilibrium is characterized by constant masses of firms entering an industry $M_{ez}$ and firms

[18] Lu (2010) explores the possibility that $\Lambda_z < 1$, i.e., exporters are less productive than non-exporters in the labor-intensive sectors of China. Dai et al. (2016) find that after accounting for processing exporters and using TFP as the productivity measure, exporters are still more productive than non-exporters.

producing $M_z$. The mass of firms entering equals the mass of firms exiting $(1 - G(\bar{\varphi}_z))M_{ez} = \delta M_z$. The entry cost is given by $f_{ez}r^z w^{1-z}$. The expected profit of entry comes from two parts: the *ex-ante* probability of successful entry times the expected profit from the domestic market until death and the *ex-ante* probability of export times the expected profit from exports until death. Free entry implies

$$\frac{1 - G(\bar{\varphi}_z)}{\delta} \left(\pi_{zd}(\widehat{\varphi}_z) + \chi(z)\pi_{zx}(\widehat{\varphi}_{zx})\right) = f_{ez}r^z w^{1-z}, \tag{12}$$

where $\pi_{zd}(\widehat{\varphi}_z)$ and $\chi(z)\pi_{zd}(\widehat{\varphi}_{zx})$ are the expected profit from Home and Foreign, respectively. $\widehat{\varphi}_z$ is the average productivity of all producing firms, and $\widehat{\varphi}_{zx}$ is the average productivity of exporters.

## 3.4 Market Clearing

In equilibrium, the sum of domestic and foreign spending on domestic varieties equals industry revenue:

$$R_z = b(z)RM_z \left(\frac{p_{zd}(\widehat{\varphi}_z)}{P(z)}\right)^{1-\sigma} + \chi(z)b(z)R^* M_z \left(\frac{p_{zx}(\widehat{\varphi}_{zx})}{P^*(z)}\right)^{1-\sigma}, \tag{13}$$

where the domestic price index $P(z)$ of good $z$ is given by:[19]

$$P(z) = \left[M_z p_{zd}(\widehat{\varphi}_z)^{1-\sigma} + \chi(z)^* M_z^* p_{zx}^*(\widehat{\varphi}_{zx}^*)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{14}$$

and $R$ and $R^*$ are home and foreign aggregate revenues. Factor market clearing conditions are:

$$L = \int_0^1 l(z)dz, \; K = \int_0^1 k(z)dz, \tag{15}$$

where $l(z)$ and $k(z)$ are the sectoral factor demand. Similar conditions hold in foreign.

## 3.5 Equilibrium

The equilibrium consists of the vector of $\{\bar{\varphi}_z$, $\bar{\varphi}_{zx}$, $P(z)$, $p_z(\varphi)$, $p_{zx}(\varphi)$, $r$, $w$, $R$, $\bar{\varphi}_z^*$, $\bar{\varphi}_{zx}^*$, $P^*(z)$, $p_z^*(\varphi)$, $p_{zx}^*(\varphi)$, $r^*$, $w^*$, $R^*\}$ for $z \in [0, 1]$, which is determined by the following conditions: a) firms' optimal

[19] The foreign price index $P^*(z)$ is defined in a symmetric way to $P(z)$.

pricing (4); b) free entry condition (12), and the relationship between productivity cut-offs (10); c) the price index (14) for each country and each industry; d) factor market clearing condition (15) in both countries; and e) goods market clearing condition (13).

**Proposition 1.** *There exists a unique equilibrium given by* $\{\bar{\varphi}_z, \bar{\varphi}_{zx}, P(z), p_z(\varphi), p_{zx}(\varphi), r, w, R, \bar{\varphi}_z^*, \bar{\varphi}_{zx}^*, P^*(z), p_z^*(\varphi), p_{zx}^*(\varphi), r^*, w^*, R^*\}$.

*Proof. See Appendix A.1.1.*

# 4 Equilibrium Analysis

The presence of trade cost, multiple factors, heterogeneous firms, asymmetric countries, and infinite industries make it challenging to find a closed-form solution to the model. We make two assumptions to simplify the analysis: 1) the productivity is Pareto distributed with the following probability density function: $g(\varphi) = a\theta^a \varphi^{-(a+1)}, a + 1 > \sigma$, where $\theta$ is a lower bound of productivity; 2) the coefficients of fixed costs are the same for all industries: $f_z = f_{z'},\ f_{zx} = f_{z'x},\ f_{ez} = f_{ez'},\ \forall z \neq z'$.[20]

**Proposition 2.** ***(a)*** *There exist two factor-intensity cut-offs* $0 \leq \underline{z} < \overline{z} \leq 1$ *such that the home country specializes in production within* $[0, \underline{z}]$*, the foreign country specializes in production within* $[\overline{z}, 1]$*, and both countries produce within* $(\underline{z}, \overline{z})$*.*

***(b)*** *If there is no variable trade cost* ($\tau = 1$)*, and the fixed cost of export equals the fixed cost of production in each industry* ($f_{zx} = f_z, \forall z$)*, then* $\underline{z} = \overline{z}$ *and the two countries completely specialize.*

*Proof. See Appendix A.1.2.*

Proposition 2 presents the equilibrium production and trade pattern. Given our assumption that the home country has a comparative advantage in labor-intensive industries, it would specialize in relatively more labor-intensive industries. The foreign would specialize in relatively more capital-intensive industries. Countries engage in inter-industry trade for industries of specialization. Hence, half of the potential trade flows are zeros.[21] This is where the comparative advantage in factor abundance or technology (clas-

[20]The Pareto assumption is widely adopted in the literature, such as Bernard et al. (2007) and Chaney (2008). Head et al. (2014) examined the welfare implication of non-Pareto distributions. Not all our analytical results depend on the Pareto distribution assumption. We will point it out when that's the case. The fixed costs still vary across industries due to industry variation in factor intensity.

[21]Helpman, Melitz, and Rubinstein (2008) and Chor (2010) generate zeros in trade flow with bounded productivity distribution. Zeros in trade flows can arise even with unbounded productivity distribution in our model if specialization occurs.

sical trade theory) dominates trade costs and the power of increasing return and imperfect competition (new trade theory). Countries engage in intra-industry trade in industries within $(\underline{z}, \overline{z})$, where the power of increasing return to scale and imperfect competition dominate the power of comparative advantage. Thus, if the two countries are similar in technology and factor endowments, the strength of comparative advantage could be relatively weak. There would be no specialization and only intra-industry trade. That is to say, $\underline{z} = 0$ and $\overline{z} = 1$. But the specialization pattern can reverse if Home gains a Ricardian comparative advantage strong enough to overturn the HO comparative advantage such that Home specializes in $[\overline{z}, 1]$ and Foreign specializes in $[0, \underline{z}]$. Finally, if international trade is free, the classical trade force dominates, and complete specialization arises since $\underline{z} = \overline{z}$, just like in the DFS model.

Proposition 2 shares similarities with Romalis (2004). Nevertheless, his assumption of homogeneous firms leads to the stark feature that all firms export in all industries that a country produces, which contracts stylized fact 2 that export participation varies across industries. In the presence of heterogeneous firms, export propensity varies across industries, as shown in the following two propositions.

**Proposition 3.** ***(a)*** *Under a general productivity distribution $G(\varphi)$, the home country's zero-profit productivity cut-offs decrease with the capital intensity, and export cut-offs increase with capital intensity within $(\underline{z}, \overline{z})$. The converse holds in the foreign country.*

***(b)*** *The cut-offs remain constant in industries that either country specializes in.*

*Proof. See Appendix A.1.3.*

The above result extends the analysis of Bernard et al. (2007a). They focus on the case that countries produce within the diversification cone. We further consider cases with specialization when factor endowments or relative productivity are sufficiently different across countries.

Figure 4 visualizes Proposition 3. Given that the cut-offs vary across industries, we expect export participation to vary as well and investigate it next.

**Proposition 4.** ***(a)*** *Under a general productivity distribution $G(z)$, export propensity $\chi(z)$ is constant for industries that either country specializes in and decreases with capital intensity in Home for $z \in (\underline{z}, \overline{z})$, and vice versa in Foreign.*

***(b)*** *If productivity is Pareto-distributed, Home export propensity is given by*

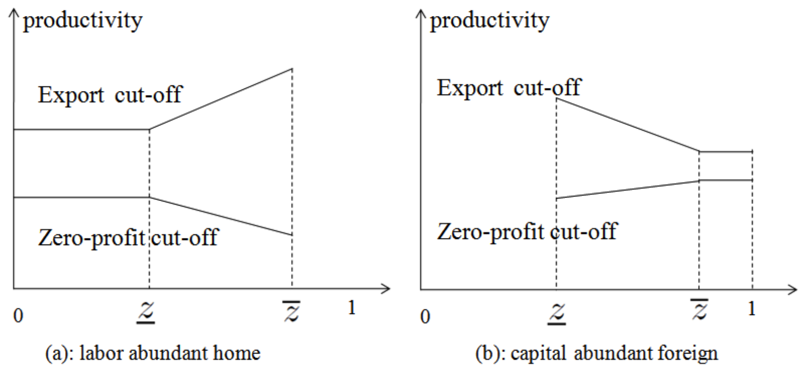



Figure 4: Productivity Cut-offs

$$\chi(z) = \begin{cases} \frac{R^*}{fR}, & z \in [0, \underline{z}] \\ \frac{\widetilde{\tau}^{-a} f - \Psi(z)^a h(z)}{\Psi(z)^a h(z) f - \widetilde{\tau}^a}, & z \in (\underline{z}, \overline{z}) \end{cases}$$

*where* $h(z) \equiv \left(\frac{w}{w^*}(\frac{r/w}{r^*/w^*})^z\right)^{\frac{a\sigma}{1-\sigma}}$, $f \equiv \frac{f_{zx}}{f_z}$, *and* $\widetilde{\tau} \equiv \tau f^{\frac{1}{\sigma-1}}$*. For* $z \in (\underline{z}, \overline{z})$*, we have*

$$\frac{\partial \chi(z)}{\partial z} = B(z)\left[\ln(A) - \frac{\sigma}{\sigma - 1}\ln\left(\frac{r/w}{r^*/w^*}\right)\right], \tag{16}$$

*where* $B(z) > 0$*.*

***(c)*** *Export intensity,* $\gamma(z)$*, which is the share of goods exported, satisfies*

$$\gamma(z) = \frac{f\chi(z)}{1 + f\chi(z)}, \tag{17}$$

*and shares the same pattern as* $\chi(z)$*.*

*Proof. See Appendix A.1.4.*

Proposition 4 implies that export participation tends to increase with comparative advantage, as illustrated in Figure 5. According to equation (16), export propensity depends on the Ricardian and HO comparative advantages in industries that both countries produce. Since we assume the home country has both Ricardian and HO comparative advantages in labor-intensive industries, we expect $\partial\chi(z)/\partial z < 0$, i.e., export propensity decreases with capital intensity. In contrast, if $A > 1$, the home country has Ricardian comparative advantages in capital-intensive industries, then the sign of $\partial\chi(z)/\partial z$ depends on which comparative advantage is stronger. Export propensity can rise with capital intensity if the Ricardian comparative advantage is strong enough to overturn the HO comparative advantage.

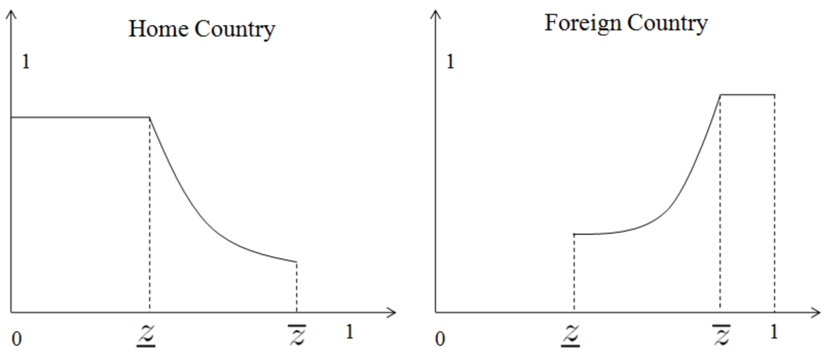



Figure 5: Export Propensity or Intensity

Export selection leads to within-industry resource reallocation and productivity gains (Melitz, 2003). Bernard et al. (2007a) find that reallocation is stronger in the comparative advantage industry. The differential reallocation effect generates productivity differences across industries and countries, which they call "*the endogenous Ricardian comparative advantage*." The following result provides a way to quantify such a mechanism.

**Proposition 5.** ***(a)*** *The average firm-specific productivity of industry $z$ given by $\widehat{\varphi}_z \equiv \mathbb{E}_\varphi(\varphi|\varphi \geq \bar{\varphi}_z)$, is proportional to $(1+f\chi(z))^{1/a}$.*

***(b)*** *Relative sectoral productivity can be decomposed as:*

$$\frac{A(z)\widehat{\varphi}_z}{A^*(z)\widehat{\varphi}^*_z} = \underbrace{\lambda A^z}_{exogenous} \underbrace{\left(\frac{1+f\chi(z)}{1+f\chi^*(z)}\right)^{1/a}}_{endogenous}, \; z \in (\underline{z}, \overline{z}). \tag{18}$$

*Proof. See Appendix A.1.5.*

Conclusion (a) implies that opening to trade brings productivity gains which increase with export propensity $\chi(z)$. Conclusion (b) shows that the endogenous Ricardian comparative advantage depends on the extent of export selection in the home country relative to the foreign.

The above result provides a way to decompose relative productivity. We next show how to infer $A(z)/A(z)^*$, the relative industry-specific productivity, via sufficient statistics. This is not easy because the observed trade outcomes are endogenous to selection (Costinot et al., 2012). The existing approach to infer technology parameters from trade flows relies on the gravity equation and the Eaton and Kortum (2002) framework of perfect competition (Waugh, 2010; Costinot et al., 2012; Levchenko and Zhang, 2016). The following proposition provides a way to do it in an environment with imperfect competition and export selection of heterogeneous firms.

**Proposition 6.** *For industries that both countries produce, we have*

$$\frac{A(z)}{A^*(z)} = \left[\frac{\widetilde{\tau}^a \chi(z) + \widetilde{\tau}^{-a} f}{1 + f\chi(z)}\right]^{1/a} \left(\frac{w^z}{w^{*z}} \frac{r^{1-z}}{r^{*1-z}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{19}$$

*Proof. See Appendix A.1.6.*

Therefore, as long as we observe export propensity $\chi(z)$, iceberg trade cost $\tau$, fixed cost of export relative to domestic sales $f$, the Pareto shape $a$, the elasticity of substitution $\sigma$, we can infer the productivity of home country relative to the foreign for each industry $A(z)/A(z)^*$ by netting out the influence of relative factor prices $w/w^*$ and $r/r^*$.

# 5 Quantitative Analysis

We next apply the model to study the Chinese economy, treating China as Home and RoW as Foreign. As shown by the numerical comparative statics in appendix A.2, changes in endowment, technology, or trade costs alone cannot reconcile the stylized facts 1 and 2 observed in Section 2. For example, if there were only capital deepening, similar to Romalis (2004), who has generalized the Rybczynski Theorem in a multi-sector HO model with imperfect competition, Chinese production and export would become more capital-intensive. It would also imply that export propensity and intensity increase in capital-intensive industries and decrease in labor-intensive industries. However, these are not consistent with fact 2.

In this section, we first estimate model parameters by fitting the model to data from 1999 and 2007 separately. Using the estimated model, we next disentangle the driving forces behind the observed adjustments in production and trade patterns during 1999-2007. We show that the estimated model is able to reconcile all the stylized facts. Finally, we extend the analysis to the period of 2007 to 2017.[22]

[22] In principle, we can extend the analysis to more recent years. Nevertheless, the US-China trade war started in 2018, which was then followed by the COVID-19 pandemic, both are beyond the scope of our model.

## 5.1 Parametrization and Estimation

We calibrate a subset of our parameters and estimate the remaining. First, according to Chaney (2008), models with the CES demand and Pareto-distributed productivity generate sales that are Pareto-distributed, with the Pareto shape given by $\widetilde{a} \equiv \frac{a}{\sigma-1}$. We can estimate $\widetilde{a}$ by regressing the rank of firms' sales on firms' sales (both in logarithms). However, the Pareto distribution fits mostly the right tail of the firm distribution, and we need $a > \sigma - 1$ to ensure that expectations of model moments are bounded. We follow Head et al. (2014) to estimate the Pareto shape across sales quantiles. We use the shape parameter estimated from the top 50% firms as the baseline estimate and get an estimated $\widetilde{a}$ is 1.0130. It implies that $a = (\sigma - 1)\widetilde{a} = 3.038$ if we use a medium value of 4 for the elasticity of substitution $\sigma$.[23]

We normalize the labor supply of China, $L = 1$. The relative labor endowment $L^*/L$ is calculated as the ratio of industrial employment between RoW and China using data from the World Bank.[24] Similarly, the relative capital endowment $K^*/K$ is calculated as the ratio of industrial capital stock between China and RoW, while capital stocks are measured by capital at current PPP from the Penn World Table 10.0. As shown in Table 3, from 1999 to 2007, $L^*/L$ decreased slightly from 2.272 to 2.196 while $K^*/K$ dropped dramatically from about 10.0 to about 5.0, as a result of rapid capital accumulation and industrialization in China. Therefore, China had become more capital-abundant during this period. Still, the implied capital-labor ratios between RoW and China $\frac{K^*/K}{L^*/L}$, was about 4.41 in 1999 and 2.29 in 2007, both of which are above 1. Therefore, China was relatively more labor-abundant than RoW.

Equation (17) from Proposition 4 allows us to infer the fixed cost of export relative to domestic sales from the export intensity and propensity using the following moment condition: $f \equiv \frac{f_{zx}}{f_z} = \mathbb{E}_z\{\frac{\gamma(z)}{\chi(z)(1-\gamma(z))}\}$. We estimated $f$ as the sample average across industries, and we found it was 1.007 in 1999 and 1.773 in 2007, respectively.[25] We estimate $b(z)$, the expenditure share of industry $z$, by its share in total expenditure. The expenditure for each industry is estimated as outputs plus net imports, using imports inferred from matched firm survey and customs data from 2000 to 2006.[26] Appendix Figure

[23] Appendix A.3.1 provides the details on the estimation of $\widetilde{a}$. Later, we conduct robustness checks by varying $\sigma$ from 3 to 7 and using an $\widetilde{a}$ estimated from the top 1%, 5%, and the full sample of firms in subsection 5.5.

[24] Industrial employment is computed by multiplying the total labor force by industrial employment share and employment rate. Ideally, we would like to use manufacturing employment. However, it was not available for the RoW and China in 1999.

[25] The fixed cost of export does not necessarily increase over time. It could be that both fixed costs of domestic sales and exports had declined, but the fixed cost of exports declined slower than the fixed cost of selling in the domestic market.

[26] The customs dataset has different firm identifiers from the firm survey. Following standard practice in the literature (Yu,

A.5 (b) plots the estimated $b(z)$ for each industry.

Table 3: Calibrated Parameters

| Parameters | Value | Source |
|---|---|---|
| Pareto shape $a$ | 3.038 | estimated from firms' sales distribution |
| elasticity of substitution $\sigma$ | 4 | a medium number in the literature |
| relative labor endowment $L^*/L$ | $year$ 1999 : 2.272<br>$year$ 2007 : 2.196 | industrial labor force (World Bank). |
| relative capital endowment $K^*/K$ | $year$ 1999 : 10.03<br>$year$ 2007 : 5.02 | industrial capital stock (Penn World Table 10.0) |
| relative fixed costs of export and domestic sales $f$ | $year$ 1999 : 1.007<br>$year$ 2007 : 1.773 | estimated using $f = \mathbb{E}_z\{\frac{\gamma(z)}{\chi(z)(1-\gamma(z))}\}$ |
| expenditure share $b(z)$ | see appendix<br>Figure A.5 (b) | expenditure =outputs+net imports, with imports<br>inferred from matched firm and customs data |

**Notes:** Industrial labor force and capital force are the total employment and capital stock multiplied by the share of industrial production in aggregate GDP, respectively. The export propensity $\chi(z)$ corresponds to the fraction of firms that export. The export intensity $\gamma(z)$ corresponds to the fraction of sales exported. The estimated $f$ is the sample across industries in each year. b(z) is averaged across 2000-2006.

Turning to the remaining parameters $\{K/L,\, A,\, \lambda,\, \tau\}$, we estimate them using method of moments. We target the following four moments: $i$), the average export propensity of labor-intensive industries (i.e., industries with capital intensity $z \leq 0.5$); $ii$), the aggregate export propensity, i.e., total exports divided by total sales; $iii$), the average capital intensity across all firms; and $iv$), the average capital intensity across all exporters.[27] We estimate $\{K/L,\, A,\, \lambda,\, \tau\}$ separately for 1999 and 2007 by minimizing the Euclidean distance between the model and data for these moments. The details of the estimation algorithm are provided in appendix A.1.7.

Table 4 reports the estimated parameters and the associated standard errors estimated by bootstrapping. There are several findings from the estimation result. Firstly, as China became more capital-abundant, the capital-labor ratio $K/L$ increased from 0.308 in 1999 to 0.647 in 2007. This closely matches the observed magnitude of capital deepening in China. Appendix Figure A.5 (c) plots the capital-labor ratio of China's industrial sector. It increased from 36.7 thousand USD per worker in 1999 (in 2017 US$) to 77.3 thousand USD per worker in 2007. In both the model and data, the capital-labor ratio grows by a factor of 2.10.

2015), we match them by firm name, address, postcode, and phone number.

[27]In appendix Appendix A.3, we demonstrate that $K/L$, $A$, $\lambda$, and $\tau$ directly affect production and trade patterns. In contrast, other model parameters, including the lower bound of the Pareto distribution, $\theta$, the exogenous death probability of firms $\delta$, the fixed entry cost $f_{ez}$ and fixed cost production $f_z$ are irrelevant for these moments.

Secondly, the parameter capturing the absolute advantage $\lambda$ increases from $0.110$ to $0.374$. Hence, China's productivity relative to RoW has increased over time. In addition, the parameter capturing Ricardian comparative advantage $A$ decreases from $5.861$ to $1.804$. As shown by the solid lines in Figure 6 (e), which plots $\frac{A(z)}{A^*(z)} = \lambda A^z$, the industry-specific productivity of China relative to RoW grew relatively faster in the labor-intensive industries than in capital-intensive industries. We remain agnostic on the source of such a labor-biased growth in the exogenous component of industry productivity.[28] But this is consistent with the finding of Levchenko and Zhang (2016) that countries' productivity grew systematically faster in initially relatively less productive sectors, given that the estimated $A$ is greater than one in both years and thus China's productivity relative to RoW was lower in labor-intensive industries than in capital-intensive industries. It is also consistent with Fact 3 from Section 2 that the observed TFP growth in China was faster among labor-intensive than capital-intensive industries. According to these estimates, the geometric average of China's productivity relative to RoW was 0.287 in 1999 and 0.579 in 2007, which are in the ballpark of the estimates of Di Giovanni et al. (2014) for the same period.[29] Finally, we find that the iceberg trade cost $\tau$ decreased by about $25.1\%$ from $2.695$ in 1999 to $2.018$ in 2007. This is expected, given the drastic trade liberalization of China after its 2001 WTO accession.[30]

Our quantitative model performs well in matching salient features observed in the data. Panel (a) of Table 5 shows the model fit for the targeted moments, while panel (b) shows the fit for the non-targeted moments. First, it captures stylized facts 1 and 2, i.e., from 1999 to 2007, Chinese production became more capital-intensive, but exports tilted slightly towards labor-intensive industries, and export participation rose in labor-intensive industries but fell among capital-intensive industries. Second, although not targeted in the estimation, our model captures the rise of Chinese manufacturing relative to RoW. The model-predicted value added of RoW relative to China, $R^*/R$, fell from 18.95 in 1999 to 7.71 in

[28]International trade changes firms' incentive to adopt new technology (Sampson, 2016; Perla et al., 2021). Such a productivity-enhancing effect can rationalize our finding if it is stronger in labor-intensive industries than in capital-intensive industries. Empirically, we do find firms in labor-intensive industries had higher R&D intensity than in capital-intensive (see appendix Figure A.4). It could also be that access to foreign intermediate inputs brought productivity gains (Halpern et al., 2015), which benefited labor-intensive industries more than capital-intensive ones.

[29]Using a multi-country multi-sector Ricardian model of Eaton and Kortum (2002), Di Giovanni et al. (2014) estimated that the geometric average of China's productivity relative to the world frontier productivity was about 0.34 during 2000-2007.

[30]For example, Tombe and Zhu (2019) estimated that from 2002 to 2007, trade costs between China and RoW declined by $23\%$ for agricultural goods and $8\%$ for non-agricultural sectors. For simplicity, we assume that the iceberg trade costs are symmetric between China and the RoW. If we follow Waugh (2010) in adopting asymmetric trade costs, we need export propensity to China in the RoW. However, we lack such data.

2007, close to the data magnitudes of 18.01 and 9.04, respectively.[31] Third, the model also captures the increasing trade openness of China and RoW's exposure to Chinese exports (i.e., the "China shock"). As the model-predicted export intensity rose from 0.193 in 1999 to 0.282 in 2007, China's trade openness, measured by the total exports and imports divided by total value-added, increased from 0.385 to 0.562, closely matching the observed trade openness of 0.335 in 1999 and 0.622 in 2007.[32] At the same time, RoW's exposure to Chinese exports, as measured by RoW imports from China divided by total value added, grew by a factor of 3.65 from $1.0\%$ in 1999 to $3.65\%$ in 2007. The data numbers are smaller than the model numbers, but they grew a similar factor of 3.63 from $0.63\%$ to $2.29\%$. Last but not least, beyond these aggregate statistics, the model also matches the distribution of firms and export propensity across industries and their changes over time reasonably well, as shown in Figure 6 (a) and (b).

Table 4: Estimated Parameters

| Parameters | $K/L$ | $A$ | $\lambda$ | $\tau$ |
|---|---|---|---|---|
| Year 1999 | 0.308 | 5.861 | 0.110 | 2.695 |
| | (0.003) | (0.04) | (0.001) | (0.009) |
| Year 2007 | 0.647 | 1.804 | 0.374 | 2.018 |
| | (0.005) | (0.004) | (0.002) | (0.003) |

**Notes:** This table presents the estimation results. $K/L$ is the capital-labor ratio of the home country. $A$ captures the Ricardian comparative advantage. $\lambda$ captures the absolute comparative advantage. $\tau$ measures the iceberg trade cost. The numbers in the parentheses are bootstrapped standard errors. In each bootstrap, we use a sample with replacement from the data to generate the target moments and redo the estimation. We perform 25 bootstraps each year.

Our model allows us to examine income inequality between labor and capital in China and RoW. Since China was labor-abundant compared to RoW, the model implies that China had a labor cost advantage given that $r/w$ was higher than $r^*/w^*$ in both 1999 and 2007, as shown in Panel (b) of Table 5.[33] Over time, as the world became more capital-abundant, interest rates fell relative to the wage rates everywhere. However, $r/w$ fell much faster than $r^*/w^*$ due to labor-biased productivity growth and a larger rise in the capital-labor ratio in China than in RoW.

Although we lack the data to examine RoW's production and trade patterns, our model also sheds light on their adjustments over time. As mentioned above, interest rates fell relative to wage rates as the

[31] The value added of China and RoW are calculated by multiplying GDP with industrial value-added share using data from the World Bank.

[32] Note that because of balanced trade, trade openness is twice as large as aggregate export intensity.

[33] Relatedly, Mitchener and Yan (2014) study the change in factor prices, particularly wage premium of skilled versus unskilled workers during a much earlier export boom that China experienced in the 1910s-1920s.

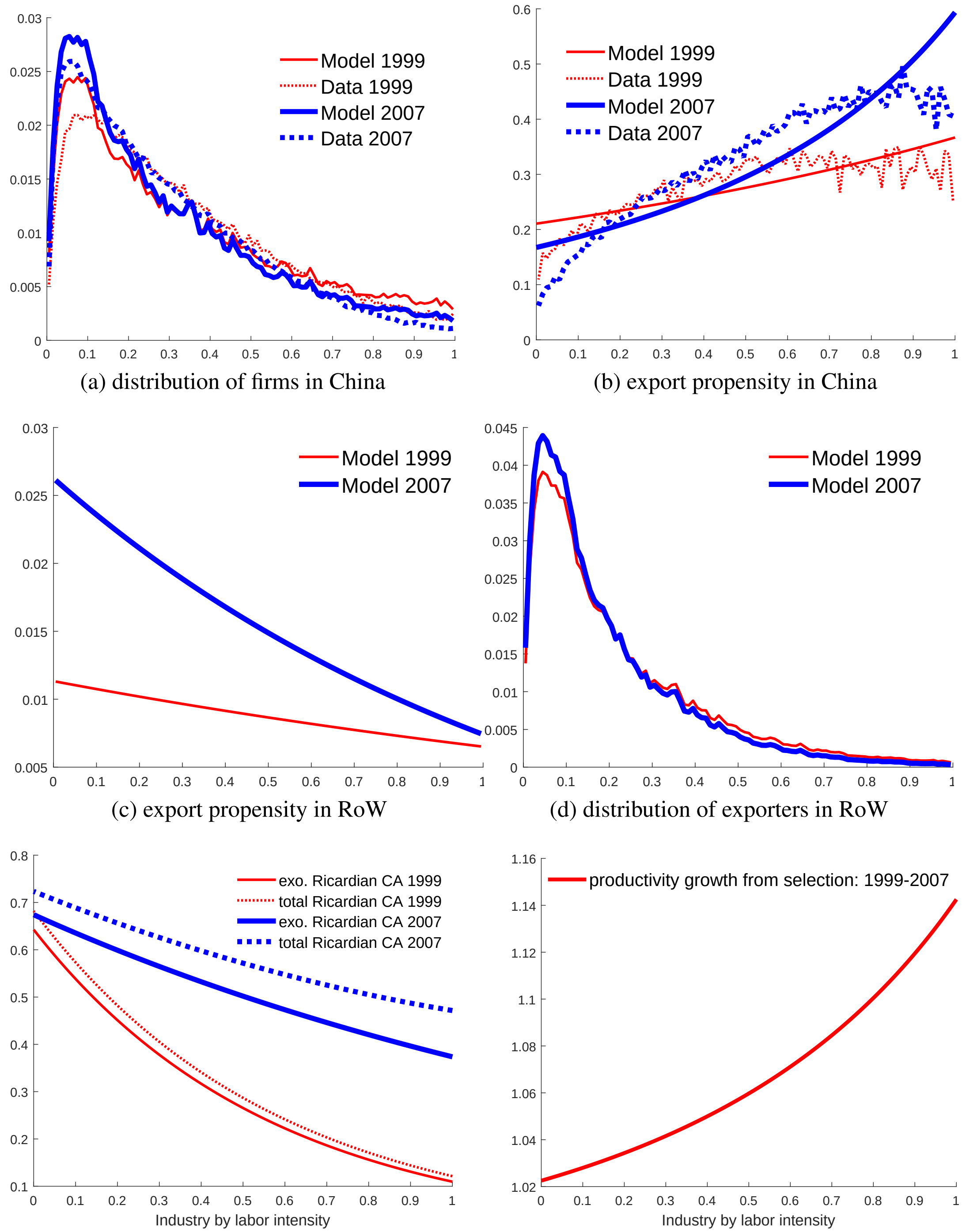
Table 5: Model Fit: Targeted and Non-targeted Aggregate Moments

| Moments | Data | | Model | |
|---|---|---|---|---|
| | 1999 | 2007 | 1999 | 2007 |
| **Panel (a)**: targeted moments | | | | |
| average export propensity of labor-intensive industries | 0.318 | 0.420 | 0.319 | 0.421 |
| aggregate export propensity | 0.257 | 0.249 | 0.255 | 0.246 |
| capital intensity for all firms | 0.667 | 0.707 | 0.664 | 0.703 |
| capital intensity for all exporters | 0.623 | 0.619 | 0.625 | 0.622 |
| **Panel (b)**: non-targeted moments | | | | |
| average export propensity of capital-intensive industries | 0.244 | 0.234 | 0.242 | 0.224 |
| share of labor-intensive firms | 0.234 | 0.182 | 0.252 | 0.197 |
| share of labor-intensive exporters | 0.292 | 0.297 | 0.308 | 0.312 |
| aggregate export intensity | 0.184 | 0.208 | 0.193 | 0.282 |
| value added of China relative to RoW ($R^*/R$) | 18.01 | 9.04 | 18.95 | 7.71 |
| trade openness ((exports+imports)/R) | 0.335 | 0.622 | 0.385 | 0.562 |
| China shock (exports of China/R*) | 0.0063 | 0.0229 | 0.010 | 0.0365 |
| relative factor income in home country: r/w | – | – | 11.89 | 5.021 |
| relative factor income in foreign country: r*/w* | – | – | 2.841 | 2.665 |

**Notes:** The model moments are computed using the parameters shown in Table 4. Labor-intensive industries are industries that have a labor intensity of greater than 0.5. Capital-intensive industries are industries that have a labor intensity of less than 0.5.

world became more capital-abundant. It induces more RoW firm entries in capital-intensive industries than labor-intensive industries. In addition, RoW firms' propensity to export to China increased in every industry, the magnitude of which is larger in capital-intensive industries than in labor-intensive industries, as shown in Figure 6 (c). These two forces imply that the distribution of RoW exporters shifted toward capital-intensive industries over time, which is shown in Figure 6 (d). Therefore, the capital intensity of RoW exports to China should have increased over time. To verify this prediction, we compute the average capital intensity of Chinese imports from RoW in appendix Figure A.5 (d) using Chinese customs data from 2000-2006 and the NBER-CES Manufacturing Industry Database.[34] Consistent with the model prediction, the capital intensity of Chinese imports increased over time.

[34]Using the NBER-CES Manufacturing Industry Database (Becker et al., 2021), we calculate the labor share of each industry as payroll divided by value-added. We then obtain the labor intensity of each imported product using a mapping between industries and products. The labor intensity of Chinese imports is a weighted average across products by import value. Capital intensity is measured by one minus labor intensity.




(a) distribution of firms in China

(b) export propensity in China

(c) export propensity in RoW

(d) distribution of exporters in RoW

(e) Ricardian comparative advantage

(f) Selection driven productivity growth

**Notes**: Figures (a) and (b) plot the estimated model distribution of firms across industries and their propensity to export together with data. Figures (c) and (d) plot the estimated export propensity and distribution of exporters across industries in RoW. Figure (e) plots the estimated exogenous Ricardian comparative advantage (CA) of China ("exo."), i.e., $A(z)/A^*(z)$, and the Ricardian CA that incorporates firm selection ("total."), i.e., $\frac{A(z)}{A^*(z)}(\frac{1+f\chi(z)}{1+f\chi^*(z)})^{1/a}$ according to equation (18). Figure (f) plots productivity growth induced by firm selections from 1999-2007 via equation (20).

Figure 6: Estimated Model Outcomes across Industries and over Time

## 5.2 Productivity Gains from Export Selections

Export selections of heterogeneous firms generate aggregate productivity gains (Melitz, 2003). Sectoral variations in selection give rise to endogenous Ricardian comparative advantage (Bernard et al., 2007a; Huang and Ottaviano, 2024). Using the estimated model, this subsection quantifies the effect of export selections on the Ricardian comparative advantage and productivity growth of China from 1999-2007.

First, Proposition 5 allows us to evaluate the importance of endogenous Ricardian comparative advantage, which is captured by $(\frac{1+f\chi(z)}{1+f\chi^*(z)})^{1/a}$. Estimating it requires $\chi^*(z)$, the propensity of RoW's firms to export to China, which is calculated via the model and shown in Figure 6 (c). The dashed lines in Figure 6 (e) plot the estimated overall Ricardian comparative advantage, i.e., $\frac{A(z)}{A^*(z)}(\frac{1+f\chi(z)}{1+f\chi^*(z)})^{1/a}$, for 1999 and 2007, which differs from the exogenous Ricardian comparative advantage, i.e., $A(z)/A^*(z)$, due to the presence of $(\frac{1+f\chi(z)}{1+f\chi^*(z)})^{1/a}$. The differences are non-trivial. It increased the productivity of China relative to RoW, ranging from 6.1% in the most capital-intensive industries to 10.7% in the most labor-intensive industries in 1999, and from 7.3% to 26.2% respectively in 2007. Since the magnitudes were relatively higher in labor-intensive industries than in capital-intensive industries, endogenous Ricardian comparative advantage amplified China's HO comparative advantage in labor-intensive industries, which is similar to Bernard et al. (2007a). However, the exogenous Ricardian comparative advantage was dampened in both years, as the estimated exogenous Ricardian comparative advantage was stronger in capital-intensive industries than labor-intensive ones.

The model also allows us to account for the contribution of export selection to productivity growth over time. Let $x'$ be the value of $x$ in a future period. The productivity growth of industry $z$ can be decomposed as:[35]

$$\frac{\mathbb{E}_{\varphi}(A(z)'\varphi|\varphi \geq \bar{\varphi}'_z)}{\mathbb{E}_{\varphi}(A(z)\varphi|\varphi \geq \bar{\varphi}_z)} = \frac{A(z)'}{A(z)}\frac{\widehat{\varphi}'_z}{\widehat{\varphi}_z} = \frac{A(z)'}{A(z)}(\frac{1+f'\chi(z)'}{1+f\chi(z)})^{\frac{1}{a}}, \tag{20}$$

where $\frac{A(z)'}{A(z)}$ absorbs the industry-wide productivity growth and $(\frac{1+f'\chi(z)'}{1+f\chi(z)})^{\frac{1}{a}}$ captures productivity growth due to changes in export selection. Figure 6 (f) plots the estimated productivity growth from 1999-2007 driven by changes in export selections. We find export selection led to disproportionally more productivity growth in labor-intensive industries than capital-intensive industries. Export selection increased

[35] This an immediate implication of Proposition 5 (a).

productivity by around 14.3% in the most labor-intensive industries and just 2.25% in the most capital-intensive industries. Therefore, part of the faster productivity growth in labor-intensive industries found in Fact 3 can be explained by export selections.

Overall, the estimated average TFP growth rate weighted by industry value-added is 4.439% per annum. The weighted average of productivity growth driven by export selection is 0.490% per annum. Hence, export selections contribute 11.2% to the overall productivity growth.[36]

## 5.3 Model Counterfactuals for 1999-2007

In this subsection, we conduct three counterfactual experiments to investigate the driving forces behind the observed evolution of Chinese production and trade patterns from 1999 to 2007. In each experiment, we replaced the estimated parameters of 1999 with those of 2007, one subset of parameters at a time. The first experiment replaces the technological parameters $\{A, \lambda\}$.[37] The second one replaces the trade cost parameters $\{\tau, f\}$. The last one replaces the endowment parameters $\{L^*/L, K^*/K, K/L\}$.

Table 6: Counterfactual 1999-2007

| Model moments | Baseline model | | Counterfactual | | |
|---|---|---|---|---|---|
| | 1999 | 2007 | technology | trade costs | endowments |
| | (1) | (2) | (3) | (4) | (5) |
| (a) export propensity of labor-intensive industries | 0.319 | 0.421 | 0.543 | 0.454 | 0.069 |
| (b) export propensity of capital-intensive industries | 0.242 | 0.224 | 0.179 | 0.365 | 0.160 |
| (c) capital intensity of all firms | 0.664 | 0.703 | 0.663 | 0.658 | 0.733 |
| (d) capital intensity of all exporters | 0.625 | 0.622 | 0.493 | 0.628 | 0.801 |
| (e) aggregate export propensity | 0.255 | 0.246 | 0.247 | 0.382 | 0.161 |
| (f) trade openness ((exports+imports)/R) | 0.385 | 0.562 | 0.304 | 0.779 | 0.304 |
| (g) China shock (exports of China/R*) | 0.010 | 0.0365 | 0.016 | 0.0214 | 0.015 |
| (h) value added of China relative to RoW ($R^*/R$) | 18.95 | 7.71 | 9.60 | 18.24 | 10.13 |

**Notes:** Column (1) and (2) are model results for 1999 and 2007, respectively, using the estimated parameters in Table 4. Columns (3) - (5) conduct counterfactual simulations by replacing the model parameters for 1999 with those of 2007, one subset at a time. Column (3) replaces the technological parameters $\{A, \lambda\}$. Column (4) replaces trade cost parameters $\{\tau, f\}$, and column (5) replaces the endowment parameters $\{\frac{L^*}{L}, \frac{K^*}{K}, \frac{K}{L}\}$.

Our first finding is that changes in factor endowments are the primary driver of more capital-intensive

[36]The relatively modest contribution of export selections to overall productivity growth is not unique to this study. For example, Baldwin and Gu (2003) found that the contribution of Canadian plants entering and exiting export markets to overall labor productivity growth was 23.1%. Other margins can account for China's productivity growth, such as reductions in goods- and labor-market frictions (Tombe and Zhu, 2019).

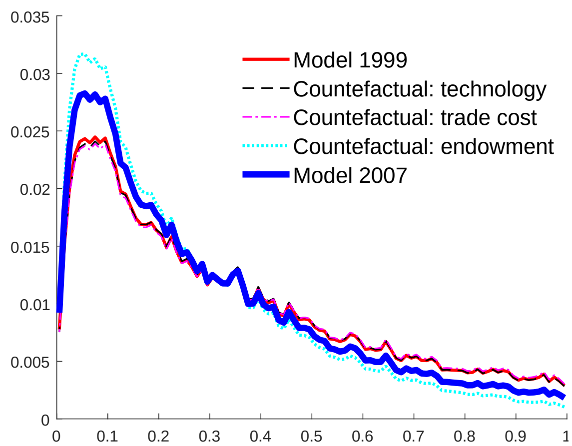
[37]We reduced $A$ to 3.406, rather than 1.817 when export propensity approaches 100%, i.e., all firms exports.

production over time. As row (c) of Table 6 indicates, the average capital intensity of firms decreased slightly when we replaced the technology and trade cost parameters but increased significantly from 0.664 to 0.733 when we replaced the endowment parameters. As China became more capital-abundant in 2007, it gained comparative advantages in capital-intensive industries, which raised the expected profits from entry into these industries. This is reflected in Figure 7 (b), where the counterfactual export propensity falls with labor intensity. Besides, as capital became relatively cheaper, the fixed cost of entry in capital-intensive industries decreased more than in labor-intensive industries. As shown in Figure 7 (a), these forces induce relatively more firms to enter capital-intensive industries than labor-intensive industries, which raises the overall capital intensity of production.

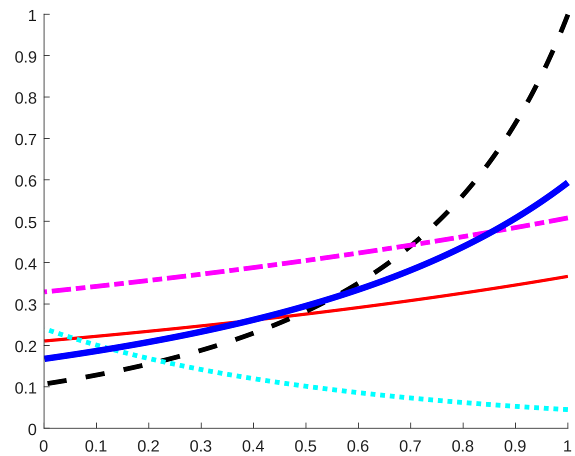
In contrast, changes in technological parameters and trade costs have small effects on the capital intensity of Chinese production, as indicated in row (c) of Table 6. While labor-biased productivity growth implied a strengthened Ricardian comparative advantage in labor-intensive industries for China, which induced entry into labor-intensive industries, it also increased wages and discouraged entry into labor-intensive industries. In the end, the two channels roughly balanced each other, leaving the distribution of firms almost unchanged. Similarly, trade liberalization would spur more firms to enter China's comparative advantage industries, i.e., the labor-intensive industries. However, it also raised wage rates relative to interest rates, which hindered further entries.

Our second finding is that all three forces we consider jointly explain why the capital intensity of Chinese exports stayed almost unchanged, albeit export propensity increased in labor-intensive industries and decreased in capital-intensive industries. As is evident from row (d) of Table 6, the average capital intensity of exporters increases when we replace the endowment parameters, declines when we replace the technological parameters and stays almost unchanged when we change trade costs. As for export propensity, from rows (a) and (b) of Table 6 and Figure 7 (b), we find that it increases in every industry with changes in trade costs and declines almost in every industry when we replace endowment parameters. Only when we change the technology parameters does it increase in labor-intensive industries and decline in capital-intensive industries. Therefore, without technological change, export propensity would have declined with labor intensity in 2007 rather than increasing with labor intensity.

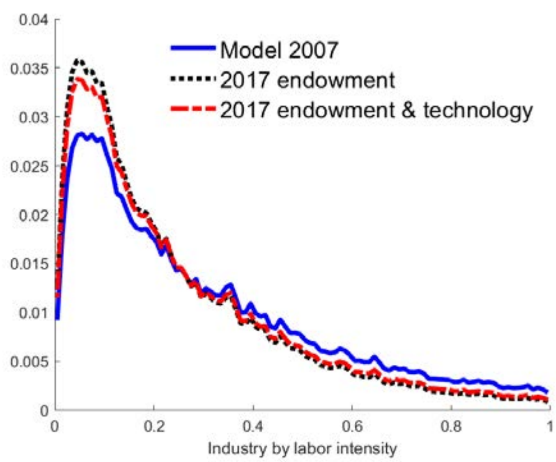
In addition to these adjustments in the pattern of production and exports, these counterfactual simulations also shed light on the overall rise of Chinese manufacturing production and exports. From rows (f) and (g) of Table 6, we find that the rise of trade openness in China and the increasing exposure of RoW to Chinese exports were mostly due to changes in trade costs. However, changes in technology and endowments contribute more than trade liberalization to the rise of Chinese production relative to RoW, as shown in row (h).[38]



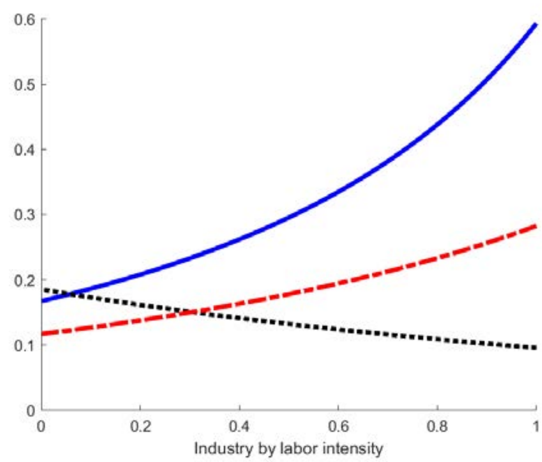

(a) firm mass distribution 1999-2007



(b) export propensity 1999-2007




(c) firm mass distribution 2007-2017




(d) export propensity 2007-2017

**Notes**: Figures (a) and (b) plot results from simulations that replace the technology (i.e., $\lambda$ and $A$), trade costs (i.e, $\tau$ and $f$), and endowments (i.e., $K/L$, $K^*/K$ and $L^*/L$) for the 1999 economy with those of the 2007 economy. Figures (c) and (d) replace the technology and endowment parameters of the 2007 economy with those of the 2017 economy.

Figure 7: Counterfactual Simulations

[38]If trade liberalization affected changes in technology and endowments, we would have underestimated its contribution.

## 5.4 Model Counterfactuals for 2007-2017

We now extend our quantitative analyses and show that our model also helps us to understand changes in the Chinese economy till 2017, before the start of the U.S.-China trade war in 2018.

Ideally, we would like to estimate model parameters for 2017 and conduct analyses similar to those we have done for 1999-2007. However, the most recent Chinese firm-level survey data we have is for 2013, not to say that its quality is not as good as data from earlier periods. To make progress, we have to rely on alternative methods. In particular, we will calibrate the endowment and technology parameters for 2017 and run counterfactual simulations with respect to the estimated 2007 economy.

For endowment parameters of the 2017 economy, we continue to normalize $L = 1$. Relative capital and labor are calibrated in the same way as 1999 and 2007 in Table 3. We find that $K^*/K = 2.899$ for 2017, which is about half as large as in 2007, and $L^*/L = 2.307$, which is slightly larger than in 2007. Hence, capital deepening continued in China. But $\frac{K^*}{K}/\frac{L^*}{L} = \frac{2.899}{2.307} = 1.257 > 1$ and China was still relatively more labor-abundant than RoW. For $K/L$, as mentioned above, we find it grew by a factor of 2.10 both in the data and model from 1999-2007. In appendix Figure A.5 (c), we observe that the capital-labor ratio of China grew by a factor of 1.971 from 77.3 thousand USD per worker in 2007 to 152.3 thousand USD per worker in 2017. Hence, we assume that in the model, $K/L$ grew by the same factor from $0.647$ in 2007 to $1.275 = 1.971 \times 0.647$ in 2017.

For technology parameters, we first use Proposition 6 to estimate the productivity of China relative to RoW, $A(z)/A^*(z)$, via sufficient statistics. We then extrapolate the relative productivity to 2017 based on its average growth rate from 2007-2013. Before that, we have to classify firms in the 2013 data into industries based on their labor shares as we did for 1999 and 2007. However, as mentioned above, the 2013 firm-level data does not report firms' value-added, which prevents us from measuring firms' labor share. To circumvent this problem, we infer firms' value added from their reported value-added tax (VAT) by dividing a VAT rate of $17\%$, which was the statutory VAT rate in China before it was lowered to $16\%$ in 2018 and 13% in 2019.[39] Dividing firms' inferred value added by wages, we get firms' labor shares,

[39] A lower VAT rate of 13% was applied to a subset of industries throughout the study period, mostly for food processing, agricultural inputs, and household utilities. We have tried a VAT rate of 13% for all firms and got similar results. A caveat we need to point out is that effective VAT rates, i.e., tax rates implemented by local governments, can differ from the statutory rate due to differential enforcement (Chen, 2017). We compared the value added with the inferred value when it was not missing in the data and found them highly correlated.

which are used to classify them into 100 bins. For each bin, we calculate the share of exporters, which are plotted in appendix Figure A.5 (e). The patterns for 1999 and 2007 are similar to the baseline patterns observed in Figure 2 (e). Therefore, the value-added inferred from VAT is not perfect but quite reliable.

To implement the sufficient statistics estimate from Proposition 6, we adopt the same Pareto shape $a$ and elasticity of substitution $\sigma$ as the baseline (see Table 3). In addition, we assume that the iceberg trade costs $\tau$ and relative fixed costs of exports $f$ are the same as in 2007. Finally, we follow Huang and Ottaviano (2024) to estimate relative factor prices $w/w^*$ and $r/r^*$ using data from the Penn World Table.[40] Appendix Figure A.5 (f) plots the estimated relative productivity for 2007 and 2013. We find that productivity growth in China continued to be labor-biased as the productivity relative to RoW in labor-intensive industries increased and declined in capital-intensive industries.[41] Extrapolating this growth in relative productivity between 2007 and 2013, we can get the relative productivity for 2017, which is also plotted in the figure. We fit the extrapolated 2017 relative productivity using $A(z)/A^*(z) = \lambda A^z$ where $z$ is the capital intensity of the industry and get $\lambda = 0.840$ and $A = 0.955$. Both numbers are closer to 1 than those in 1999 and 2007, indicating productivity convergence between China and RoW across industries.[42]

These calibrated parameters imply that China became more similar to RoW in terms of endowments and technologies. We examine their implication by replacing the endowment and technology parameters of the 2007 economy with those of 2017. The results are shown in Figures 7 (c) and (d) and Table 7. As the figures indicate, the continued deepening of capital made Chinese production more capital-intensive and strengthened its comparative advantage in capital-intensive industries. However, biased technology growth that favored labor-intensive industries provided a counter-balancing force. Their combined effect is that Chinese production became more capital-intensive, but export propensity declined in every industry despite nil changes in trade costs. Consequently, aggregate export intensity declined by about 8.1% from 28.2% to 20.1%, which is close to the data magnitude of 7.7% (row e). Trade openness declined from 56.2% to 40.1%, which is close to the data magnitude of 62.2% and 37.6%, respectively. Therefore, even without changes in trade costs, China had become less open in trade from 2007-2017. Intuitively,

[40]Wage rate is estimated as real GDP multiplied by labor share divided by total employment. Interest rate is measured by the real internal rate of return. Wage and interest rates in RoW are calculated as weighted averages across countries.

[41]Reassuringly, we have also tried implementing sufficient statistics estimates for 1999 and found growth in $A(z)/A^*(z)$ was labor-biased during 1999-2007, which is consistent with the estimation result by the method of moments.

[42]Still, the implied industry-specific productivity of China relative to RoW in 2017 is less one across all industries.

Table 7: Counterfactual 2007-2017

| Model Moments | Data | | Model | Counterfactual 2017 | |
|---|---|---|---|---|---|
| | 2007 | 2017 | 2007 | edmt. | edmt. & tech. |
| | (1) | (2) | (3) | (4) | (5) |
| (a) export propensity of labor-intensive industries | 0.420 | – | 0.421 | 0.113 | 0.226 |
| (b) export propensity of capital-intensive industries | 0.234 | – | 0.224 | 0.157 | 0.145 |
| (c) capital intensity of all firms | 0.707 | – | 0.703 | 0.756 | 0.744 |
| (d) capital intensity of all exporters | 0.623 | – | 0.622 | 0.784 | 0.697 |
| (e) aggregate export intensity | 0.208 | 0.131* | 0.282 | 0.224 | 0.201 |
| (f) trade openness ((exports+imports)/R) | 0.622 | 0.376 | 0.562 | 0.448 | 0.401 |
| (g) China shock (exports of China/R*) | 0.023 | 0.035 | 0.036 | 0.047 | 0.054 |
| (h) value added of China relative to RoW ($R^*/R$) | 9.04 | 3.21 | 7.713 | 4.818 | 3.728 |

**Notes:** * The export intensity for 2017 is calculated for manufacturing industries using the input-output table published by the National Bureau of Statistics of China. Columns (1) and (2) are the data for 2007 and 2017, respectively. Columns (3) -(5) are model results: column (3) shows the estimated 2007 economy, columns (4) conduct counterfactual simulations by replacing the endowment parameters $\{\frac{L^*}{L}, \frac{K^*}{K}, \frac{K}{L}\}$ of 2007 with those of 2017, and column (5) further replaces the technological parameters $\{\lambda$, A$\}$ of 2007 with those of 2017.

this is because there was less comparative advantage to be exploited for international trade when China and RoW became more similar.

The declining trade openness of China does not mean that Chinese exports have become less significant for RoW. In contrast, the RoW might have faced more import competition from China. First, as China grew relatively larger over time (row h) due to the increase in endowments and better technologies, RoW's exposure to Chinese exports increased (see row g) despite China's declining export intensity. Second, Chinese exports became more capital-intensive over time (row d). Although export propensity declined in every industry, it declined more dramatically in labor-intensive industries than in capital-intensive industries (rows a and b). Together with the result that Chinese production became more capital-intensive over time, we expect RoW to face more competition from China in their comparative advantage industries, i.e., the capital-intensive industries.

## 5.5 Robustness

Next, we conduct robustness checks on our baseline estimation result. We have chosen a medium elasticity of substitution $\sigma = 4$, and used a Pareto shape estimated from the top 50% of firms. We would like to know the robustness of the result to alternative parameter values. In panel (a) of Table 8, we vary the trade elasticity from 3, which is at the lower end of estimates in the literature, to 7, which is at the higher end. By the nature of our calibration, the Pareto shape parameter $a$ also varies accordingly. It turns out that the point estimates of each parameter vary with trade elasticity. However, the direction of the changes in the estimated parameters are the same as our baseline estimation: across all cases, $A$ and $\tau$ decrease from 1999 to 2007, *vice versa* for $K/L$ and $\lambda$. In panel (b), we use the estimated Pareto shape of firms' sales distribution from the top 1% and 5% to the full sample while fixing the trade elasticity at 4. The point estimates of the parameters also change. However, the pattern of changes in the estimated parameters over time is again consistent with the baseline.

Table 8: Robustness Checks

| Parameters | | | Estimated Parameters | | | |
|---|---|---|---|---|---|---|
| $\sigma$ | $a$ | year | K/L | A | $\lambda$ | $\tau$ |
| **Panel (a): Elasticity of substitution** | | | | | | |
| 3 | 2.025 | 1999 | 0.308 | 6.935 | 0.090 | 4.543 |
| | | 2007 | 0.641 | 1.796 | 0.105 | 3.729 |
| 5 | 4.05 | 1999 | 0.308 | 5.391 | 0.086 | 2.169 |
| | | 2007 | 0.642 | 1.850 | 0.157 | 1.857 |
| 7 | 6.076 | 1999 | 0.308 | 4.953 | 0.117 | 1.642 |
| | | 2007 | 0.643 | 1.868 | 0.175 | 1.499 |
| **Panel (b): Pareto shape** | | | | | | |
| 4 | 3.774 | 1999 | 0.308 | 6.022 | 0.113 | 2.185 |
| | | 2007 | 0.643 | 1.920 | 0.175 | 1.825 |
| | 3.563 | 1999 | 0.308 | 5.982 | 0.115 | 2.291 |
| | | 2007 | 0.643 | 1.896 | 0.182 | 1.910 |
| | 2.249 | 1999 | 0.308 | 5.581 | 0.099 | 4.057 |
| | | 2007 | 0.641 | 1.676 | 0.137 | 3.495 |

**Notes:** The baseline result in Table 4 is obtained with a Pareto shape of sales $\tilde{a} = 1.013$ estimated from the top 50% of firms. It implies that $a = 3.038$ given $\sigma = 4$. Panel (a) varies $\sigma$ from 3 to 7, while fixing $\tilde{a} = 1.013$. Panel (b) fixes $\sigma$ but uses $\tilde{a}$ estimated from different samples: $1.258$ from the top $1\%$, $1.188$ for the top $5\%$, and $0.750$ for the full sample of firms (see Table A.4), with the corresponding Pareto shape $a$ that equals 3.774, 3.563 and 2.249, respectively.

# 6 Conclusion

In this paper, we first document the seemingly puzzling patterns of evolution in production and export for China during the period 1999-2007 based on comprehensive firm-level data: Chinese manufacturing production became more capital-intensive, whereas the capital intensity of exports stayed almost unchanged, and export propensity and intensity increased in labor-intensive industries but declined in capital-intensive ones. These results counter predictions of the Rybczynski Theorem of HO theory.

To explain these findings, we built a quantitative general equilibrium trade model that embeds the Melitz-type heterogeneous firm model into the Ricardian and HO trade theory with continuous industries. Our estimation results indicate that although capital deepening has made Chinese production more capital-intensive over time, labor-biased productivity growth provided a counter-balancing force that favored exports in labor-intensive industries more than capital-intensive industries. Meanwhile, trade liberalization helped export all industries and significantly raised China's trade openness and RoW's exposure to Chinese exports. Export selection generated endogenous productivity gains, which reshaped comparative advantage significantly and contributed to around 11.2% of productivity growth from 1999-2007.

We extended our quantitative analysis to 2017 to shed further light on production in China and its trade with RoW before the start of the US-China trade war in the subsequent year. We find that the continued capital deepening and labor-biased productivity growth of China had made it more similar to RoW than in 2007, which reduced its trade openness by 16% even without changes in trade costs. Nevertheless, RoW's exposure to Chinese import competition continued to increase for two reasons: $i$) the rise in the size of the Chinese economy relative to RoW and $ii$) the rising capital intensity of Chinese exports.

The rise of China and its growing role in the global economy is perhaps the most important event in the past few decades. Understanding such a drastic transformation is of paramount importance. We have shown that a standard trade model of comparative advantage and heterogeneous firms goes a long way in demystifying some puzzling facts observed in the data and identifying possible causes of the reversing trend in its integration with the global economy.

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# Accounting for the Evolution of China's Production and Trade Patterns

(For Online Publication)

by

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## A.1 Appendix

### A.1.1 Proof of Proposition 1

The proof is similar to the proof of Proposition 3 in Bernard, Redding and Schott (2007a). The complication is that we allow for specialization while they focus on cases within the diversification cone.[43] The idea of the proof is as follows. We first write factor demands as functions of the factor prices $\{w, w^*, r, r^*\}$, taking into account the specialization pattern. Then we use factor market clearing conditions to determine the equilibrium factor prices. Once the factor prices are known, all the other equilibrium variables are also determined.

For given factor prices, the total revenue for the home country and foreign country is $R = wL + rK$ and $R^* = w^*L^* + r^*K^*$, respectively. For industries that the home country specializes, the factor demands are $l(z) = (1-z)b(z)(R+R^*)/w$, $k(z) = zb(z)(R+R^*)/r$. Factor demands in the foreign country are symmetric. For industries that both countries produce, the industry revenue function is given by equation (13), thus we need to know the firm mass $M_z$ and $M_z^*$, the pricing index $P(z)$ and $P(z)^*$, and industry average productivity $\widehat{\varphi}_z$ and $\widehat{\varphi}_z^*$ in order to settle their factor demands. We will use the model conditions to substitute for these terms. Starting from equation (13), we find that:

$$\frac{r(\widehat{\varphi}_z)}{r(\widehat{\varphi}_z^*)} = \widetilde{p}_z^{1-\sigma}\frac{(\frac{P(z)}{P(z)^*})^{\sigma-1} + \frac{R^*}{R}\tau^{1-\sigma}\chi(z)^{\frac{a+1-\sigma}{a}}}{\frac{R^*}{R} + \chi(z)^{*\frac{a+1-\sigma}{a}}\tau^{1-\sigma}(\frac{P(z)}{P(z)^*})^{\sigma-1}} \tag{E1}$$

where $r(\widehat{\varphi}_z) = \frac{R_z}{M_z}$ is the average firm revenue, and $\widetilde{p}_z \equiv \frac{p_{zd}(\widehat{\varphi}_z)}{p_{zd}(\widehat{\varphi}_z^*)} = \frac{\widehat{\varphi}_z^* w}{\Psi(z)\widehat{\varphi}_z w^*}(\frac{r/w}{r^*/w^*})^z$ is the relative average domestic price between the two countries, with $\Psi(z) \equiv \frac{A(z)}{A^*(z)}$.[44]

At the same time, using the zero profit conditions (9) and the fact that $\frac{r(\widehat{\varphi}_z)}{r(\bar{\varphi}_z)} = (\frac{\widehat{\varphi}_z}{\bar{\varphi}_z})^{\sigma-1}$, we find that the average firm revenue is $r(\widehat{\varphi}_z) = (f_z(\frac{\widehat{\varphi}_z}{\bar{\varphi}_z})^{\sigma-1} + \chi(z)f_{zx}(\frac{\widehat{\varphi}_{zx}}{\bar{\varphi}_{zx}})^{\sigma-1})\sigma r^z w^{1-z}$. Plugging it into the free entry condition, we find that the ratio of average productivity between home and foreign country is $\frac{\widehat{\varphi}_z^*}{\widehat{\varphi}_z} = (\frac{1+f\chi^*(z)}{1+f\chi(z)})^{\frac{1}{a}}$ while $f \equiv \frac{f_{zx}}{f_z}$. Combining these results, it can be shown that:

$$\frac{r(\widehat{\varphi}_z)}{r(\widehat{\varphi}_z^*)} = \Psi(z)\widetilde{p}_z(\frac{1+f\chi(z)}{1+f\chi(z)^*})^{\frac{a+1}{a}}, \tag{E2}$$

[43] We will show how to determine the specialization pattern in proposition 2.

[44] When deriving the equation (E1), we have used the result that $\frac{\widehat{\varphi}_z}{\bar{\varphi}_z} = \frac{\widehat{\varphi}_{zx}}{\bar{\varphi}_{zx}} = (\frac{a}{a+1-\sigma})^{\frac{1}{\sigma-1}}$ and $\chi(z) = \frac{1-G(\bar{\varphi}_{zx})}{1-G(\bar{\varphi}_z)} = \Lambda_z^{-a}$ due to the Pareto distribution assumption. $\Lambda_z = \frac{\bar{\varphi}_{zx}}{\bar{\varphi}_z}$ is defined in equation (10).

Using the definition of $\widetilde{p}_z$ and combining equations (E1) and (E2), we have:

$$\chi(z) = \frac{\widetilde{\tau}^{-a} f - \Psi(z)^a h(z)}{\Psi(z)^a f h(z) - \widetilde{\tau}^a}, \tag{E3}$$

where $h(z) = (\frac{w}{w^*}(\frac{r/w}{r^*/w^*})^z)^{\frac{a\sigma}{1-\sigma}}$ and $\widetilde{\tau} = \tau f^{\frac{1}{\sigma-1}}$. Equation (E3) implies that $\chi(z)$ is a function of the factor prices. From Equation (10) we have $\Lambda_z = \chi(z)^{-1/a} = \frac{\tau P(z)}{P(z)^*}(\frac{fR}{R^*})^{1/(\sigma-1)}$, then $\frac{P(z)}{P(z)^*} = \frac{\chi(z)^{-1/a}}{\tau}(\frac{R^*}{fR})^{1/(\sigma-1)}$. which is also function of the factor prices. Combined with equations (13) and (14), the revenue functions for those industries that both countries produce are:

$$R_z = b(z)[\frac{R}{1 - \widetilde{\tau}^{-a}\Psi(z)^a f h(z)} - \frac{fR^*}{\widetilde{\tau}^a \Psi(z)^a h(z) - f}], \tag{E4}$$

$$R_z^* = b(z)\Psi(z)^a h(z)[\frac{R^*}{\Psi(z)^a h(z) - f\widetilde{\tau}^{-a}} - \frac{fR}{\widetilde{\tau}^a - \Psi(z)^a f h(z)}]. \tag{E5}$$

Both equations above are functions of factor prices. Using $l(z) = (1-z)b(z)R_z/w$ and $k(z) = zb(z)R_z/r$, the factor market clearing conditions for the home country are given by:

$$\int\limits_{I(s)} (1-z)\frac{b(z)(R+R^*)}{w}dz + \int\limits_{I(b)} (1-z)\frac{R_z}{w} = L,$$

$$\int\limits_{I(s)} z\frac{b(z)(R+R^*)}{r}dz + \int\limits_{I(b)} z\frac{R_z}{r} = K.$$

Another two symmetric equations can be written for the foreign country. $I(s)$ is the set of industries that the home country specializes and $I(b)$ is the set of industries that both countries produce. They are determined by cut-off industries where either the domestic or foreign firm mass is zero using the result $\frac{M_z}{M_z^*} = \widetilde{p}_z^{\sigma-1}\frac{(\frac{P(z)}{P(z)^*})^{1-\sigma} - \chi(z)^{-\frac{a+1-\sigma}{a}}\widetilde{\tau}^{-2(a+1-\sigma)}\tau^{1-\sigma}}{1-\chi(z)^{\frac{a+1-\sigma}{a}}\tau^{1-\sigma}(\frac{P(z)}{P(z)^*})^{1-\sigma}}$, which is also determined by factor prices.[45] Therefore, we have four factor market clearing equations determining the four factor prices $\{w, r, w^*, r^*\}$.

Once the factor prices are known, we can determine the productivity cut-offs $\bar{\varphi}_z$ and $\bar{\varphi}_{zx}$, and the export propensity, $\chi(z)$ for all industries. Once the cut-offs are known, the average revenue for each industry given by $r(\widehat{\varphi}_z) = (f_z(\frac{\widehat{\varphi}_z}{\bar{\varphi}_z})^{\sigma-1} + \chi(z)f_{zx}(\frac{\widehat{\varphi}_{zx}}{\bar{\varphi}_{zx}})^{\sigma-1})\sigma r^z w^{1-z}$ is also known. Then we use the goods market clearing condition Equation (13) to determine the firm mass for each industry. The price index for each industry is pinned down by equation (14). ■

### A.1.2 Proof of Proposition 2

Suppose $M_z^* \neq 0$, the relative firm mass between home and foreign can be inferred from equation (14) as:

$$\frac{M_z}{M_z^*} = \widetilde{p}_z^{\sigma-1}\frac{(\frac{P(z)}{P(z)^*})^{1-\sigma} - \chi(z)^{-\frac{a+1-\sigma}{a}}\widetilde{\tau}^{-2(a+1-\sigma)}\tau^{1-\sigma}}{1-\chi(z)^{\frac{a+1-\sigma}{a}}\tau^{1-\sigma}(\frac{P(z)}{P(z)^*})^{1-\sigma}},$$

[45] This is derived from the price index equation (14). Further details are discussed in the next proof.

where we have used the result that $\chi(z)\chi(z)^* = \widetilde{\tau}^{-2a}$ to replace $\chi(z)^*$ by $\chi(z)^{-1}\widetilde{\tau}^{-2a}$.[46] Since $\frac{P(z)}{P(z)^*} = \frac{\chi(z)^{-1/a}}{\tau}(\frac{R^*}{fR})^{1/(\sigma-1)}$ and $\widetilde{p}_z = \frac{\widehat{\varphi}_z^* w}{\Psi(z)\widehat{\varphi}_z w^*}(\frac{r/w}{r^*/w^*})^z$, we have:

$$\frac{M_z}{M_z^*} = \Psi(z)^{1-\sigma}(\frac{1+f\chi(z)^*}{1+f\chi(z)})^{\frac{\sigma-1}{a}}[\frac{w}{w^*}(\frac{r/w}{r^*/w^*})^z]^{\sigma-1}\frac{\frac{fR}{R^*}-\chi(z)^{-1}\widetilde{\tau}^{-2a}f^2}{1-\chi(z)\frac{fR}{R^*}}\tau^{\sigma-1}\chi(z)^{\frac{\sigma-1}{a}}.$$

If $\chi(z) = \frac{R^*}{fR}(\frac{f}{\widetilde{\tau}^a})^2$, we have $\frac{M_z}{M_z^*} = 0$. Since $M_z^* > 0$, it must be that $M_z = 0$. If $\chi(z)$ decreases such that $\chi(z) < \frac{R^*}{fR}(\frac{f}{\widetilde{\tau}^a})^2$, we have $\frac{M_z}{M_z^*} < 0$. Since $M_z$ cannot be negative, we should have $M_z = 0$ and foreign will specialize in these industries. On the other hand, if $\chi(z)$ increases such that $\chi(z)$ approaches $\frac{R^*}{fR}$ and $\frac{M_z}{M_z^*} \to +\infty$, or say $\frac{M_z^*}{M_z} \to 0$, which implies $M_z^* = 0$. If $\chi(z)$ further increases such that $\chi(z) > \frac{R^*}{fR}$, we again have $\frac{M_z^*}{M_z} < 0$. Since $M_z^*$ cannot be negative, $M_z^*$ stays at zero, and home will specialize in these industries. In sum, to maintain positive firm mass for both countries in each industry, we must have the following:

$$\frac{R^*}{fR}(\frac{f}{\widetilde{\tau}^a})^2 < \chi(z) < \frac{R^*}{fR},$$

where $\frac{f}{\widetilde{\tau}^a} = \frac{f}{\tau^a f^{\frac{a}{\sigma-1}}} < \frac{f}{f^{\frac{a}{\sigma-1}}} < 1$. If $\chi(z)$ falls out of this range, one country's firm mass is zero, and the other is positive. This is when specialization happens. For industries that both countries produce, we have

$$\chi(z) = \frac{\widetilde{\tau}^{-a}f - \Psi(z)^a h(z)}{\Psi(z)^a f h(z) - \widetilde{\tau}^a}, \tag{E6}$$

which is a continuous and monotonic between $[\underline{z}, \overline{z}]$.[47] For the boundary industries $\underline{z}$ and $\overline{z}$, since we have

$$\chi_{\underline{z}} = \frac{R^*}{fR} \text{ and } \chi_{\overline{z}} = \frac{R^*}{fR}(\frac{f}{\widetilde{\tau}^a})^2,$$

evaluating equation (E6) at $\underline{z}$ and $\overline{z}$, we have:

$$\begin{aligned}
\underline{z} &= \frac{\ln(\frac{\chi_{\underline{z}}\widetilde{\tau}^a + f\widetilde{\tau}^{-a}}{1+f\chi_{\underline{z}}}) - \frac{a\sigma}{1-\sigma}\ln(\frac{w}{w^*}) - a\ln(\lambda)}{\frac{a\sigma}{1-\sigma}\ln(\frac{r/w}{r^*/w^*}) + a\ln(A)}, \\
\overline{z} &= \frac{\ln(\frac{\chi_{\overline{z}}\widetilde{\tau}^a + f\widetilde{\tau}^{-a}}{1+f\chi_{\overline{z}}}) - \frac{a\sigma}{1-\sigma}\ln(\frac{w}{w^*}) - a\ln(\lambda)}{\frac{a\sigma}{1-\sigma}\ln(\frac{r/w}{r^*/w^*}) + a\ln(A)},
\end{aligned}$$

which are also determined given the factor prices. If we have free trade such that $\tau = f = 1$, we have $\chi_{\underline{z}} = \chi_{\overline{z}} = \frac{R^*}{R}$, and $\underline{z} = \overline{z}$. The two countries completely specialize. ■

[46] Since $\chi(z) = \Lambda_z^{-a}$ and $\chi(z)^* = \Lambda_z^{*-a}$, $\Lambda_z = \chi(z)^{-1/a} = \frac{\tau P(z)}{P(z)^*}(\frac{fR}{R^*})^{1/(\sigma-1)}$, and $\Lambda_z^* = \chi^*(z)^{-1/a} = \frac{\tau P^*(z)}{P(z)}(\frac{fR^*}{R})^{1/(\sigma-1)}$, we have $\chi(z)^*\chi(z) = (\tau f^{\frac{1}{\sigma-1}})^{-2a} = \tilde{\tau}^{-2a}$.

[47] As shown in the proof of proposition 1.

### A.1.3 Proof of Proposition 3

First, we note that combining the free entry condition (12) with the zero profit conditions (9), the productivity cut-offs $\bar{\varphi}_z$ and $\bar{\varphi}_{zx}$ satisfy:

$$\frac{f_z}{\delta}\int_{\bar{\varphi}_z}^{\infty}\left[(\frac{\varphi}{\bar{\varphi}_z})^{\sigma-1}-1\right]dG(\varphi)+\frac{f_{zx}}{\delta}\int_{\bar{\varphi}_{zx}}^{\infty}\left[(\frac{\varphi}{\bar{\varphi}_{zx}})^{\sigma-1}-1\right]dG(\varphi)=f_{ez}. \tag{E7}$$

Let's focus on the home country. For any two industries $z$ and $z'$, suppose $z<z'$, using the definition of $\Lambda_z$ equation (10), and the assumption that variable trade costs and fixed costs are the same for all industries, we have:

$$\frac{\Lambda_z}{\Lambda_{z'}}=\frac{P(z)/P(z')}{P(z)^*/P(z')^*}.$$

If $\frac{P(z)}{P(z')}<\frac{P(z)^*}{P(z')^*}$, that is labor-intensive products are relatively cheaper at the home country, then $\Lambda_z<\Lambda_{z'}$. This is what we will show next. The idea is that if $\frac{P(z)}{P(z')}<\frac{P(z)^*}{P(z')^*}$ under autarky and $\frac{P(z)}{P(z')}=\frac{P(z)^*}{P(z')^*}$ under free trade, then the costly trade case will fall between.

Under free trade, all firms export. The price of each variety and the number of varieties are the same for both countries. Thus the pricing index $P(z)=P(z)^*$ for all industries and we have $\frac{P(z)}{P(z')}=\frac{P(z)^*}{P(z')^*}$.

At the other extreme of the closed economy, no firms export, and from equation (14), we have $P(z)=M_z^{\frac{1}{1-\sigma}}p_{zd}(\widehat{\varphi}_z)$. Firm mass for each industry is $M_z=\frac{b(z)R}{r(\widehat{\varphi}_z)}=\frac{b(z)R}{r(\bar{\varphi}_z)}(\frac{\bar{\varphi}_z}{\widehat{\varphi}_z})^{\sigma-1}$. So $\frac{P(z)}{P(z')}=(\frac{w}{r})^{(z'-z)/\rho}(\frac{b(z)}{b(z')})^{\frac{1}{1-\sigma}}\frac{A(z')\bar{\varphi}_{z'}}{A(z)\bar{\varphi}_z}$. Using equation (E7) we have homogeneous cut-offs for all industries under autarky: $\bar{\varphi}_{z'}=\bar{\varphi}_z$. Then it can be verified that

$$\frac{P(z)/P(z')}{P(z)^*/P(z')^*}=(\frac{w/r}{w^*/r^*})^{\frac{z'-z}{\rho}}A^{z'-z}.$$

Since $z'>z$ and $A<1$, then $\frac{w}{r}<\frac{w^*}{r^*}\iff\frac{P(z)}{P(z')}<\frac{P(z)^*}{P(z')^*}$. We just need to show that $\frac{w}{r}<\frac{w^*}{r^*}$ under autarky. Using the factor market clearing condition, given the Cobb-Douglas forms for production function, entry costs, and payments of fixed costs, we find that:

$$\frac{K}{L}=\frac{w}{r}\frac{\int_0^1 zb(z)dz}{\int_0^1(1-z)b(z)dz},\quad\frac{K^*}{L^*}=\frac{w^*}{r^*}\frac{\int_0^1 zb(z)dz}{\int_0^1(1-z)b(z)dz}.$$

Thus $\frac{K}{L}<\frac{K^*}{L^*}\iff\frac{w}{r}<\frac{w^*}{r^*}$ and we establish that $\Lambda_z<\Lambda_{z'}$, or say $\Lambda_z$ increases with z in home country.

For industries that both countries produce, equation (E7) determines the cut-offs. It is easy to see that the first term in the left-hand side of the equation is a decreasing function of $\bar{\varphi}_z$, and the second term is a decreasing function of $\bar{\varphi}_{zx}$, given that $g(\varphi)>0$, $\bar{\varphi}_z\leq\varphi$ and $\bar{\varphi}_{zx}\leq\varphi$ . Since $\Lambda_z$ increases with z, it can be shown that either $\frac{\partial\bar{\varphi}_z}{\partial z}>0$ or $\frac{\partial\bar{\varphi}_z}{\partial z}=0$ cannot maintain the equality of the equation.[48] So it must be the case that $\frac{\partial\bar{\varphi}_z}{\partial z}<0$. Then the first term of equation (E7) increases with z. The second term must decrease with z to maintain the equation. Thus $\bar{\varphi}_{zx}$ should be an increasing function of z. Similar logic applies for

[48] This is a proof by contradiction. Suppose $\frac{\partial\bar{\varphi}_z}{\partial z}>0$, so will $\bar{\varphi}_{zx}$ given $\frac{\partial\Lambda_z}{\partial z}>0$. Then the left-hand side of equation (E7) will decrease with z. But the right-hand side is a constant. Contradiction. Similar argument applies if $\frac{\partial\bar{\varphi}_z}{\partial z}=0$.

the foreign country: $\frac{\partial\bar{\varphi}_z^*}{\partial z}>0$ and $\frac{\partial\bar{\varphi}_{zx}^*}{\partial z}<0$ .

For industries that home country specializes: $M_z^*=0$ and $M_z>0$. Thus the price indexes at home and foreign are: $P(z)=M_z^{\frac{1}{1-\sigma}}p_{zd}(\widehat{\varphi}_z)$ and $P(z)^*=\chi_z^{\frac{1}{1-\sigma}}M_z^{\frac{1}{1-\sigma}}p_{zx}(\widehat{\varphi}_{zx})$. So we have $\Lambda_z=\frac{\tau P(z)}{P(z)^*}(\frac{fR}{R^*})^{\frac{1}{\sigma-1}}=\chi(z)^{\frac{1}{\sigma-1}}\frac{\widehat{\varphi}_{zx}}{\widehat{\varphi}_z}(\frac{fR}{R^*})^{\frac{1}{\sigma-1}}$. Then we have $\Lambda_z=(\frac{\int_{\Lambda_z\bar{\varphi}_z}^{\infty}\varphi^{\sigma-1}g(\varphi)d\varphi}{\int_{\bar{\varphi}_z}^{\infty}\varphi^{\sigma-1}g(\varphi)d\varphi})^{\frac{1}{\sigma-1}}(\frac{fR}{R^*})^{\frac{1}{\sigma-1}}$ using the definition of $\widehat{\varphi}_z$ and $\widehat{\varphi}_{zx}$. This is an implicit function of $\Lambda_z$ and $\bar{\varphi}_z$. Moreover, the free entry condition $\frac{f_z}{\delta}\int_{\bar{\varphi}_z}^{\infty}\left[(\frac{\varphi}{\bar{\varphi}_z})^{\sigma-1}-1\right]g(\varphi)d\varphi+\frac{f_{zx}}{\delta}\int_{\Lambda_z\bar{\varphi}_z}^{\infty}\left[(\frac{\varphi}{\bar{\varphi}_{zx}})^{\sigma-1}-1\right]g(\varphi)d\varphi=f_{ez}$ is also an implicit function of $\Lambda_z$ and $\bar{\varphi}_z$. Solving these two equations together we would have $\Lambda_z$ and $\bar{\varphi}_z$. Since these same functions hold for all the industries that home specializes in, the solution would be the same for all these industries within $[0,\underline{z}]$ under our assumption that $f_z$, $f_{zx}$ and $f_{ez}$ do not vary with $z$.■

### A.1.4 Proof of Proposition 4

The conditional probability of export is given by $\chi(z)=\frac{1-G(\bar{\varphi}_{zx})}{1-G(\bar{\varphi}_z)}$. From Proposition 3, we know that $\frac{\partial\bar{\varphi}_z}{\partial z}<0$ and $\frac{\partial\bar{\varphi}_{zx}}{\partial z}>0$ for $z\in(\underline{z},\overline{z})$. Thus we have $\frac{\partial G(\bar{\varphi}_z)}{\partial z}<0$ and $\frac{\partial G(\bar{\varphi}_{zx})}{\partial z}>0$ as long as the cumulative distribution function $G(\varphi)$ is continuous and $G(\varphi)'>0$ . Then it is easy to see that $\frac{\partial\chi(z)}{\partial z}<0$ for $z\in(\underline{z},\overline{z})$. For $z\in[0,\underline{z}]$, we know that $\frac{\partial\bar{\varphi}_z}{\partial z}=0$ and $\frac{\partial\bar{\varphi}_{zx}}{\partial z}=0$ from Proposition 3, so $\frac{\partial\chi(z)}{\partial z}=0$.

Under the assumption that $G(\varphi)$ is Pareto distributed, we have $\chi_z=\Lambda_z^{-a}$ and the $\Lambda_z=\frac{\bar{\varphi}_{zx}}{\bar{\varphi}_z}=\frac{\widehat{\varphi}_{zx}}{\widehat{\varphi}_z}$. Thus using the result that $\Lambda_z=\chi(z)^{\frac{1}{\sigma-1}}\frac{\widehat{\varphi}_{zx}}{\widehat{\varphi}_z}(\frac{fR}{R^*})^{\frac{1}{\sigma-1}}$ from the proof of Proposition 2, we have $\chi(z)=\frac{R^*}{fR}$ for industries that home specializes. For industries that both countries produce, we know that

$$\chi(z)=\frac{\widetilde{\tau}^{-a}f-\Psi(z)^a h(z)}{\Psi(z)^a fh(z)-\widetilde{\tau}^a} \tag{E8}$$

from the proof of Proposition 1. Using the chain rule, we have $\frac{\partial\chi(z)}{\partial z}=\frac{(1-\widetilde{\tau}^{-2a}f^2)\Psi(z)^a h(z)\widetilde{\tau}^a a}{(\Psi(z)^a h(z)f-\widetilde{\tau}^a)^2}(\ln(A)-\frac{\sigma}{\sigma-1}\ln(\frac{r/w}{r^*/w^*}))$. Let $B(z)=\frac{(1-\widetilde{\tau}^{-2a}f^2)\Psi(z)^a h(z)\widetilde{\tau}^a a}{(\Psi(z)^a fh(z)-\widetilde{\tau}^a)^2}$ which is positive, immediately, we have

$$\frac{\partial\chi(z)}{\partial z}=B(z)(\ln(A)-\frac{\sigma}{\sigma-1}\ln(\frac{r/w}{r^*/w^*})),$$

whose sign depends only on $\ln(A)$ and $\frac{\sigma}{\sigma-1}\ln(\frac{r/w}{r^*/w^*})$.[49] For average export intensity for each sector is $\gamma(z)\equiv\frac{\chi(z)r(\widehat{\varphi}_{zx})}{r(\widehat{\varphi}_z)+\chi(z)r(\widehat{\varphi}_{zx})}=\frac{\chi(z)f_{zx}(\frac{\widehat{\varphi}_{zx}}{\bar{\varphi}_{zx}})^{\sigma-1}\sigma r^z w^{1-z}}{(f_z(\frac{\widehat{\varphi}_z}{\bar{\varphi}_z})^{\sigma-1}+\chi(z)f_{zx}(\frac{\widehat{\varphi}_{zx}}{\bar{\varphi}_{zx}})^{\sigma-1})\sigma r^z w^{1-z}}=\frac{f_{zx}\chi(z)}{f_z+f_{zx}\chi(z)}=\frac{f\chi(z)}{1+f\chi(z)}$, thus $\frac{\partial\gamma(z)}{\partial\chi(z)}=\frac{f}{(1+f\chi_z)^2}>0$. So $\gamma(z)$ is a monotonic increasing function of $\chi_z$ and should follow the same pattern as $\chi(z)$.■

[49] We note that $B(z)>0$ as long as $\widetilde{\tau}^{-a}f<1$, which has been shown in the proof of Proposition 2.

### A.1.5 Proof of Proposition 5

From equation (E7) for free entry equation, we can calculate the average of idiosyncratic firm productivity as

$$\widehat{\varphi}_z = (\frac{a}{a+1-\sigma})^{\frac{1}{\sigma-1}}\bar{\varphi}_z = (\frac{a}{a+1-\sigma})^{\frac{1}{\sigma-1}}[\frac{(\sigma-1)\theta^a}{(a+1-\sigma)\delta\widetilde{f}}(1+f\chi(z))]^{\frac{1}{a}}$$

where $\widetilde{f} = \frac{f_{ez}}{f_z}$. Let $C = (\frac{a}{a+1-\sigma})^{\frac{1}{\sigma-1}}[\frac{(\sigma-1)\theta^a}{(a+1-\sigma)\delta\widetilde{f}}]^{\frac{1}{a}}$, we immediately have

$$\widehat{\varphi}_z = C(1+f\chi(z))^{1/a}.$$

From the equation above, $\widehat{\varphi}_z$ is monotonic increasing function of $\chi(z)$. As we have proved in Proposition 4, $\chi(z)$ is higher in industries with larger comparative advantage, so is $\widehat{\varphi}_z$. Then the average productivity for each industry is

$$\widehat{A(z)} = E_\varphi\{A(z)\varphi|\varphi > \overline{\varphi}_z\} = A(z)\widetilde{\varphi}_z$$

Thus the measured Ricardian comparative advantage is given by $\frac{\widehat{A(z)}}{\widehat{A^*(z)}} = \frac{A(z)}{A^*(z)}\frac{\widetilde{\varphi}_z}{\widetilde{\varphi}_z^*}$. Under our assumption that $\frac{A(z)}{A^*(z)} = \lambda A^z$ and using the expression for $\widehat{\varphi}_z$ above, we have

$$\frac{\widehat{A(z)}}{\widehat{A^*(z)}} = \lambda A^z(\frac{1+f\chi(z)}{1+f\chi(z)^*})^{1/a},$$

which is the second result of the proposition. ■

### A.1.6 Proof of Proposition 6

From opposition 4, we know that for $z \in (\underline{z}, \overline{z})$, export propensity $\chi(z)$ is given by

$$\chi(z) = \frac{\left[\frac{A(z)}{A^*(z)}(\frac{w^z r^{1-z}}{w^{*z} r^{*1-z}})^{\frac{\sigma}{\sigma-1}}\right]^a - \widetilde{\tau}^{-a} f}{\widetilde{\tau}^a - \left[\frac{A(z)}{A^*(z)}(\frac{w^z r^{1-z}}{w^{*z} r^{*1-z}})^{\frac{\sigma}{\sigma-1}}\right]^a f}.$$

From the above expression, we can solve for $\frac{A(z)}{A^*(z)}$ and find

$$\frac{A(z)}{A^*(z)} = (\frac{w^z r^{1-z}}{w^{*z} r^{*1-z}})^{\frac{\sigma}{\sigma-1}}\left[\frac{\widetilde{\tau}^a\chi(z) + \widetilde{\tau}^{-a} f}{1+f\chi(z)}\right]^{1/a}. \tag{E9}$$

### A.1.7 Estimation Algorithm

For a given set of parameters $\{\frac{K^*}{K}, \frac{L^*}{L}, \frac{K}{L}, A, \lambda, a, f, \tau, \sigma, \mathrm{b(z)}\}$, we follow the idea of the proof for Proposition 1 to solve the endogenous factor prices {w, w*, r, r*} using the factor market clearing conditions. First, the aggregate revenue for home and foreign are: $R = wL + rK$ and $R^* = w^*L^* + r^*K^*$. The factor intensity cut-offs are: $\underline{z} = \frac{\ln(\frac{\chi_{\underline{z}}\widetilde{\tau}^a + f\widetilde{\tau}^{-a}}{1+f\chi_{\underline{z}}}) - \frac{a\sigma}{1-\sigma}\ln(\frac{w}{w^*}) - a\ln(\lambda)}{\frac{a\sigma}{1-\sigma}\ln(\frac{r/w}{r^*/w^*}) + a\ln(A)}$ and $\overline{z} = \frac{\ln(\frac{\chi_{\overline{z}}\widetilde{\tau}^a + f\widetilde{\tau}^{-a}}{1+f\chi_{\overline{z}}}) - \frac{a\sigma}{1-\sigma}\ln(\frac{w}{w^*}) - a\ln(\lambda)}{\frac{a\sigma}{1-\sigma}\ln(\frac{r/w}{r^*/w^*}) + a\ln(A)}$, where $\chi_{\underline{z}} = \frac{R^*}{fR}$ and $\chi_{\overline{z}} = \frac{R^*}{fR}(\frac{f}{\tau^a})^2$. The factor market clearing conditions for the home country are

$$\int_0^{\underline{z}} (1-z)\frac{b(z)(R+R^*)}{w}dz + \int_{\underline{z}}^{\overline{z}} (1-z)\frac{R_z}{w} = L, \int_0^{\underline{z}} z\frac{b(z)(R+R^*)}{r}dz + \int_{\underline{z}}^{\overline{z}} z\frac{R_z}{r} = K.$$

where $R_z$ is given by equation (E4). There are two similar equations for the foreign. So we have four equations to solve for the four unknown factor prices {w, w*, r, r*}.

Once {w, w*, r, r*} are known, we compute domestic and foreign aggregate revenues $R$ and $R^*$, the probability of export for each industry $\chi(z)$ and the firm mass for each industry. This is done without the need to know other parameters of the model: $f_z, f_{zx}, f_{ez}, \delta$ and $\theta$, which is shown in Appendix A.3.

Then we compute the targeted moments from the model and their distance from the empirical counterpart. Our estimation takes $\{\frac{L^*}{L}, \frac{K^*}{K}, f, a, \sigma$, b(z)} as given and search for $\{\frac{K}{L}, A, \lambda, \tau\}$ to minimize the distance. In essence, there are two loops: an inner loop for solving the factor prices and computing the model moments and an outer loop to search for model parameters that match the moments.

### A.1.8 Additional Tables

Table A.1: Statistical Summary of Main Variables

| Variables | mean in 1999 | mean in 2007 |
|---|---|---|
| Panel **(a)**: Statistical Summary of Main Variables | | |
| total sales | 48,899 | 115,067 |
| total exports | 9,008 | 23,972 |
| number of employee | 325 | 218 |
| value added | 14,011 | 31,893 |
| total profit | 1,866 | 6,835 |
| Panel **(b)**: Aggregate factor allocation and export participation | | |
| capital share of all manufacturers | 0.667 | 0.707 |
| capital share of exporters | 0.623 | 0.619 |
| proportion of exporters | 0.257 | 0.249 |
| exports/gross sales | 0.184 | 0.208 |

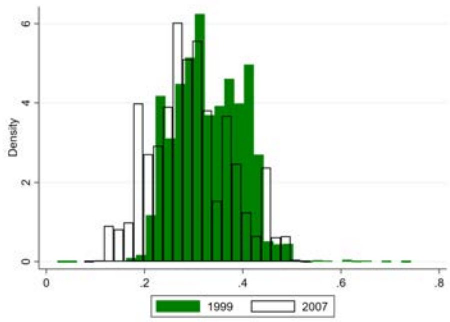
**Notes**: We follow Brandt et al. (2012) only to include manufacturing firms with more than 8 employees, positive output, and fixed assets and drop firms with capital intensities less than zero or greater than one. We are left with 114,777 and 291,204 firms in 1999 and 2007, which represent about 84.4% and 94.0% of the original sample, respectively. The units are sales, export, value-added, total profit, and wages are 1,000 Chinese Yuan.

Table A.2: Labor Share of Chinese Firms Cross Industries

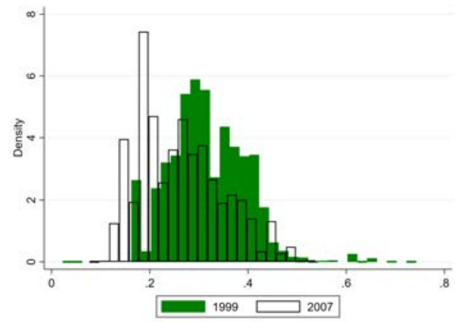
| industry code | description | (1) average | (2) standard deviation | (3) average labor share: non-exporters | (4) average labor share: exporters | (5) (4) minus (3) |
|---|---|---|---|---|---|---|
| 13 | Processing of Foods | 0.182 | 0.186 | 0.173 | 0.236 | 0.063 |
| 14 | Manufacturing of Foods | 0.251 | 0.207 | 0.242 | 0.294 | 0.052 |
| 15 | Manufacture of Beverages | 0.206 | 0.181 | 0.204 | 0.222 | 0.018 |
| 16 | Manufacture of Tobacco | 0.233 | 0.193 | 0.264 | 0.096 | -0.168 |
| 17 | Manufacture of Textile | 0.309 | 0.213 | 0.283 | 0.372 | 0.089 |
| 18 | Manufacture of Apparel, Footwear & Caps | 0.444 | 0.243 | 0.400 | 0.486 | 0.086 |
| 19 | Manufacture of Leather, Fur, & Feather | 0.411 | 0.249 | 0.356 | 0.465 | 0.109 |
| 20 | Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm & Straw Products | 0.269 | 0.202 | 0.260 | 0.313 | 0.053 |
| 21 | Manufacture of Furniture | 0.366 | 0.238 | 0.315 | 0.441 | 0.126 |
| 22 | Manufacture of Paper & Paper Products | 0.274 | 0.198 | 0.265 | 0.353 | 0.087 |
| 23 | Printing, Reproduction of Recording Media | 0.335 | 0.213 | 0.326 | 0.405 | 0.080 |
| 24 | Manufacture of Articles For Culture, Education & Sport Activities | 0.423 | 0.240 | 0.359 | 0.462 | 0.104 |
| 25 | Processing of Petroleum, Coking, &Fuel | 0.153 | 0.164 | 0.148 | 0.220 | 0.072 |
| 26 | Manufacture of Raw Chemical Materials | 0.217 | 0.188 | 0.211 | 0.249 | 0.038 |
| 27 | Manufacture of Medicines | 0.228 | 0.191 | 0.222 | 0.256 | 0.034 |
| 28 | Manufacture of Chemical Fibers | 0.203 | 0.177 | 0.197 | 0.234 | 0.037 |
| 29 | Manufacture of Rubber | 0.304 | 0.225 | 0.270 | 0.392 | 0.121 |
| 30 | Manufacture of Plastics | 0.308 | 0.218 | 0.276 | 0.400 | 0.124 |
| 31 | Manufacture of Non-metallic Mineral goods | 0.272 | 0.210 | 0.258 | 0.369 | 0.111 |
| 32 | Smelting & Pressing of Ferrous Metals | 0.178 | 0.168 | 0.178 | 0.181 | 0.003 |
| 33 | Smelting & Pressing of Non-ferrous Metals | 0.182 | 0.182 | 0.176 | 0.222 | 0.046 |
| 34 | Manufacture of Metal Products | 0.316 | 0.217 | 0.289 | 0.388 | 0.099 |
| 35 | Manufacture of General Purpose Machinery | 0.294 | 0.205 | 0.281 | 0.349 | 0.068 |
| 36 | Manufacture of Special Purpose Machinery | 0.300 | 0.214 | 0.282 | 0.366 | 0.084 |
| 37 | Manufacture of Transport Equipment | 0.311 | 0.213 | 0.301 | 0.351 | 0.050 |
| 39 | Electrical Machinery & Equipment | 0.306 | 0.220 | 0.272 | 0.389 | 0.117 |
| 40 | Computers & Other Electronic Equipment | 0.385 | 0.242 | 0.348 | 0.423 | 0.075 |
| 41 | Manufacture of Measuring Instruments & Machinery for Cultural Activity & Office Work | 0.359 | 0.235 | 0.312 | 0.440 | 0.129 |
| 42 | Manufacture of Artwork | 0.392 | 0.239 | 0.336 | 0.434 | 0.099 |
| | All Industries | 0.293 | 0.222 | 0.264 | 0.381 | 0.117 |

**Notes:** This table examines the labor share of Chinese manufacturing firms in 2007. Labor share is measured by labor cost divided by value added for each firm. Columns (1) and (2) are each industry's average and standard deviation, respectively. Columns (3) and (4) are the average labor share of non-exporters and exporters, respectively. Column (5) is the difference in average labor share between exporters and non-exporters, i.e., column (4) minus column (3).

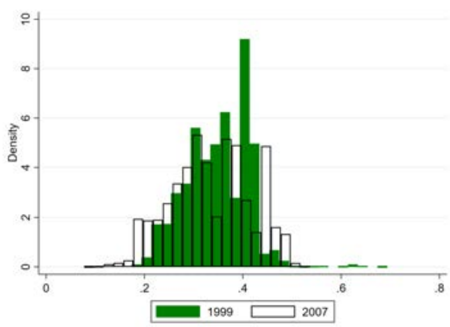
### A.1.9 Additional Figures



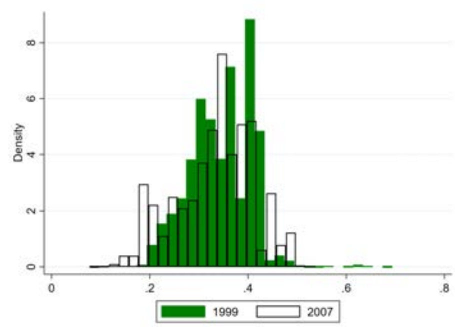

(a) firm mass



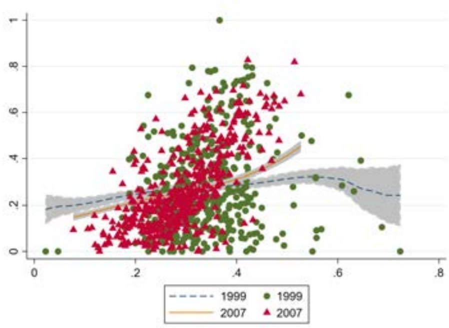

(b) value added



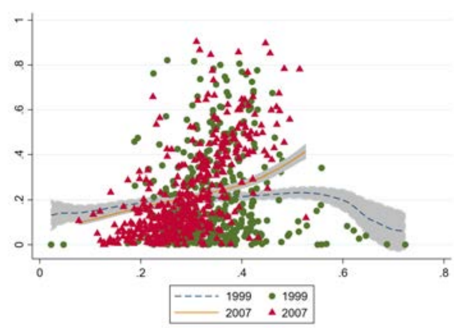

(c) exporter distribution



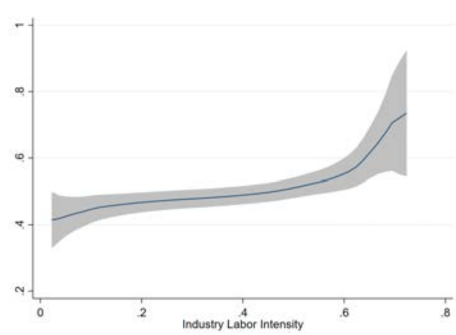

(d) export volume




(e) exporter share



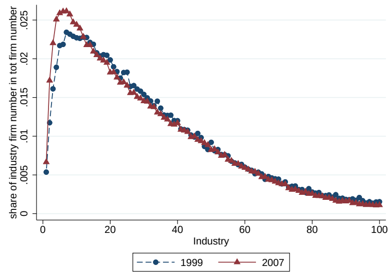

(f) export intensity



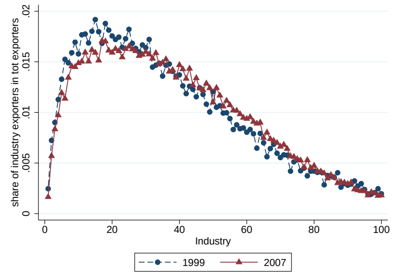

(g) Sectoral TFP growth

**Notes**: The horizontal axis is the labor intensity of each industry. Non-parametric local polynomials are used to capture the trend in the data.

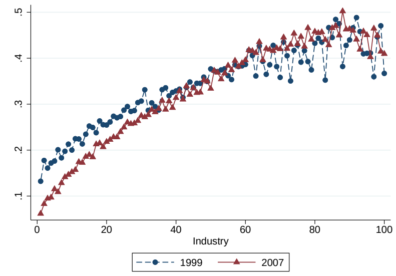
Figure A.1: Motivating Evidence using the Four-digit CIC Industry Classification



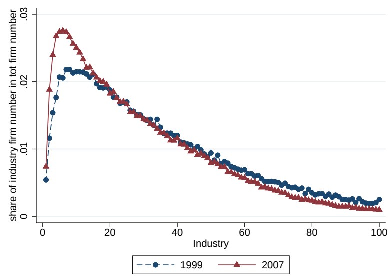

(a) SOE: firm count



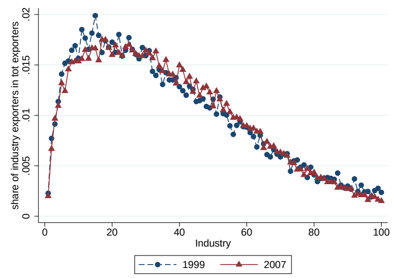

(b) exporter count



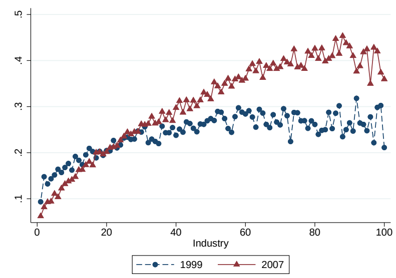

(c) export propensity



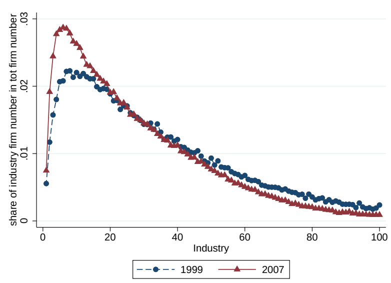

(d) MFA: firm count



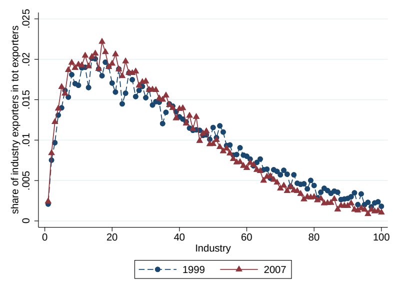

(e) exporter count



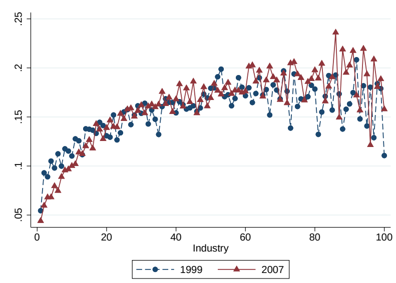

(f) export propensity



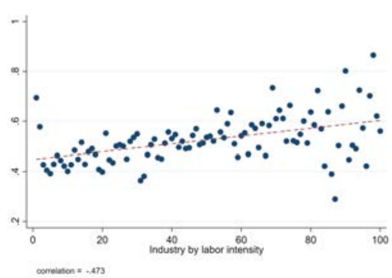

(g) Pure exporter: firm count



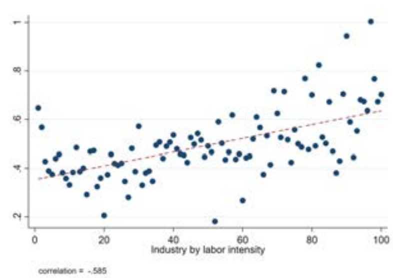

(h) exporter count



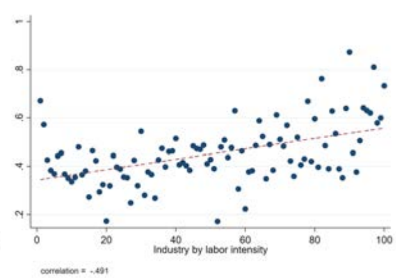

(i) export propensity




(j) TFP: non-SOEs



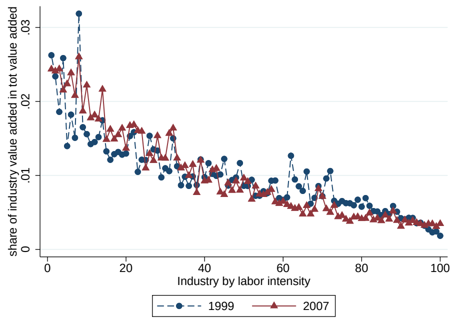

(k) TFP: non-MFAs



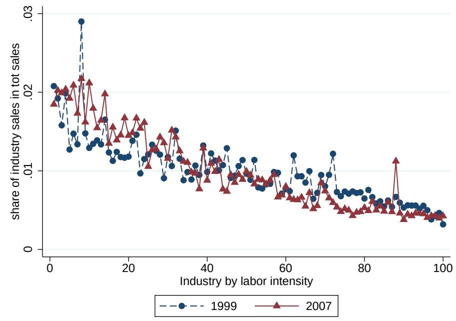

(l) TFP: non-pure exporters

**Notes**: (a) Industry classification is "HO aggregate," as in the main text. (b) The charts on SOE exclude state-owned firms (figures a, b, c, and j). (c) The charts on MFA are produced by excluding the textile industries (figures d, e, f, and k): 2-digit CIC industries of 17 and 18. (d) The charts on Pure Exporters exclude pure exporters (figures g, h, i, and l), i.e., firms that export more than 70% of outputs.

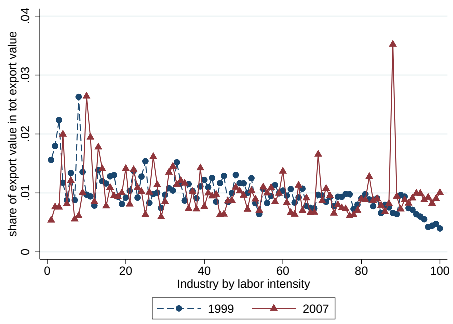
Figure A.2: Robustness by Sub-samples



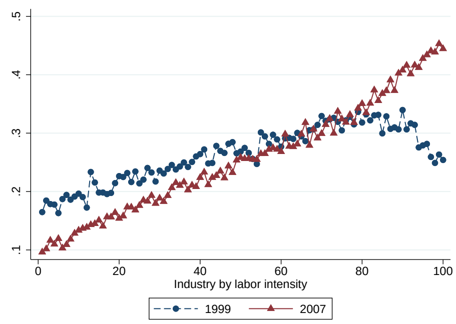

(a) distribution of value added



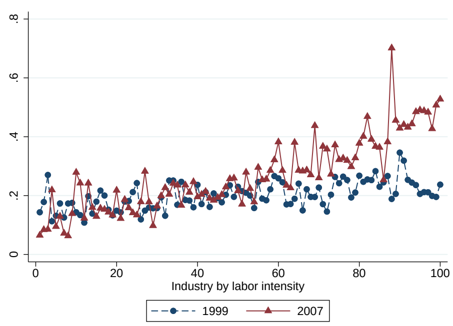

(b) distribution of sales



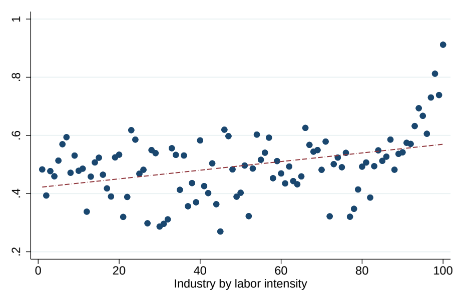

(c) distribution of exports




(d) export propensity



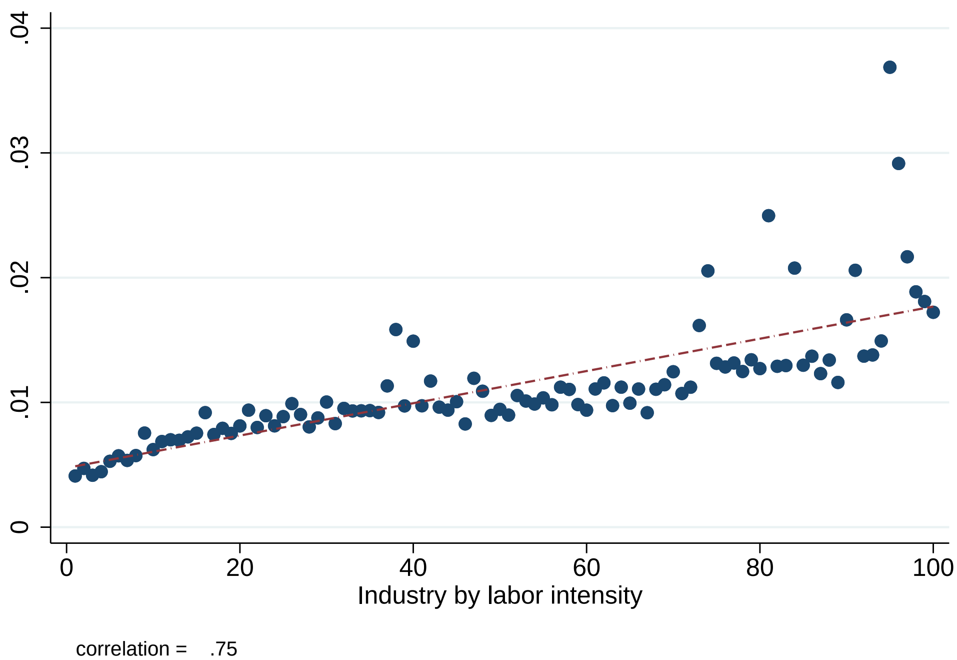

(e) export intensity




(f) TFP growth

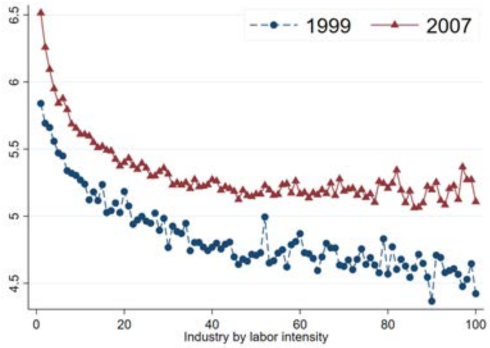
**Notes**: (a) These figures are generated using a sample that drops the top and bottom 5% of firms in terms of capital intensity. (b) We rank the firms within each year according to their labor intensities and divide them into 100 bins with an equal number of firms.

Figure A.3: Robustness Checks: Censoring and Divide the Sample by Percentiles

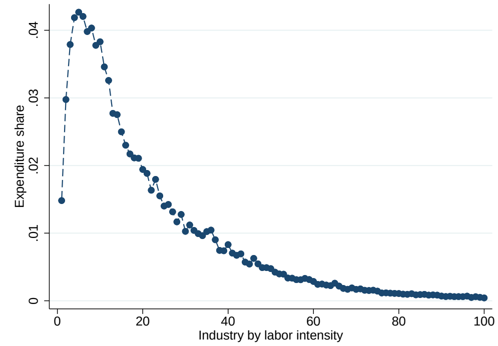



**Notes**: This figure plots the average intensity of R&D, measured by expenditure on R&D divided by total output, averaged across 2005-2007.

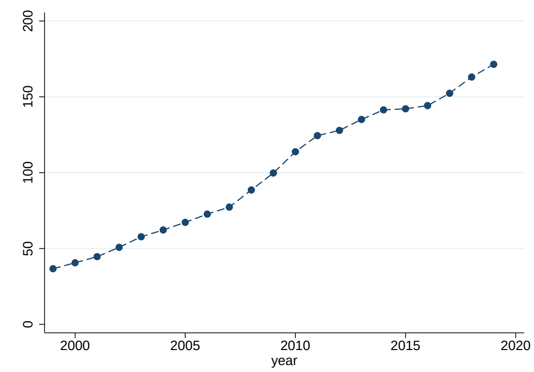
Figure A.4: R&D Intensity by Industry



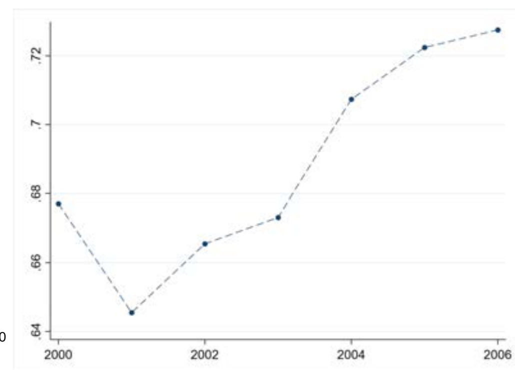

(a) Estimated industry average TFP



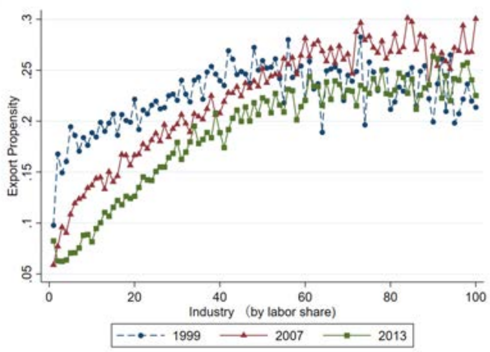

(b) expenditure share by industry



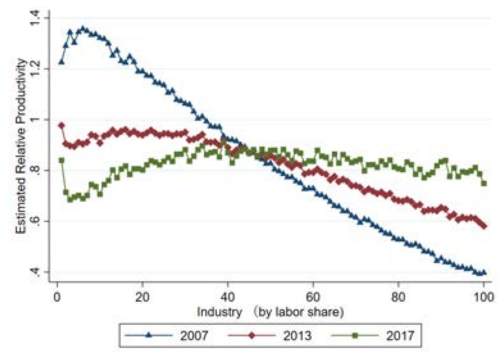

(c) capital-labor ratio of China



(d) capital intensity of Chinese imports




(e) rest of the world export propensity




(f) estimated relative productivity

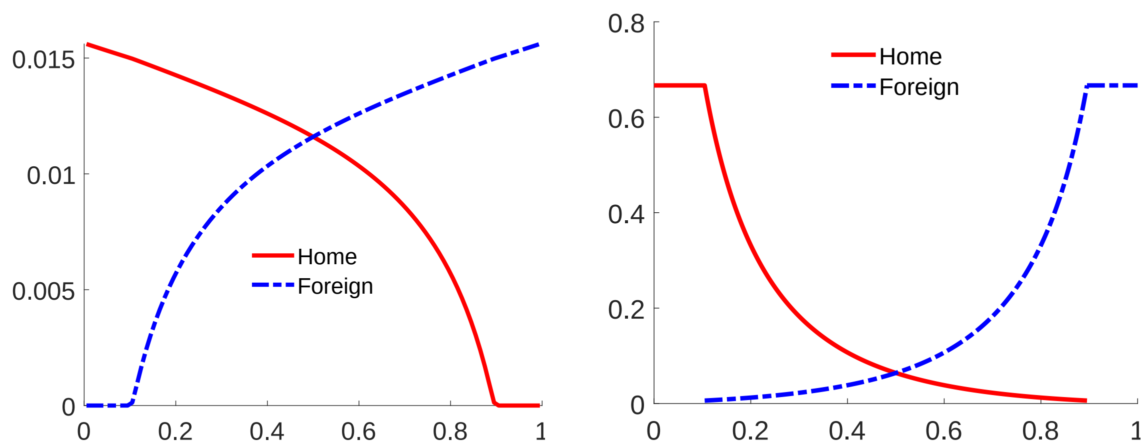
**Notes**: Figure (a) plots the estimated average TFP for each industry (in logarithm). Figure (b) plots the estimated expenditure share function $b(z)$. The expenditure for each industry is estimated as outputs plus net imports. We compute the average ratio between aggregate imports and exports for matched firms in each industry during 2000-2006. Total imports of each industry are estimated as the aggregate exports by all surveyed firms multiplied by the ratio. Figure (c) plots the estimated capital-labor ratio for China (unit: 1000 USD per worker in 2017 US$). Capital is measured by capital stock at current PPPs from Penn World Table 10.0, which is further multiplied by the industrial share in GDP (source: World Bank). Labor is measured by the total labor force multiplied by industrial employment share and employment rate (source: World Bank). Figure (d) computes the capital intensity of Chinese imports. Capital intensity of Chinese imports is measured by the capital intensity of US production from the NBER-CES data, using $1 - payroll/value\text{-}added$ for each industry and a mapping between industries and 6-digit HS products. Figure (e) plots the export propensity of firms for 1999, 2007, and 2013. The industries are classified according to labor shares, with labor shares measured by wages divided by inferred value added from value-added tax paid by firms. Figure (f) plots the estimated productivity of China relative to RoW across industries for 2007 and 2013 using sufficient statistics according to Proposition 6. For 2017, it is extrapolated from the average growth rate during 2007-2013 for each industry.

Figure A.5: Complementary Figures

## A.2 Numerical Analysis

Given the nonlinearity and high dimensionality, it is challenging to get other analytical properties of our model. In this appendix, we parametrize the model and solve it numerically. The primary purpose is to study how the equilibrium responds to changes in factor endowments, technology, and trade costs by numerical comparative statistics.

The parameterization of the model is shown in Appendix Table A.3. We neutralize the Ricardian comparative advantage and set $A = \lambda = 1$. We choose factor endowments such that the home country has an HO comparative advantage in labor-intensive industries and the foreign country has an HO comparative advantage in capital-intensive industries. We assume that the expenditure share function $b(z) = 1$ in all industries so that the distribution of firms is driven only by supply-side conditions. Figure A.6 (a) plots firm mass $M_z$, and (b) plots export propensity $\chi(z)$ across industries. Given our choice of endowments, the patterns of production and exports are symmetric between the two countries with respect to the industry $z = 0.5$. As expected, production and exports increase with the strength of the comparative advantage of the respective country.




(a) Distribution of firms (b) Export propensity

**Notes**: The figures are generated using the parameters specified in Appendix Table A.3. The horizontal axis indexes industry capital intensity. Panel (a) plots the distribution of firms, while panel (b) plots the export propensity.

Figure A.6: Benchmark Solution

### A.2.1 Comparative Statics

We conduct numerical comparative statics by changing one parameter at a time. We focus on the effects of increasing $K$ (capital deepening in home country), decreasing $A$ (strengthening home country's Ricardian comparative advantage in labor-intensive industries), and reducing iceberg trade costs $\tau$ (trade liberalization). We are interested in their effects on production and exports.

The first exercise is to increase $K$. The results are shown in Appendix Figure A.7 (a) - (c). We have the following findings. 1) $\overline{z}$ increases and $\underline{z}$ decreases. That is, as the similarity in factor endowments increases when the labor-abundant home country has more capital, the measure of industries that both countries produce, $[\underline{z}, \overline{z}]$, increases. 2) For firm mass $M_z$, as Figure A.7 (a) indicates, there exists a cut-off $z_1$ such that $M_z$ increases for $z \geq z_1$ and decreases for $z < z_1$. In particular, we have $\frac{\partial(M'_z - M_z)}{\partial z} > 0$, while $M'_z$ is the firm mass of industry $z$ when $K$ increases. This is consistent with the well-known *Rybczynski*

Table A.3: Numerical Simulation: Parametrization

| Variables | Definition | Value |
|---|---|---|
| $K$ | home capital stock | 100 |
| $L$ | home labor stock | 300 |
| $K^*$ | foreign capital stock | 300 |
| $L^*$ | foreign labor stock | 100 |
| $f_{zx}/f_z$ | relative fixed cost of export | 1.5 |
| $f_{ez}/f_z$ | relative fixed cost of entry | 30 |
| $\tau$ | iceberg trade cost | 1.8 |
| $a$ | shape parameter of Pareto Distribution | 3.8 |
| $\theta$ | lower bound of Pareto Distribution | 0.4 |
| $\delta$ | exogenous death probability of firms | 0.025 |
| $\sigma$ | elasticity of substitution | 3.4 |
| $A$ | strength of comparative advantage | 1 |
| $\lambda$ | strength of absolute advantage | 1 |
| $b(z)$ | expenditure share | 1 |

*theorem* that production shifts toward capital-intensive industries as the country becomes more capital-abundant. 3) For export propensity $\chi(z)$ and average firm productivity $\widehat{\varphi}_z$, as figures (b) and (c) indicate, there exists a cutoff above which $\chi(z)$ and $\widehat{\varphi}_z$ increase and below which they decrease. In particular, we have $\frac{\partial(\chi(z)'-\chi(z))}{\partial z} > 0$ and $\frac{\partial(\widehat{\varphi}_z'-\widehat{\varphi}_z)}{\partial z} > 0$. Therefore, exports become more capital-intensive, and capital deepening begets Ricardian productivity differences favoring capital-intensive industries.

The second exercise reduces $A$, the parameter capturing Ricardian comparative advantage, from 1 to 0.5. Such a technological change generates productivity differences between home and foreign countries such that the home country is relatively more productive than the foreign country in labor-intensive industries, while the foreign country is relatively more productive in capital-intensive industries. Therefore, the home country gains Ricardian comparative advantage in labor-intensive industries. Figure A.7 (d) - (f) plot the results. We have the following findings. 1) $\overline{z}$ decreases and $\underline{z}$ increases; therefore, the home country specializes in more labor-intensive industries; 2) Production and export both become more labor-intensive as $\frac{\partial(M'(z)-M(z))}{\partial z} < 0$ and $\frac{\partial(\chi(z)'-\chi(z))}{\partial z} < 0$; 3) Export selection reinforces Ricardian productivity differences as $\frac{\partial(\widehat{\varphi}_z'-\widehat{\varphi}_z)}{\partial z} < 0$.

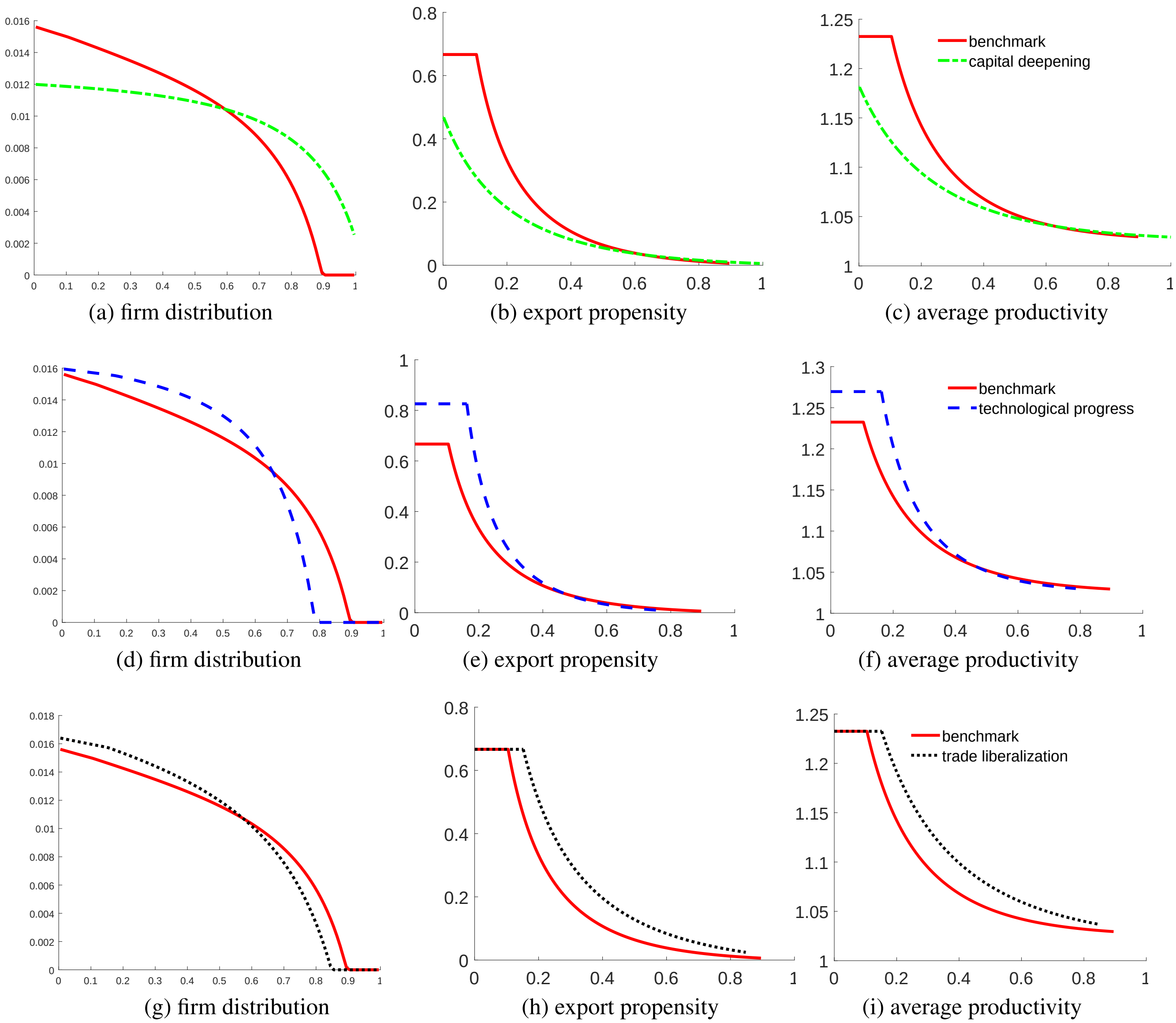
The third exercise reduces the iceberg trade cost $\tau$ from 1.8 to 1.5. Proposition 2 predicts that free trade leads to complete specialization such that $\underline{z} = \overline{z}$. In general, reducing $\tau$ brings in more specialization, raising $\underline{z}$ and reducing $\overline{z}$, and shifting production toward industries of comparative advantage. This is indeed the case in Figure A.7 (g) - (i). In addition, trade liberalization increases export propensity and average firm productivity in all industries except industries of specialization.

The key lessons from the simulations can be summarized as follows.

**Property 1**: Capital deepening in the labor-abundant home country generates "single crossings" in the distribution of firm and export propensity and average firm productivity across industries.

**Property 2**: Technological change that strengthens Ricardian comparative advantage in labor-intensive industries generates "single crossings" in the distribution of firms and export propensity and average firm productivity.

**Property 3**: Trade liberalization strengthens existing comparative advantage by widening the range of industries in which each country specializes and shifts production and exports toward comparative advantage industries.




(a) firm distribution (b) export propensity (c) average productivity

(d) firm distribution (e) export propensity (f) average productivity

(g) firm distribution (h) export propensity (i) average productivity

**Notes**: The solid lines plot the benchmark equilibrium of the home country. In figures (a)-(c), we increase the domestic capital stock $K$ from 100 to 200. In figures (d)-(f), we decrease the parameter capturing Ricardian comparative advantage from 1 to 0.5. In figures (g)-(i), we reduce the iceberg trade cost $\tau$ from 1.8 to 1.5.

Figure A.7: Numerical Comparative Statics

### A.2.2 Discussions

If we believe capital had been deepening in China from 1999-2007, Figure A.7 (a) is consistent with stylized fact 1 that Chinese production became more capital-intensive over time. However, Figure A.7 (b) contradicts stylized fact 2, and Figure A.7 (c) contradicts stylized fact 3. If trade liberalization was the main story and China had a comparative advantage in labor-intensive industries, Figure A.7 (g) is at odds with stylized fact 1 that China's firm distribution shifted toward capital-intensive industries. If sector-biased technological change was the sole driving force, production, and exports should both become more labor-intensive or capital-intensive according to Figure A.7 (d) and (e), depending on which industries the technological change favors. But it contradicts stylized facts 1 and 2 that production and export shifted toward different industries. Hence, none of these forces alone can simultaneously explain stylized facts 1-3. We need to estimate and gauge the movement of each force over time to disentangle their effect. This is what we do in the next section.

## A.3 Identification

We first prove that given b(z), $\chi_z$ and $\frac{R^*}{R}$ only depend on $\{\frac{K^*}{K}, \frac{L^*}{L}, A, \lambda, a, f, \tau, \sigma\}$. Then we prove that firm mass distribution $m_z$ depends on $\{\frac{K^*}{K}, \frac{L^*}{L}, A, \lambda, a, f, \tau, \sigma\}$ and $\frac{K}{L}$. Starting from factor market clearing condition, for sectors that are specialized by either country, we have

$$
\begin{aligned}
L_s &= \int_0^{\underline{z}} l(z)dz = \frac{R+R^*}{w}\int_0^{\underline{z}}(1-z)b(z)dz = \frac{R+R^*}{w}N, \\
K_s &= \int_0^{\underline{z}} k(z)dz = \frac{R+R^*}{r}\int_0^{\underline{z}} zb(z)dz = \frac{R+R^*}{r}B, \\
L_s^* &= \int_{\overline{z}}^{1} l^*(z)dz = \frac{R+R^*}{w^*}\int_{\overline{z}}^{1}(1-z)b(z)dz = \frac{R+R^*}{w^*}C, \\
K_s^* &= \int_{\overline{z}}^{1} k^*(z)dz = \frac{R+R^*}{r^*}\int_{\overline{z}}^{1} zb(z)dz = \frac{R+R^*}{r^*}D,
\end{aligned}
$$

where $N \equiv \int_0^{\underline{z}}(1-z)b(z)dz$, $B \equiv \int_0^{\underline{z}} zb(z)dz$, $C \equiv \int_{\overline{z}}^{1}(1-z)b(z)dz$ and $D \equiv \int_{\overline{z}}^{1} zb(z)dz$.

For sectors that are produced by both countries, we have:

$$L_{int} = \frac{1}{w}\int_{\underline{z}}^{\overline{z}} b(z)(1-z)[\frac{R}{1-\widetilde{\tau}^{-a}\Psi(z)^a fh(z)} - \frac{fR^*}{\widetilde{\tau}^a\Psi(z)^a h(z) - f}]dz = \frac{R}{w}E - \frac{R^*}{w}F,$$

$$K_{int} = \frac{1}{r}\int_{\underline{z}}^{\overline{z}} b(z)z[\frac{R}{1-\widetilde{\tau}^{-a}\Psi(z)^a fh(z)} - \frac{fR^*}{\widetilde{\tau}^a\Psi(z)^a h(z) - f}]dz = \frac{R}{r}G - \frac{R^*}{r}H,$$

$$L^*_{int} = \frac{1}{w^*}\int_{\underline{z}}^{\overline{z}} b(z)(1-z)\Psi(z)^a h(z)[\frac{R^*}{\Psi(z)^a h(z) - f\widetilde{\tau}^{-a}} - \frac{fR}{\widetilde{\tau}^a - \Psi(z)^a fh(z)}]dz = \frac{R^*}{w^*}I - \frac{R}{w^*}J,$$

$$K^*_{int} = \frac{1}{r^*}\int_{\underline{z}}^{\overline{z}} b(z)z\Psi(z)^a h(z)[\frac{R^*}{\Psi(z)^a h(z) - f\widetilde{\tau}^{-a}} - \frac{fR}{\widetilde{\tau}^a - \Psi(z)^a fh(z)}]dz = \frac{R^*}{r^*}X - \frac{R}{r^*}Y,$$

where $E \equiv \int_{\underline{z}}^{\overline{z}} \frac{b(z)(1-z)}{1-\widetilde{\tau}^{-a}\Psi(z)^a fh(z)}dz$, $F \equiv \int_{\underline{z}}^{\overline{z}} \frac{fb(z)(1-z)}{\widetilde{\tau}^a\Psi(z)^a h(z)-f}dz$, $G \equiv \int_{\underline{z}}^{\overline{z}} \frac{b(z)z}{1-\widetilde{\tau}^{-a}\Psi(z)^a fh(z)}dz$, $H \equiv \int_{\underline{z}}^{\overline{z}} \frac{fb(z)z}{\widetilde{\tau}^a\Psi(z)^a h(z)-f}dz$, $I \equiv \int_{\underline{z}}^{\overline{z}} \frac{b(z)(1-z)\Psi(z)^a h(z)}{\Psi(z)^a h(z)-f\widetilde{\tau}^{-a}}dz$, $J \equiv \int_{\underline{z}}^{\overline{z}} \frac{fb(z)(1-z)\Psi(z)^a h(z)}{\widetilde{\tau}^a-\Psi(z)^a fh(z)}dz$, $X \equiv \int_{\underline{z}}^{\overline{z}} \frac{b(z)z\Psi(z)^a h(z)}{\Psi(z)^a h(z)-f\widetilde{\tau}^{-a}}dz$ and $Y \equiv \int_{\underline{z}}^{\overline{z}} \frac{fb(z)z\Psi(z)^a h(z)}{\widetilde{\tau}^a-\Psi(z)^a fh(z)}dz$.

Using factor market clearing condition,

$$L_s + L_{int} = L, K_s + K_{int} = K$$
$$L^*_s + L^*_{int} = L^*, K^*_s + K^*_{int} = K^*$$

We have

$$L = \frac{R}{w}(N+E) + \frac{R^*}{w}(N-F), K = \frac{R}{r}(B+G) + \frac{R^*}{r}(B-H)$$
$$L^* = \frac{R}{w^*}(C-J) + \frac{R^*}{w^*}(C+I), K^* = \frac{R}{r^*}(D-Y) + \frac{R^*}{r^*}(D+X)$$

Moreover, given $R = wL + rK$ and $R^* = w^*L^* + r^*K^*$,we have

$$\frac{R^*}{R} = \frac{1-N-E-B-G}{N-F+B-H} = \frac{C+D-J-Y}{1-C-D-X-I}.$$

Since N, B, C,..., I, J, X and Y only depend on $\{\frac{r^*}{r}, \frac{w^*}{w}, A, \lambda, a, f, \tau, \sigma\}$[50], according to the equation above, $\frac{R^*}{R}$ also depends on $\{\frac{r^*}{r}, \frac{w^*}{w}, A, \lambda, a, f, \tau, \sigma\}$ only.

[50]Given b(z), N, B, C, ..., I, J, X, and Y are integrals of the function of $\Psi(z)^a h(z)$ defined over a intersection given by 0, $\underline{z}$, $\overline{z}$ and 1. $\Psi(z)^a h(z)$, $\underline{z}$ and $\overline{z}$ are functions of $\{\frac{r^*}{r}, \frac{w^*}{w}$ $\Psi$,$\lambda$,a,f,$\tau$,$\sigma\}$ only.

Moreover,

$$\frac{L^*}{L} = \frac{w}{w^*}\frac{C - J + (C+I)\frac{R^*}{R}}{N + E + (N-F)\frac{R^*}{R}}$$
$$\frac{K^*}{K} = \frac{r}{r^*}\frac{(D-Y) + (D+X)\frac{R^*}{R}}{B + G + (B-H)\frac{R^*}{R}}$$

Then given $\{A, \lambda, a, f, \tau, \sigma\}$, there is an one-to-one mapping between $\{\frac{K^*}{K}, \frac{L^*}{L}\}$ and $\{\frac{r^*}{r}, \frac{w^*}{w}\}$.
So $\chi(z) = \begin{cases} \frac{R^*}{fR} & z \in [0, \underline{z}] \\ \frac{\widetilde{\tau}^{-a} f - \Psi(z)^a h(z)}{\Psi(z)^a f h(z) - \widetilde{\tau}^a} & z \in (\underline{z}, \overline{z}) \end{cases}$ depends on $\{\frac{K^*}{K}, \frac{L^*}{L}, A, \lambda, a, f, \tau, \sigma\}$ only.

Next, we prove that firm mass distribution $m_z$ depends on $\{\frac{K^*}{K}, \frac{L^*}{L}, A, \lambda, a, f, \tau, \sigma\}$ and $\frac{K}{L}$. We define the firm mass distribution as

$$m_z = \frac{M_z}{\int_0^{\overline{z}} M_z dz}$$

For industries that the home country specializes

$$\begin{aligned} b(z)(R + R^*) &= M_z r(\widetilde{\varphi}_z) \\ &= M_z \frac{a\sigma f_z r^z w^{1-z}(1 + f\chi(z))}{a + 1 - \sigma} \end{aligned}$$

Thus

$$\begin{aligned} M_z(\frac{r}{w})^z &= \frac{b(z)(R + R^*)}{\frac{a\sigma f_z w}{a+1-\sigma}(1 + f\chi(z))} \\ &= b(z)L\frac{(1 + \frac{rK}{wL})(1 + \frac{R^*}{R})}{\frac{a\sigma f_z}{a+1-\sigma}(1 + f\chi(z))} \end{aligned}$$

Similarly, for industries that both countries produce:

$$M_z = \frac{b(z)L(1 + \frac{rK}{wL})(1 + \frac{R^*}{R})}{\frac{a\sigma f_z}{a+1-\sigma}(1 + f\chi(z))(1 + \frac{M_z^* r(\widetilde{\varphi}_z^*)}{M_z r(\widetilde{\varphi}_z)})(\frac{r}{w})^z}$$

Then, according to the definition of m(z), we have

$$\begin{aligned} m_z &= \frac{M_z}{\int_0^{\overline{z}} M_z dz} \\ &= \frac{b(z)L\frac{(1+\frac{rK}{wL})(1+\frac{R^*}{R})}{\frac{a\sigma f_z}{a+1-\sigma}(\frac{r}{w})^z(1+f\chi(z))}}{\int_0^{\underline{z}} b(z)L\frac{(1+\frac{rK}{wL})(1+\frac{R^*}{R})}{\frac{a\sigma f_z}{a+1-\sigma}(1+f\chi(z))(\frac{r}{w})^z}dz + \int_{\underline{z}}^{\overline{z}} \frac{b(z)L(1+\frac{rK}{wL})(1+\frac{R^*}{R})}{\frac{a\sigma f_z}{a+1-\sigma}(1+f\chi(z))(1+\frac{M_z^* r(\widetilde{\varphi}_z^*)}{M_z r(\widetilde{\varphi}_z)})(\frac{r}{w})^z}dz} \\ &= b(z)\frac{(\frac{r}{w})^{-z}(1 + f\chi(z))^{-1}}{\int_0^{\underline{z}} b(z)(\frac{r}{w})^{-z}(1 + f\chi(z))^{-1}dz + \int_{\underline{z}}^{\overline{z}} \frac{b(z)(\frac{r}{w})^{-z}}{(1+\frac{M_z^* r(\widetilde{\varphi}_z^*)}{M_z r(\widetilde{\varphi}_z)})(1+f\chi(z))}dz} \end{aligned}$$

for the industries that home specializes in. As for industries that both countries produce:

$$
\begin{aligned}
m_z &= \frac{M_z}{\int_0^{\overline{z}} M_z dz} \\
&= b(z) \frac{\frac{(\frac{r}{w})^{-z}}{(1+\frac{M_z^* r(\widetilde{\varphi}_z^*)}{M_z r(\widetilde{\varphi}_z)})(1+f\chi(z))}}{\int_0^{\underline{z}} b(z)(\frac{r}{w})^{-z}(1+f\chi_z)^{-1}dz + \int_{\underline{z}}^{\overline{z}} \frac{b(z)(\frac{r}{w})^{-z}}{(1+\frac{M_z^* r(\widetilde{\varphi}_z^*)}{M_z r(\widetilde{\varphi}_z)})(1+f\chi(z))} dz}
\end{aligned}
$$

It is obvious that $m_z$ depends on $\frac{r}{w}$ which is determined by

$$
\begin{aligned}
\frac{r}{w} &= \frac{L}{K} \frac{R(B+G) + R^*(B-H)}{R(N+E) + R^*(N-F)} \\
&= \frac{L}{K} \frac{(B+G) + \frac{R^*}{R}(B-H)}{(N+E) + \frac{R^*}{R}(N-F)}
\end{aligned}
$$

Thus $\frac{r}{w}$ depends not only on $\{\frac{K^*}{K}, \frac{L^*}{L}, A, \lambda, a, f, \tau, \sigma\}$ but also $\frac{K}{L}$. So does $m_z$.

### A.3.1 Estimating the Pareto Shape

To estimate the Pareto shape of the productivity distribution, we estimate a regression that regresses the natural logarithm of the rank of a firm in terms of sales within each year and HO-bin on the natural logarithm of sales, controlling for the year by HO-bin fixed effects. The estimated coefficient corresponds to $\frac{a}{\sigma-1}$. Following Head et al. (2014), we estimate the coefficient using different sub-samples. Table A.4 presents the result. As we can see, Pareto Distribution fits large firms well.

Table A.4: Fitting the Pareto Distribution 1999-2007

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Sample | top 1% | top 2% | top 3% | top 4% | top 5% | top 6% | top 25% | top 50% | All |
| ln Sales | -1.258$^a$ | -1.216$^a$ | -1.201$^a$ | -1.194$^a$ | -1.188$^a$ | -1.182$^a$ | -1.102$^a$ | -1.013$^a$ | -0.750$^a$ |
| | (0.00384) | (0.00234) | (0.00173) | (0.00139) | (0.00118) | (0.00103) | (0.000392) | (0.000325) | (0.000524) |
| $R^2$ | 0.989 | 0.993 | 0.995 | 0.996 | 0.996 | 0.997 | 0.997 | 0.992 | 0.919 |
| No. of observations | 16704 | 33413 | 50123 | 66830 | 83539 | 100250 | 434423 | 852131 | 1670890 |

**Notes**: The dependent variable is the natural logarithm of the rank of a firm in terms of sales within each year and HO-bin. The estimation method is OLS. Robust standard errors are reported in the parentheses. The constants are absorbed by the year and HO-bin fixed effects. Significance levels are indicated by $a$, $b$, and $c$ at 0.01, 0.05, and 0.1, respectively.