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Essays on International Trade

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by

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The dissertation of Xiao Ma is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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Chapter 1 is currently being prepared for submission of publication of the material. It is sole authored by the dissertation author.

Chapter 2 is currently being prepared for submission of publication of the material, and is coauthored with Chen Liu. The dissertation author was a primary investigator of this material.

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All errors are my own.

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ABSTRACT OF THE DISSERTATION

Essays on International Trade

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Doctor of Philosophy in Economics

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I combine micro-level data and structural models to study the interaction between trade, innovation, and human capital. In the first Chapter, I examine how China's expansion of college education since 1999 affects innovation and exports' skill content. This policy change is interesting because of its sizable scale: the annual quota on the number of newly admitted college students increased from 1 million in 1998 to 7 million in the 2010s; as a result, the number of college-educated workers more than tripled between 2000–2015. I develop a two-country spatial equilibrium model, featuring skill intensity differences across industries and heterogeneous firms' innovation and exporting choices. I highlight three main channels at work, including: (1) with an

increasing number of college-educated workers, China shifts production to more skill-intensive industries and converts the excess supply of skill-intensive goods into exports; (2) the growing supply of college-educated workers promotes innovation; and (3) as skill-intensive industries tend to be more innovative, trade-induced industry reallocation reinforces the innovation surge. I empirically validate my model mechanisms about how the college expansion affects innovation and exports, exploiting differential supply shocks of college-educated workers across regions due to historical college endowments. Using the calibrated model, I find that China's college expansion explained 40–70% of increases in China's manufacturing R&D intensity between 2003–2018 and triggered export skill upgrading. I also find that trade openness amplified the impact of this education policy change on China's innovation and production.

In Chapter 2, coauthored with Chen Liu, we build a multi-sector spatial general equilibrium model to account for China's export surge between 1990 and 2005. We focus on the role of the reductions in tariffs and internal migration costs during that period. Our model generates a closed-form aggregate trade elasticity that can be decomposed into four margins of adjustments. Two are the commonly studied intensive and extensive margins of exports. The remaining two margins are the new-firm margin and the export-regime margin, for which we have found empirical support and used our reduced-form evidence to discipline the structural parameters. We find that reductions in China's tariffs accounted for 21% of China's export growth in the 1990-2005 period, whereas reductions in migration barriers accounted for another 8%. We also find firms' location switches are important: in the absence of firms' relocation, the portion of China's export surge explained by the three policies combined would drop from 29% to 16%.

In Chapter 3, coauthored with Alejandro Nakab, we study how exporting shapes experience-wage profiles. Using detailed Brazilian employer-employee and customs data, we document that workers' experience-wage profiles are steeper in exporters than in non-exporters. Aside from self-selection of firms with higher returns to experience into exporting, we show that workers' experience-wage profiles are steeper when firms export to high-income destinations. We propose that this destination-specific effect is likely driven by faster human capital accumulation with exposure to high-income destinations.

Chapter 1

College Expansion, Trade, and Innovation: Evidence from China

“Made in China” is often viewed as low-skilled. Largely neglected is the recent skill upgrading of China’s exports. For example, China’s primary export product gradually shifted from “Clothing” to “Telecommunications Equipment” after 2000, and three of the worldwide top 5 smartphone companies are nowadays from China (Huawei, Xiaomi, and Vivo).[1] Another notable trend of the Chinese economy is the rise of manufacturing firms’ innovative activities, with the number of domestic invention applications growing by more than 30 times after 2000.[2] The literature has proposed several causes for China’s innovation, such as R&D tax incentives (Chen et al. 2018) and misallocation (König et al. 2018).

This chapter examines how China’s unprecedented expansion of college education contributes to these two trends. With a strict control of the college system, the Chinese government has increased the yearly quota on the number of newly admitted students since 1999, from 1 million in 1998 to 7–8 million in the 2010s (Figure 1.1). As a result, the number of college-educated workers more than tripled between 2000–2015, while the total employment only increased by 7%.

I employ theoretical, empirical, and quantitative analysis to highlight three channels through which China’s college expansion affects trade and innovation. First, with an increasing number of college-educated workers, trade openness allows China to shift production to more skill-intensive industries and convert the excess supply of skill-intensive goods into exports. This force reduces the diminishing returns of accumulating college-educated workers, often recognized as quasi-Rybczynski effects (Rybczynski 1955). Second, the growing pool of college-educated workers lowers R&D costs and promotes innovation because the R&D process intensively uses college-educated workers. Third, trade and innovation also interact. As skill-intensive industries tend to be more innovative, trade-induced industry reallocation reinforces the innovation surge.

[1] The export data on export products are drawn from the WTO database, which decomposes exports into 10 products (most finely disaggregated level in the database) based on SITC Revision 3 Industry Classification. The market shares of smartphone companies are from the IDC data.

[2] The data on manufacturing firms’ patent applications in domestic patent offices are from China’s Statistical Yearbook on Science and Technology. There are three types of patents (invention, utility model, and design) in China, and invention patents are arguably the most technology-intensive category. The growth pattern is more pronounced for Chinese patents in foreign patent offices (Wei et al. 2017).

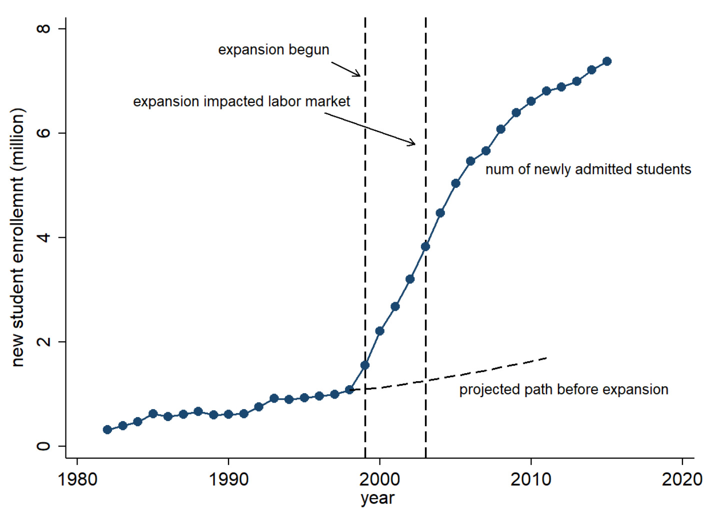


Figure 1.1: China's College Expansion

Note: The data come from China's Statistical Yearbooks.

I first document several facts on innovation and trade. I find that after China's college expansion impacted the labor market: (1) Manufacturing firms' innovative activities increased dramatically—in particular, the share of R&D workers in total manufacturing employment increased from 1% in 2004 to 4% in 2016, and R&D intensity (the ratio of R&D to sales) nearly doubled in the meantime; (2) China's manufacturing exports experienced a massive skill upgrading, with the share of low-skill processing exports decreasing steeply, and ordinary exports shifting to more skill-intensive industries; and (3) The increase in innovative activities mainly occurred among exporters, suggesting possible interactions between exports and innovation.

To implement quantitative analysis, I develop a general equilibrium model with two countries (China and Foreign), two types of labor (educated and less educated), and multiple industries, each hosting many firms. In each period, incumbent firms employ two types of workers with different intensities across industries and make exporting decisions in the face of variable and fixed trade costs (Melitz 2003). Firms also determine their optimal R&D level to improve productivity and maximize future profits. In particular, educated workers are intensively used in R&D activities, following the recent growth literature (Acemoglu et al. 2018).[3] In my baseline

[3]See also Aghion et al. (2006), Aghion et al. (2009), Akcigit et al. (2018) and Zacchia (2019), among others.

model, I assume a fixed number of new firms in each region-industry pair in each period. My empirical evidence indicates that larger exposure to the college expansion induces more new firms' entry. I thus consider analternative assumption to allow endogenous firm entry: the creation of a new firm requires R&D inputs (Atkeson & Burstein 2010) and is thus affected by changes in revenues and R&D costs after the college expansion.

To validate the model mechanisms and discipline the related parameters, I exploit the differential magnitude of the college expansion across regions. However, taking these region-level reduced-form estimates to a nation-level aggregate model faces the well-known problem that there could be regional spillovers via trade and migration networks (Allen & Arkolakis 2014, Mian & Sufi 2014). Therefore, I also model multiple regions within China and between-region trade and migration. In particular, I model workers' period-to-period movements following Artuc et al. (2010).

I analytically present the model mechanisms about how China's college expansion impacts exports and innovation. I show that when there is an influx of educated workers, the economy shifts production and demand to more skill-intensive industries, and trade helps the economy convert the excess output of skill-intensive goods into exports. In this way, the economy can avoid the diminishing returns from more skill-intensive production of the same goods. An increase in the supply of educated workers affects innovation by lowering R&D costs and altering innovation returns through its impact on firms' revenues. In particular, exporters in more skill-intensive industries experience faster sales growth and thus invest more in R&D activities.

Using firm-level data for 2005 and 2010, I empirically validate the model mechanisms about exports and innovation. Guided by my analytical model, I measure a firm's exposure to the college expansion by growth in the local supply of college-educated workers, interacted with the firm's affiliated-industry skill intensity. To disentangle college-educated workers' supply from demand shocks, I exploit the differential magnitude of the college expansion across regions due to historical college endowments, as the expansion was attained mainly by the scale-up of enrollments in previously existing colleges. I show that with larger exposure to the college expansion, a firm's export prices decreased, and its ordinary exports and domestic sales both increased. The differential responses of export prices, domestic sales, and ordinary exports allow me to pin down the key structural parameters that govern the magnitude of export expansion and demand reallocation across industries. Moreover, I confirm the presence of an interaction between exports and innovation by showing that firms with larger exposure to the college expansion increased their innovative activities, especially when these firms also exported intensively.

I combine data on migration flows, trade flows, R&D, employment, and output from multiple sources between 2000–2018 to calibrate a version of my model that incorporates 33 industries and 30 Chinese provinces. With the calibrated model, I quantify the effects of China's college expansion on export skill upgrading and innovation. In the counterfactual exercise of "no college expansion," I set the number of newly admitted college students between 2000–2018 according to the policy objective before 1999, and noncollege workers replace the "missing" college-educated workers.

I find that the college expansion explained a sizable portion of China's export skill upgrading and innovation surge. When the number of new firms is fixed, China's college expansion explained 69% of increases in manufacturing R&D intensity, 33% of increases in the share of high-skill ordinary exports, and 12% of declines in the share of processing exports between 2003–2018. When firm entry is endogenous, China's college expansion generated disproportionately more firms in highly skill-intensive industries, reinforcing China's export skill upgrading yet discouraging innovation due to reduced innovation returns per firm. Moreover, I find that trade openness played a considerable role in amplifying the impact of China's college expansion on production and innovation. Finally, I show that the yearly GDP increase due to the college expansion started to exceed yearly education expenses and production losses of additional college enrollments in 2006–2009.

Previous Literature. I contribute to the trade literature in three aspects. First, I make contact with a broad literature on China's trade. I closely relate to Amiti & Freund (2010) who find no changes in China's exports' skill content before 2005. In contrast, I document a massive skill upgrading of China's exports after 2005 and show that it is partly caused by the education expansion, which also relates to Romalis (2004) who shows that changes in a country's factor endowments would alter its product mix. A large body of papers study how China's economy reacts to trade liberalization (Khandelwal et al. 2013, Brandt et al. 2017, Fan 2019). In this paper, I emphasize the role of trade openness in helping China adjust to domestic education policy shocks.[4] Second, much empirical evidence shows that trade liberalization or export demand impacts firms' innovation (Lileeva & Trefler 2010, Aghion et al. 2017). In contrast, I look into the impact of a domestic education shock on innovation, which is amplified by trade openness. Third, I also relate to the literature that uses quantitative models to study trade and innovation (Eaton & Kortum 2001, Grossman & Helpman 2014, Somale 2017, Arkolakis et al. 2018). My model builds on Atkeson & Burstein (2010), enriched with industry heterogeneity and worker types to study policy shocks in China. In particular, I model heterogeneous innovative opportunities across industries, which, together with industry-specific skill intensities, generate the interaction between trade and innovation.

I also make contact with studies on China's innovation. Despite China's extraordinary increases in R&D investments and patents in recent decades (Wei et al. 2017), few macro studies explore the causes of this innovation surge.[5] Ding & Li (2015) provide a comprehensive summary of government R&D policies in China, and Chen et al. (2018) show that China's reform of R&D tax incentives in 2008 changed firms' R&D behavior, especially for firms near thresholds of tax incentives. König et al. (2018) evaluate the role of output wedges in shaping Chinese firms' R&D efficiency in stationary equilibrium. In contrast with these studies, I study the time-series pattern of China's innovation between 2000–2018 and focus on the role of China's expansion of college

[4]In a similar vein, Ventura (1997) emphasizes that trade is essential for absorbing the extra capital for miracle economies of East Asia.

[5]There are also empirical studies on China's innovation (Hu & Jefferson 2009, Ding & Li 2015).

education.

Finally, I relate to research about colleges and innovation (Jaffe 1989, Aghion et al. 2009, Kantor & Whalley 2014, Andrews 2017, Valero & Van Reenen 2019), especially those focusing on China's college expansion (Che & Zhang 2018, Feng & Xia 2018, Li et al. 2020). My contributions are twofold. First, these studies show that colleges affect innovation through human capital, academic research, knowledge diffusion, or migration. I find a new channel: trade openness could facilitate shifts of production to high-skill industries and amplify the effect of college education on innovation. Second, these studies mostly provide cross-sectional evidence of colleges on innovation,[6] but aggregate effects are unclear. In contrast, I take reduced-form evidence to calibrate a spatial general equilibrium model and *quantify* the role of China's college expansion in affecting innovation through increases in the supply of college grads and the interaction between trade and innovation.[7]

1.1 Context

China's unprecedented expansion of college education started in 1999. Before 1999, China's education policy followed the guideline of the "steady development," planning to increase college enrollments at an annualized rate of 3.8% from 2000 to 2010.[8] However, the Asian financial crisis in 1997 and the SOE layoffs in the late 1990s forced the government to find a new stimulus to restore the economy. One advice was to enlarge the college system to accommodate more youth and boost education expenses. Despite extensive disagreement, this suggestion was

[6]Similar to Andrews (2017) and Feng & Xia (2018), I exploit cross-regional variation in historic college resources to identify the effects of college expansion.

[7]Andrews (2017) finds that human capital and migration are the most important channels for the effect of colleges on innovation in U.S. counties. With a spatial GE model, I also capture the effects of migration. I find in Section 1.7.5 that reductions in migration costs would amplify the impact of China's college expansion on aggregate innovation, though the magnitude is mild due to offsetting effects between regions.

[8]The goal before 1999 is according to The Ninth Five-Year Plan for China's Educational Development and Development Outline by 2010 (Quanguo jiaoyu shiye "jiuwu" jihua he 2010 nian fazhan guihua).

surprisingly soon adopted by China's top leadership.[9]

The college expansion was implemented through increases in the annual quota on the number of newly admitted students. The implementation relies on the government's strict control of the college system. First, most of the Chinese colleges are government-owned and naturally obey the government's commands.[10] Second, the college admissions process is strictly controlled by the Ministry of Education (Jia & Li 2020).

Even though the Chinese economy bounced back to fast growth after 2001, China's college expansion has persisted ever since 1999. The blue line in Figure 1.1 shows that the yearly number of newly admitted students increased rapidly from 1 million in 1998 to 7–8 million in the 2010s. Undoubtedly, this led to a skill upgrading of the labor market, with the share of college-educated workers in total employment increased from 4.7% in 2000 to 14.6% in 2015.[11] If college enrollments grew at 3.8% that was set before 1999 (black dashed line in Figure 1.1), the number of college-educated workers would be 46 million lower in 2015 (6% of total employment). The college expansion mainly impacted the labor market after 2003, as it takes 3–4 years for newly recruited students to graduate.

Appendix A.2 reviews the division of majors and college types in China. The distribution of the field of study remained roughly constant after the expansion, with 40–50% of students majoring in science and engineering. Although different majors could affect innovation differently, my analysis abstracts from students' majors due to the lack of micro-level data. It is also worth noting that college enrollments in Figure 1.1 correspond to regular education. Instead of spending 3–4 years fully on campus, workers may acquire a part-time college degree through on-the-job

[9] See the thorough decision process of this policy change in Wang (2014).

[10] 93% of college students were enrolled in public colleges in 2002 (the earliest year with available data).

[11] The data are from the Population Census. One caveat with the Population Census and the firm-level data used in Section 1.2.2 is that college-educated workers include not only college grads in regular schools (shown in Figure 1.1), but also those with part-time college degrees. In absolute numbers, China's total employment increased from 720 million in 2000 to 774 million in 2015. The amount of college-educated workers increased from 33 million to 113 million between 2000–2015, consistent with the total amount of part-time college grads (24 million) and regular college grads (66 million) between 2000–2015, and the small discrepancy might come from retirement and unemployment.

study. Compared with a regular degree, a part-time degree is less valuable, and enrollments in part-time education experienced much less expansion after 1999. I will focus on the quantitative effects of the expansion of regular college education and briefly discuss the effects of including the expansion in part-time education. I do not consider college grads from foreign colleges, who accounted for only 3% of the number of grads from domestic colleges between 2000–2018.

My empirical strategy exploits the differential magnitude of the college expansion across regions due to historical factors. This is motivated by two features of the college expansion. First, China's college expansion was attained mainly by the scale-up of enrollments in previously existing colleges (Feng & Xia 2018), which benefited regions with more college resources historically. Appendix Figure A.1 reveals that across cities, the relation between college enrollments in 1982 and college enrollments in 2005 is well approximated by a 45-degree line. Second, there was a mismatch between the distribution of historic regional college endowments and recent regional development. Coastal areas (like Guangdong) became well developed after China's transition to a market economy, but historically a large proportion of China's college resources were concentrated in inland China. Appendix Figure A.2 shows that the cities with more college resources in 1982 did not enjoy higher GDP and population growth afterward.

1.2 Descriptive Facts

I present several facts to inform the specification of the model developed in Section 1.3. Due to data availability and that China's innovation surge mainly happened in manufacturing after 2000 (Appendix Figure A.3), I focus on manufacturing industries/firms. Section 1.2.1 shows the aggregate pattern of manufacturing innovation. Section 1.2.2 shows a massive skill upgrading of manufacturing exports after the college expansion impacted the labor market. Section 1.2.3 provides evidence on the interaction between exports and innovation.

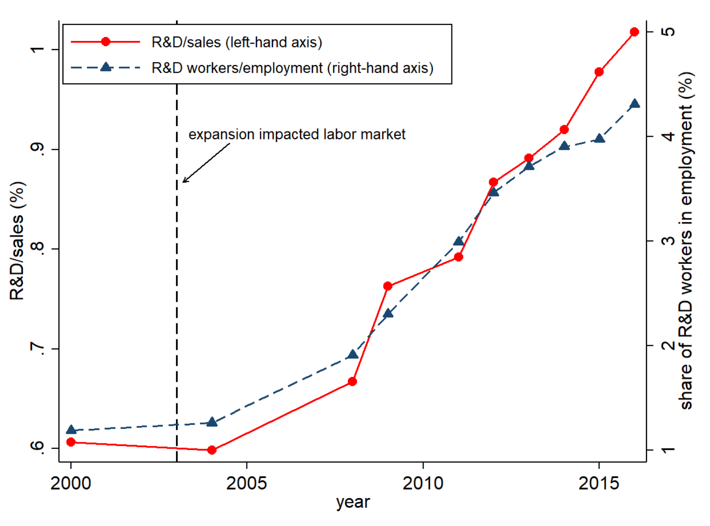


Figure 1.2: R&D Employment and Expenses

Note: The data come from China's Statistical Yearbook on Science and Technology 2000–2016. The ratios are computed using aggregate values for all above-scale manufacturing firms, which cover most of China's manufacturing employment and output (Brandt et al. 2012). In absolute numbers, the number of R&D workers in manufacturing increased from 0.5 million in 2000 to 0.6 million in 2004 and 3.7 million in 2016.

1.2.1 China's Innovation Surge

Figure 1.2 presents the aggregate pattern of manufacturing innovative activities. The manufacturing R&D intensity was flat at 0.6% between 2000–2004 and increased substantially after 2004, from 0.6% in 2004 to 1.1% in 2016. Similarly, the share of R&D workers in employment increased from 1% 2004 to 4% in 2016.

These aggregate data signal the overall impact of China's college expansion on innovation, given that R&D workers mostly hold a college degree.[12] Moreover, the impact of China's college expansion unfolded in the labor market after 2003, in line with the timing of the innovation surge. Arguably, there could be other possible drivers for China's innovation. Two possible confounding policies are China's WTO accession in 2001 and changes in R&D tax incentives in 2008 (Chen

[12]In 2009, the share of R&D workers with a college degree in all R&D workers was 99% in manufacturing, according to the Second Census of China's R&D Resources. China's colleges include universities and junior colleges. However, the R&D Census did not separate R&D workers with junior college degrees and with high school degrees. To estimate the share of R&D workers with college degrees, I assume that manufacturing employees with junior college degrees had the same participation rate in R&D as employees with university degrees. Manufacturing employment by education levels is from Firm Census 2008.

et al. 2018). I will capture these policy changes in my quantitative model to isolate the effects of the college expansion.

1.2.2 Skill Upgrading of China's Exports

Data. I utilize China's Annual Survey of Manufacturing (ASM) for 1998–2007 and 2011–2012, with detailed financial information and 4-digit industry for all manufacturing firms above certain sales thresholds.[13] I keep firms with non-missing exports and sales and compute each firm's domestic sales by deducting exports from total sales in ASM. Due to the lack of information on export regimes in ASM, I match ASM with Chinese Customs Transactions Database 2000–2016 to obtain each firm's exports by export regimes.[14]

Measuring Skill Intensities. I use each firm's industry and associate domestic sales and exports of this firm with the 4-digit industry (482 manufacturing industries in total) to which it belongs. I then aggregate sales and exports by industry. I proxy an industry's skill intensity by the share of college-educated workers in employment for that industry, and this information is available from China's ASM in 2004. For ease of description, I define a 4-digit industry as a high skill-intensity industry if its college employment share lies above the employment-weighted average across all industries.

I will decompose exports into ordinary and processing regimes. This decomposition is because processing exports typically embed foreign technology and provide assembly services for foreign clients. As shown in Appendix Table A.3, processing exports are much less skill-intensive than ordinary exports and domestic sales within the same industry. I thus expect processing exports to suffer from the college expansion, and pooling them with ordinary exports would mask

[13] In 2000–2007, the threshold of sales was 5 million RMB, and the sample includes all the state-owned enterprises. The sales threshold became 20 million RMB after 2011 for both private and state-owned firms. Because the data cover all medium-size and large firms in China, they are informative about China's manufacturing sales by industry. Brandt et al. (2012) find that below-scale firms only produced 9.9% of total industrial output in 2004.

[14] I match the two databases by firm names, after cleaning firm names according to He et al. (2018). The match between two databases is overall good: in 2005, 70% of manufacturing exports reported in ASM can be matched with customs data.

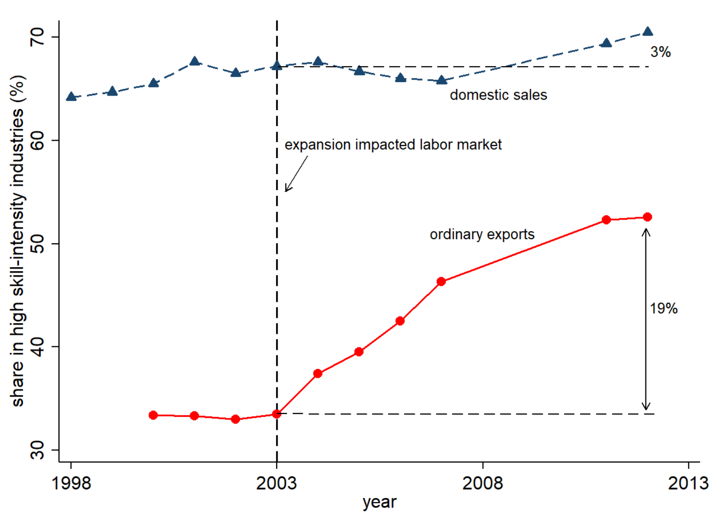


Figure 1.3: Skill Upgrading of Domestic Sales and Exports

Note: The pattern is computed using ASM 1998–2007 and 2011–2012, as well as Chinese Customs Transactions Database 2000–2016.

observed changes in the skill content of exports.[15]

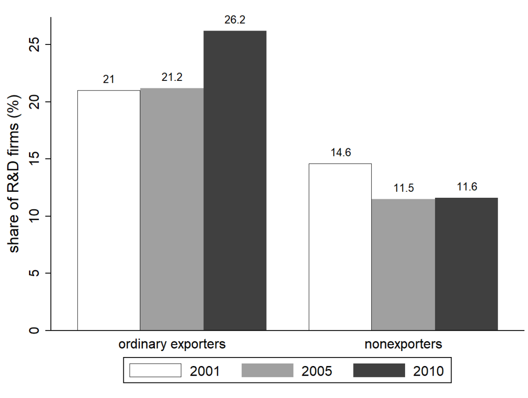
Domestic Sales and Ordinary Exports. Figure 1.3 plots the share of sales in high skill-intensity industries separately for domestic sales and ordinary exports, for years with available data. Ordinary exports shifted strongly to high skill-intensity industries after China's college expansion impacted the labor market. In contrast, China's domestic sales only moved slightly to high skill-intensity industries during the same period.

Processing Exports. Appendix Figure A.5 reports the share of processing exports in manufacturing exports. After the impact of China's college expansion unfolded, this share rapidly declined by 20 percentage points from 55% in 2003 to 35% in 2015.

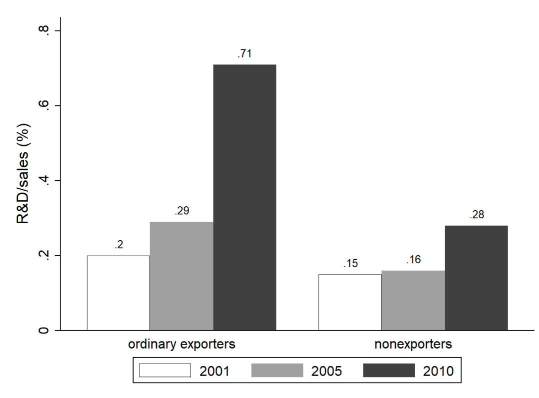
1.2.3 Interactions between Exports and Innovation

I next investigate innovative activities by exporters and nonexporters. Because the R&D variable in ASM is only available in 2001–2002 and 2005–2007, I supplement ASM with

[15]In 2005, 55% of China's processing exports were in the industry "Computer, Electronic and Optical Equipment", which requires high skills for ordinary production but low skills for processing production.



(a) Share of R&D Firms



(b) R&D/sales

Figure 1.4: Innovative Activities by Different Firms

the Chinese State Administration Survey of Tax (SAT) in 2008–2011, which records financial information (including R&D) for a sample of 340 thousand manufacturing firms in each year. To lessen the concerns of different sample coverage, I use ASM 2001, ASM 2005, and SAT 2010 to construct balanced firm panels in 2001–2005 and 2005–2010 (each with 40–50 thousand firms). Consistent with the previous subsection, I omit purely processing exporters, as they barely innovate,[16] and pooling them with ordinary exporters may mask their different responses to the college expansion.

Figure 1.4 presents the share of R&D firms and average R&D intensities, separately among ordinary exporters and non-exporting firms in 2001, 2005, and 2010.[17] Innovative activities surged more among exporters than nonexporters. The share of R&D firms among exporters increased by 5.0 percentage points between 2005–2010, while the share of R&D firms among nonexporters only rose by 0.1 percentage points. The difference was more considerable in terms of increases in average R&D intensities.

[16]I classify firms that only perform processing exports as purely processing exporters and all other exporters as ordinary exporters. In line with the low skills of processing exports, purely processing exporters in China are much less skill-intensive than all different types of firms, as shown by Appendix Table A.3. In 2005, purely processing exporters accounted for 6.8% of manufacturing sales but only 1.5% of manufacturing R&D, whereas these two ratios for ordinary exporters were 30.5% and 44.2%.

[17]I normalize the shares in two balanced panels such that the shares in 2005 computed from the balanced panel 2005–2010 match the shares in 2005 computed from the balanced panel 2001–2005.

1.3 Model

In this section, I develop a spatial general equilibrium model. There are two countries, China and Foreign. I treat Foreign as a single region. In China, I consider many regions with inter-regional trade and migration. Each region-industry has many heterogeneous firms, which differ in their productivity, product demand, and research efficiency. Firms employ two types of workers (educated and less educated) with different intensities across industries. R&D inputs are produced intensively by educated labor. In each period, incumbent firms decide whether to operate, export, and invest in R&D; and there is a fixed number of potential entrants in each region and industry. Alternatively, I also consider the scenario that the number of entrants is endogenously decided, as evidence indicates that larger exposure to the college expansion induces more entry of new firms.

In the model, firms in an industry employ the same production technology to supply domestic and foreign markets, and hence exports in the model correspond to ordinary exports in the data. This saves notation and eases the description of the model mechanisms. I will incorporate processing exports in the quantitative analysis.

I index regions by m and n, industries by j, and the set of regions in China as $\mathcal{C}$.

1.3.1 Aggregate-level Good Production

Final-good Producers

There is a nontradable final good produced in each region m, which is assembled using industry-level intermediate goods $Q_{m,j}$,

$$Q_m = \left(\sum_j \gamma_j Q_{m,j}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}. \tag{1.1}$$

Parameter $\gamma_j > 0$ governs the expenditure share on goods from industry j. Parameter $\theta > 0$ is the elasticity of substitution across industries and decides the strength of between-industry demand reallocation after the college expansion, as I will show in Section 1.4.

The final good can be either used for consumption or used as inputs to produce research inputs. With perfect competition, the price index for the final good is $P_m = \left(\sum_j \gamma_j^{\theta} P_{m,j}^{1-\theta}\right)^{1/(1-\theta)}$, where $P_{m,j}$ is the price index of industry-level intermediate goods.

Industry-level Good Producers

The industry-level intermediate good is produced competitively by:

$$Q_{m,j} = \left(\sum_n \int_{\Omega_{n,m,j}} \varepsilon_{n,m,j}(\omega)^{\frac{1}{\sigma}} q_{n,m,j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}, \tag{1.2}$$

which are composed of quantities of varieties $q_{n,m,j}(\omega)$ sourced from all domestic and foreign origins. $\Omega_{n,m,j}$ is the set of varieties selling from region n to region m in industry j. I allow for idiosyncratic demand shifters $\varepsilon_{n,m,j}(\omega)$ across varieties such that some firms may export due to a favorable draw of $\varepsilon_{n,m,j}(\omega)$. This allows me to capture that many export-intensive firms in China are unproductive small firms.[18] Parameter σ is the elasticity of substitution across varieties within an industry, governing the strength of firm-level export expansion after the college expansion, as I will show in Section 1.4.

Intermediate goods can be either used to produce final goods or used as raw materials in the firm production. The quantity demanded for a variety with price p is given by $q = \varepsilon_{n,m,j}(\omega) p^{-\sigma} P_{m,j}^{\sigma} Q_{m,j}$, where the price index $P_{m,j} = \left(\sum_n \int \varepsilon_{n,m,j}(\omega) p_{n,m,j}(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$.

[18] This evidence is discussed in Lu (2010).

Research Good

I assume that a research good is produced in each region m:

$$Q_{m,r} = A_{m,r} E_{m,r}^{1-\gamma_r} H_{m,r}^{\gamma_r}, \tag{1.3}$$

where $E_{m,r}$ and $H_{m,r}$ denote the amount of final goods and educated labor. Parameter $A_{m,r}$ is the aggregate productivity for producing research goods. Parameter γ_r governs the cost share of educated labor in total research expenditures. The unit price of research goods $P_{m,r}$ is $P_{m,r} = \frac{1}{A_{m,r}} \left(\frac{P_m}{1-\gamma_r} \right)^{1-\gamma_r} \left(\frac{S_m}{\gamma_r} \right)^{\gamma_r}$, where S_m refers to wages per unit of educated labor. Research goods can be used to pay R&D costs and firm entry costs.

In contrast with Atkeson & Burstein (2010) who assume that research goods are produced fully by final goods, I explicitly assume that educated labor is intensively used in producing research goods, similar to Acemoglu et al. (2018).[19] This allows for China's college expansion to directly affect R&D through changes in research costs.

1.3.2 Firms' Production, Innovation and Entry/exit

Setup

In region m and industry j, there is a measure $N_{m,j}$ of firms in operation. Each firm produces a unique differentiated variety ω, and I omit ω when it causes no confusion. A firm's state can be summarized as $\mathbf{s}_{m,j} = \{z_{m,j}, \varepsilon_{m,n,j}, \eta_{m,j}\}$. Productivity $z_{m,j}$ and demand shifters $\varepsilon_{m,n,j}$ are drawn randomly upon firm entry and evolve over time. Research efficiency $\eta_{m,j}$ is time-invariant and determined upon firm entry.

Production Technology. Firms employ educated labor h, less educated labor l, and raw

[19] Acemoglu et al. (2018) assume that research inputs are totally produced by educated labor. However, in Chinese data, a large proportion of research expenditures are spent on materials, which implies $\gamma_r < 1$.

materials from other industries to produce output,

$$q = z_{m,j} \left[\alpha_j l^{\frac{\rho_x - 1}{\rho_x}} + (1-\alpha_j) h^{\frac{\rho_x - 1}{\rho_x}} \right]^{\frac{\rho_x \gamma^L_{m,j}}{\rho_x - 1}} \prod_{j'=1}^{J} b_{j'}^{\gamma^{j'}_{m,j}}. \tag{1.4}$$

Parameter α_j governs the skill intensity in industry j, and parameter ρ_x determines the elasticity of substitution between educated and less educated labor. I also incorporate cross-industry production linkages to allow for amplification effects through input-output networks. Parameter $\gamma^{j'}_{m,j}$ is the share of costs spent on raw materials from industry j', and $\gamma^L_{m,j}$ is the share spent on labor, with constant returns to scale, $\gamma^L_{m,j} + \sum_{j'} \gamma^{j'}_{m,j} = 1$.

Given these assumptions, the unit cost of the input bundle for firms with $z_{m,j} = 1$ is:

$$c_{m,j} = \Phi_{m,j} \left[\frac{\alpha_j^{\rho_x}}{W_m^{\rho_x - 1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_m^{\rho_x - 1}} \right]^{\frac{\gamma^L_{m,j}}{1-\rho_x}} \prod_{j'} P_{m,j'}^{\gamma^{j'}_{m,j}} \tag{1.5}$$

where $\Phi_{m,j}$ is a constant.[20] S_m and W_m are wage rates of educated and less educated labor.

Operating and Trade Costs. Firms pay a fixed cost $f_{m,j}$ per period to remain in business. Firms compete monopolistically and expend fixed costs $f_{m,n,j}$ as well as iceberg costs $d_{m,n,j} \geq 1$ if selling to market n. The fixed costs are in units of final goods, and the iceberg costs also incorporate *ad valorem* tariffs. Incorporating tariffs in the iceberg costs allows me to capture the effects of China's WTO accession.[21]

Productivity Evolution and Innovation. The productivity of each firm evolves in the

[20]The constant can be written as: $\Phi_{m,j} = \left(\gamma^L_{m,j}\right)^{-\gamma^L_{m,j}} \prod_{j'} \left(\gamma^{j'}_{m,j}\right)^{-\gamma^{j'}_{m,j}}$.

[21]As my focus is not on tariffs *per se*, I abstract from the modelling of tariff revenues. A thorough treatment of tariffs can be found in Caliendo, Feenstra, Romalis & Taylor (2015) and Liu & Ma (2018).

end of the period as:

$$\Delta \log z_{m,j} = \underbrace{g_{m,j}}_{\text{aggregate growth}} + \underbrace{\xi_{m,j}}_{\text{idiosyncratic shock}} + \underbrace{i}_{\text{research intensity}} \times \underbrace{\exp(\eta_{m,j})}_{\text{step size of improvement}} . \tag{1.6}$$

The first term $g_{m,j}$ captures exogenous productivity growth, and the second term represents idiosyncratic productivity shocks $\xi_{m,j} \sim \mathcal{N}(0, \sigma_\xi)$. The third term $i \times \exp(\eta_{m,j})$ represents the fruits of innovation. A firm with research intensity i spends $\tilde{z}_{m,j}^{\sigma-1} \phi_{1,j} \mathbf{1}_{\{i>0\}} + z_{m,j}^{\sigma-1} \phi_{2,j} \frac{i^{\chi+1}}{\chi+1}$ units of research goods, where $\tilde{z}_{m,j}$ is the average productivity in region m and industry j.[22] I assume $\phi_{1,j} > 0$ and $\phi_{2,j} > 0$, which vary across industries to capture heterogeneous opportunities of innovation. R&D costs are strictly increasing and convex in research intensity with $\chi > 0$. The step size of innovation $\exp(\eta_{m,j})$ is larger for a firm with higher research efficiency $\eta_{m,j}$.

This innovation process builds on Atkeson & Burstein (2010), enriched to allow for fixed costs and heterogeneous innovation costs across industries. First, fixed costs of innovation allow firms with low research efficiency to opt out of innovation, in line with the fact that a small portion of firms perform innovative activities even among large firms. Second, because more skill-intensive industries tend to be more innovative in reality, reallocating production to more skill-intensive industries could promote innovation. This generates the interaction between exports and innovation after the college expansion.

Evolution of Demand Shifters. In the end of the period, demand shifters $\varepsilon_{m,n,j}$ evolve according to a log-normal AR(1) process, independently across firms and destinations, with autocorrelation parameter ρ_ε and standard deviation σ_ε of Gaussian white noises.

Firm Entry. An *exogenous* measure $N_{m,j}^e$ of new firms enter in the end of the period. Entrants imperfectly imitate incumbent firms, as in Luttmer (2007). A firm randomly draws productivity level z and idiosyncratic demand shifters ε from the distribution of incumbent firms,

[22] The dependence of innovation costs on $z_{m,j}^{\sigma-1}$ aims to eliminate the "scale effects" of innovation, as discussed in Klette & Kortum (2004). Otherwise, productive firms would have much higher R&D intensity simply because they are productive.

after evolution of productivity and demand shifters occurs. Its productivity is given by $\exp(-\delta_p)z$, where $\delta_p > 0$ captures imperfect imitation. Upon entry, it draws idiosyncratic research efficiency $\eta \sim \mathcal{N}(\mu_\eta, \sigma_\eta^2)$.

Firm Exits. In the beginning of the next period, incumbent firms and new firms face an exogenous death rate δ. A firm that does not exit exogenously can still cease to operate if their value from continuing to operate is negative.

Firm's Problem

Static Problem: Optimal Price and Exporting Decisions. Because firms' production technology is constant-returns-to-scale, a firm maximizes profits for each market n separately:

$$\begin{aligned} \pi_{m,n,j}(\mathbf{s}_{m,j}) &= \max_{p} pq - \frac{d_{m,n,j}c_{m,j}}{z_{m,j}}q - P_m f_{m,n,j} \\ s.t.\ q &= \varepsilon_{m,n,j}p^{-\sigma}P_{n,j}^{\sigma}Q_{n,j} \end{aligned} \tag{1.7}$$

By the first-order condition, the optimal price charged by the firm is:

$$p^*_{m,n,j}(\mathbf{s}_{m,j}) = \frac{\sigma}{\sigma-1}\frac{c_{m,j}d_{m,n,j}}{z_{m,j}}. \tag{1.8}$$

The firm will only serve market n if the profits are positive.

Dynamic Problem: Optimal R&D Choices. An incumbent firm determines the optimal research intensity to maximize the value of the firm,

$$
\begin{aligned}
V(\mathbf{s}_{m,j};\mathbf{X}) = \max_{i\geq 0} \Bigg[& \underbrace{(1-\zeta(\mathbf{s}_{m,j}))\left(\sum_n \pi^+_{m,n,j}(\mathbf{s}_{m,j}) - f_{m,j}P_m\right)}_{\text{after-tax profits}} \\
& \underbrace{-z^{\sigma-1}_{m,j}\phi_{1,j}\mathbf{1}_{\{i>0\}}P_{m,r} - z^{\sigma-1}_{m,j}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}P_{m,r}}_{\text{research costs}} + \underbrace{\frac{1-\delta}{1+r}\mathbb{E}\max\{V^{'}(\mathbf{s}^{'}_{m,j};\mathbf{X}^{'}),0\}}_{\text{next-period value}}\Bigg] \\
\text{s.t. } & \Delta \log z_{m,j} = g_{m,j} + \xi_{m,j} + i \times \exp(\eta_{m,j}), \;\; \log \varepsilon_{m,n,j} \sim \text{AR}(1),
\end{aligned}
\tag{1.9}
$$

where $\mathbf{X}$ denotes the set of aggregate state variables, including prices, wages, and demand, and $\pi^+_{m,n,j} = \max\{0, \pi_{m,n,j}\}$ denotes profits from serving market n. The profit tax rate $\zeta(\mathbf{s}_{m,j})$ allows me to capture changes in R&D tax incentives. $\max\{V^{'}(\mathbf{s}^{'}_{m,j};\mathbf{X}^{'})),0\}$ is the next-period firm value, reflecting endogenous exits when the firm value is negative.

The tax revenues collected from local firms are spent by the government on local final goods. I also assume that firms are owned by a representative capitalist who spends the after-tax profits (net of R&D and entry costs) on local final goods.

Endogenous Number of New Firms

I consider an alternative scenario of firm entry to allow the college expansion to directly affect the number of new firms. Following the typical assumption in the literature (Atkeson & Burstein 2010, Grossman & Helpman 2014), I assume that an entrant needs to pay $f^e_{m,j}$ units of research goods to enter region m and industry j. Let $V^e_{m,j}$ be the value of a new entrant in region m.[23] Thus, in the equilibrium, the number of potential entrants is thus *endogenously* decided by the free-entry condition:

$$
f^e_{m,j}P_{m,r} = V^e_{m,j}. \tag{1.10}
$$

[23] Define $G^e_{m,j}(\mathbf{s}_{m,j})$ as the distribution of state variables for entrants, which is determined by the distribution of incumbent firms as described earlier. I have $V^e_{m,j} = \frac{1-\delta}{1+r}\int \max\{V^{'}(\mathbf{s}_{m,j}),0\}dG^e_{m,j}(\mathbf{s}_{m,j})$.

1.3.3 Workers

I explicitly model workers' age structure following Card & Lemieux (2001), as Appendix A.6 reveals that China's college expansion had much stronger effects on the college premium of young workers relative to older ones.[24] Each worker lives for T periods. The amount of age a educated and less educated workers in region m is denoted as $H_{m,a}$ and $L_{m,a}$, with age-specific wage rates $S_{m,a}$ and $W_{m,a}$ respectively.

I also consider workers' period-to-period migration following Artuc et al. (2010). In the end of each period, old workers of age T retire, and other younger workers determine whether and where to migrate. New workers of age 0 also enter in the end of the period, make migration decisions, and then start to work in the next period.[25]

Labor Supply and Age-specific Wage Rates

As in Card & Lemieux (2001), the supply of labor services of educated (less educated) labor in region m is a CES function of educated (less educated) workers of different age groups,

$$H_m = \left(\sum_{a=1}^{T} \beta_a^H H_{m,a}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \quad L_m = \left(\sum_{a=1}^{T} \beta_a^L L_{m,a}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \tag{1.11}$$

where $\beta_a^I, I \in \{H, L\}$ captures the relative productivity of workers of different ages. Parameter $\rho_a > 1$ governs the elasticity of substitution of workers across different ages. The limiting case $\rho_a \to \infty$ refers to perfect substitution between workers of different ages.

The age-specific wages are determined by the marginal contribution of workers of different ages to aggregate labor supply:

$$S_{m,a} = \left(\frac{H_{m,a}}{H_m} \right)^{-\frac{1}{\rho_a}} \beta_a^H S_m, \quad W_{m,a} = \left(\frac{L_{m,a}}{L_m} \right)^{-\frac{1}{\rho_a}} \beta_a^L W_m. \tag{1.12}$$

[24] My finding is consistent with Card & Lemieux (2001), who show that increases in the amount of college-educated workers have age-specific effects on the college premium in the U.S., the UK, and Canada.

[25] This is motivated by that new college-educated workers may not start work in their graduation region.

Equation (1.12) shows that the elasticity of relative wages of two age groups with regard to their relative labor supply is $-\frac{1}{\rho_a} < 0$. Therefore, an influx of new college grads leads to a lower wage of young cohorts relative to that of older cohorts, in line with my evidence in Appendix A.6 that China's college expansion erected more negative effects on young workers' college premium than old workers' college premium.

Migration and Labor Market Dynamics

I abstract from international migration between China and Foreign and only consider Chinese workers' migration decisions across subnational regions within China.

A worker has per-period log utility on the final good. I abstract from savings, and hence workers spend all of their income on the final good. In the end of the period, Chinese workers draw idiosyncratic location preference shocks $\{\varphi_n\}_{n\in C}$,[26] distributed according to a Type-I Extreme Value distribution, i.i.d. over time and across locations, with ν being the scale parameter. If an educated (less educated) worker moves from region m to another region n, migration costs $\tau^H_{m,n,a}$ ($\tau^L_{m,n,a}$) need to be incurred. In the quantitative analysis, I will let bilateral migration costs within China rely on workers' birthplaces, reflecting the important effect of the Hukou policy (Tombe & Zhu 2019).

I assume that migration costs and location preference shocks are additive in the utility. These assumptions allow for an analytical solution of migration probabilities:

Proposition 1 (Migration Probability). *The migration probability from region m to n in China:*

$$\Lambda^I_{m,n,a} = \frac{\exp(\beta U^{I'}_{n,a+1} - \tau^I_{m,n,a})^{1/\nu}}{\sum_{r\in C}\exp(\beta U^{I'}_{r,a+1} - \tau^I_{m,r,a})^{1/\nu}}, \quad I \in \{H, L\}, \tag{1.13}$$

where $U^{I'}_{n,a+1}$ is the expected utility of staying in region n in the next period.

Proof: See Appendix A.3.1. □

[26]Workers of age T exit the labor market after obtaining consumption.

As expected, a higher future value in the destination or lower migration costs will induce larger migration flows. Parameter ν, which governs the dispersion of location preferences, pins down the elasticity of migration flows to the future value.

The labor supply of Chinese region n in the next period can be computed as $H^{'}_{n,a+1} = \sum_{m\in C}\Lambda^{H}_{m,n,a}H_{m,a}$ and $L^{'}_{n,a+1} = \sum_{m\in C}\Lambda^{L}_{m,n,a}L_{m,a}$, for ages $0 \leq a \leq T-1$. Therefore, given initial labor distribution across Chinese regions, the number of new workers, and sequences of wages and migration costs, I can compute the distribution of workers at any time. The labor supply in Foreign can be similarly obtained, except for no migration.

1.3.4 Equilibrium

Define $\mathcal{L} = \{H_{m,a}, L_{m,a}\}$ as the distribution of labor across regions and ages, and $\mathcal{N} = \{N_{m,j}(\mathbf{s})\}$ as the distribution of firms across regions and industries, where $N_{m,j}(\mathbf{s})$ is the measure of firms with state $\mathbf{s}$.

My model admits a sequential general equilibrium that satisfies the following conditions. First, given firm and labor distributions $\{\mathcal{N}_t, \mathcal{L}_t\}$ over time, there are a set of quantities, wages, and prices that clear goods and labor markets. Second, given sequences of wages and prices over time and initial distributions $\{\mathcal{N}_0, \mathcal{L}_0\}$: (1) the evolution of firm distribution $\mathcal{N}_t$ is consistent with firms' optimal choices of innovation, aggregate and idiosyncratic productivity growth, and firm entry and exits; and (2) the law of motion for labor distribution $\mathcal{L}_t$ is consistent with workers' migration choices as well as workers' entry and exits. I fully characterize the sequential equilibrium in Appendix A.3.2.

1.4 Main Forces at Work

This section studies an analytically tractable version of my model to highlight the model mechanisms about exports and innovation. I assume one aggregate region in China $\#\mathcal{C} = 1$. I abstract from firm entry, profit taxes, input-output linkages, operation costs, and fixed costs to sell domestically. I consider one period with no productivity shocks and demand shifters, and the fruits of innovation arrive *contemporarily*. Finally, I assume that variables in Foreign are not affected by China's labor supply shock, given a low share of foreign expenses on China's exports in reality.[27]

In what follows, I index China by C and Foreign by F. Denote by $\hat{x} = \log\left(\frac{x'}{x}\right)$ the proportional change from the initial to the current equilibrium for variable x. I will study an increase in the amount of educated labor in China.

Proposition 2 (**Wage Response**)**.** In a closed economy with no innovation,

$$\hat{S}_C - \hat{W}_C = -\Phi_C(\hat{H}_C - \hat{L}_C),$$

where the constant $\Phi_C > 0$.

Proof: See Appendix A.3.3. □

This proposition establishes an intuitive result that the skill premium declines in response to an increase of educated labor. Although I impose some regularities in Proposition 2, this result hold empirically in more general scenarios: a large empirical literature has shown that an influx of college-educated workers leads to lower skill premium (Katz & Murphy 1992, Card & Lemieux 2001). I also find that the college premium experienced larger reductions in Chinese regions with greater exposure to the college expansion, as I will discuss in the next section.

Define $R_{C,j}$ and $R_{F,j}$ as domestic sales and exports by a Chinese firm with productivity z_j and research efficiency η_j in industry j. Let $SI_{C,j}$ be the share of educated labor's wages in total labor costs in China's industry j. The next proposition shows that trade helps the economy avoid the diminishing returns of accumulating educated labor by shifting industry composition.

[27]The share of foreign manufacturing expenses on Chinese goods was only 2.9% in 2005, according to the World Input-Output Table.

Proposition 3 (Domestic Sales and Export Growth). Assume that there is no innovation.

(i) Proportional changes in domestic sales are:

$$\hat{R}_{C,j} \propto \Big[\underbrace{(\theta-1)\Pi_{C,C,j}}_{\text{shifts in domestic demand}} + \underbrace{(\sigma-1)(1-\Pi_{C,C,j})}_{\text{gains in market shares from import competition}} \Big] SI_{C,j}\left(\hat{W}_C - \hat{S}_C\right)$$

and proportional changes in exports (if the firm exports before and after the shock):

$$\hat{R}_{F,j} \propto \underbrace{(\sigma-1)SI_{C,j}\left(\hat{W}_C - \hat{S}_C\right)}_{\text{expansion in foreign market}}$$

where $\Pi_{C,C,j}$ is the share of China's expenses on domestic goods in industry j.

(ii) If the density of firms around the export threshold is identical in two industries, the more skill-intensive industry enjoys more export entry when $\hat{W}_C - \hat{S}_C > 0$.

(iii) With $\sigma > \theta \geq 1$ and similar $\Pi_{C,C,j}$ across industries,[28] if either firm productivity is Pareto distributed or there is no new entry into exporting, exports shifts more toward high skill-intensity industries than domestic sales when $\hat{W}_C - \hat{S}_C > 0$.

Proof: See Appendix A.3.4. □

Result (i) indicates how firm sales change in response to lower skill premium, which reduces production costs by $SI_{C,j}\left(\hat{W}_C - \hat{S}_C\right)$ for industry j.[29] Firms' domestic sales change due to two reasons. First, the cheaper prices of more skill-intensive goods induce between-industry reallocation of demand, the strength of which is determined by between-industry elasticity of substitution θ and the share of expenses spent on domestic goods $\Pi_{C,C,j}$. Second, firms in more skill-intensive industries enjoy lower production costs and thus gain larger market shares from

[28] Despite being viewed as a "World Factory", China's share of manufacturing expenses on domestic goods was 0.82 in 2005, and 70% of 2-digit industries had shares more than 0.8. I compute this using China's Input-Output Table in 2005.

[29] Production costs of all firms also change by a common amount $\hat{W}_C$.

foreign sellers in domestic markets. As for firms' exports, lower costs in more skill-intensive industries induce exporters to export more, the strength of which is governed by within-industry elasticity of substitution σ.

Result (ii) shows that lower costs in more skill-intensive industries also encourage more entry into exporting, which reinforces larger expansion of exports in more skill-intensive industries. Result (iii) shows that if $\sigma > \theta \geq 1$ and under certain regularities,[30] there is larger skill upgrading of exports than domestic sales after an influx of educated labor, as I found in Section 1.2.2. The intuition of $\sigma > \theta$ is that there is more substitution between varieties within an industry (e.g., Nike shoes vs. Adidas shoes) than between products in different industries (e.g., Nike shoes vs. iPhones), which is supported by empirical estimates from Broda & Weinstein (2006). I will use reduced-form estimates in the next section to discipline these two parameter values and confirm $\sigma > \theta \geq 1$.

Finally, I look into how innovation changes in my model. With little abuse of notation, I interpret $R_{C,j}$ and $R_{F,j}$ as a firm's domestic sales and exports before any innovation. By the first-order approximation, the firm's problem can be written as:

$$\max_i \underbrace{\frac{\sigma-1}{\sigma}\left(R_{C,j}+R_{F,j}\right)\exp(\eta_j)i}_{\text{expected profit growth}} - \underbrace{\phi_{1,j}\mathbf{1}_{\{i>0\}}\tilde{z}_j^{\sigma-1}P_{C,r} - \phi_{2,j}\frac{i^{\chi+1}}{\chi+1}z_j^{\sigma-1}P_{C,r}}_{\text{costs of innovation}}, \tag{1.14}$$

where $\frac{\sigma-1}{\sigma}$ captures the profit ratio $\frac{1}{\sigma}$ and the elasticity of firms' sales with regard to productivity $(\sigma-1)$. An increase of educated labor alters innovation through two channels:

- Affect research costs $P_{C,r}$. This effect is uniform for all the firms.
- Affect innovation returns through changes in before-innovation sales $R_{C,j}+R_{\mathcal{F},j}$.

Proposition 4 (**Interactions between Exports and Innovation**).

[30] These additional assumptions are made for analytical tractability to ensure that the import competition and the extensive margin of exports are identical across industries.

(i) Holding export status unchanged, proportional changes in innovation returns are:

$$\left[\sigma - 1 + (\theta - \sigma)\Pi_{C,C,j}\left(1 - \frac{R_{F,j}}{R_{C,j} + R_{F,j}}\right)\right] SI_{C,j}(\hat{W}_C - \hat{S}_C),$$

which if $\sigma > \theta \geq 1$, rises with skill intensity $SI_{C,j}$ and export-output ratio $\frac{R_{F,j}}{R_{C,j}+R_{F,j}}$.

(ii) Holding all other things constant, export entry increases R&D activities.

Proof: See Appendix A.3.5. □

With an influx of educated labor, firms in more skill-intensive industries enjoy faster sales growth, especially when they export intensely. The larger sales lead to more innovation returns, reflecting market size effects of innovation (Acemoglu & Linn 2004). This interaction between exports and innovation increases aggregate R&D, as more skill-intensive industries are also more innovative in reality. It is also worth noting that in our model, export entry and innovation activities are jointly determined. Additional revenues from foreign market access could induce export entrants to increase innovative activities, and innovative activities may help some firms to be productive enough for export entry (Lileeva & Trefler 2010, Bustos 2011).

1.5 Empirical Analysis

In this section, I estimate how China's college expansion affects exports and innovation by exploiting the differential magnitude of the college expansion across regions due to historic reasons. The results empirically validate the model mechanisms discussed in Section 1.4 and help me discipline key structural elasticities.

1.5.1 Supply Shocks of College-educated Workers and Instruments

I classify college-educated workers as educated labor in the model, and workers with high-school degree or lower as less educated labor. Using China's Population Censuses 2005 and 2010, I measure changes in the supply of college-educated workers in region m between 2005–2010 as:

$$x_m = \left(\frac{H_{m,2010} - H_{m,2005}}{H_{m,2005}} - \frac{L_{m,2010} - L_{m,2005}}{L_{m,2005}} \right), \tag{1.15}$$

where $H_{m,t}$ and $L_{m,t}$ are the total amount of college-educated and noncollege workers in region m in year t, respectively.

Changes in the relative supply of college-educated workers could be driven by shifts in the relative labor demand for them. For example, productive regions may attract high-skill immigrants, or their local government may face pressure from the private sector to increase college enrollments. To disentangle labor supply from demand shocks, I follow the immigration literature (Card 2001) to construct a Bartik-type instrument:

$$x_m^* = \underbrace{\frac{ENROLL_{m,1982}}{ENROLL_{1982}} \times GRAD_{-m,2006-10}}_{\text{predicted num of grads in region } m} / H_{m,2005} \tag{1.16}$$

where $GRAD_{-m,2006-10}$ is China's total number of college grads between 2006–2010, excluding those who graduated from colleges in region m.[31] $\frac{ENROLL_{m,1982}}{ENROLL_{1982}}$ is the ratio of region m's college enrollments to national enrollments in 1982.[32] I use this ratio to predict the number of college grads in region m between 2006–2010. This instrument's construction is motivated by that the college expansion was attained mainly by the scale-up of enrollments in previously existing colleges, as discussed in Section 1.1, and migration barriers ("Hukou") restricted college grads' movement. Overall, x_m^* predicts x_m well: across cities or provinces, the slope of x_m on x_m^* is always significantly positive at the 5% level.

The validity of this instrument relies on the key assumption that changes in labor demand between 2005–2010 were not correlated with the distribution of college resources in 1982. I

[31] China's total number of college grads between 2006–2010 is 24 million.

[32] I construct this variable using the number of people attending colleges in each region, according to micro-level Population Census 1982 from IPUMS.

provide support for this assumption as follows. First, Appendix Figure A.4 shows that my instrument was negatively correlated with changes in local workers' college premium between 2005–2009, but uncorrelated with changes in workers' college premium before 2005. Thus, regions exposed more to the college expansion did not enjoy changes in the relative labor demand for college-educated workers before the shock, consistent with the mismatch between college resources and regional development levels shown in Section 1.1. This pattern also supports that the college expansion did lead to reductions in the college premium—which is essential for the model to generate differential sales growth and the interaction between innovation and exports as discussed in Section 1.4.

Second, I will control region-specific fixed effects and trends in all my regressions. This allows me to control region-specific characteristics that are correlated with initial shares of college endowments, as well as overall changes in regional economic performance. Third, I perform pre-trend tests and also construct alternative instruments to confirm the robustness of my results, as detailed in Section 1.5.2. Finally, in the calibration, I use region-industry-specific productivity growth to match observed output growth across regions and industries over time. If changes in labor demand come from productivity growth and still bias the IV regressions, they would bias observed estimates and the estimates from the model-generated data similarly. Using the implied within-industry and between-industry elasticities of substitution from the IV regressions, Section 1.6.4 shows the model-generated data predict similar regression results as in the actual data. Thus, the IV estimates of elasticities are robust if the endogeneity concern is productivity growth,[33] and other factors not captured by the model may not substantially bias the IV regressions.

[33] If the bias in regressions is substantial, the model-generated data (using the implied elasticities from regressions of actual data) could predict very different regression results from the actual data (Simonovska & Waugh 2014). Alternatively, if productivity growth is a concern, I can apply the simulated method of moments (SMM) to estimate the elasticities, by minimizing the difference in regression results between the actual data and the model-generated data. As the model-generated data using the IV estimates of elasticities predict similar regression results as in the actual data, the SMM estimates shall be close to the IV estimates.

1.5.2 Empirical Results

Domestic Sales and Exports Growth

I use the 2005–2010 balanced firm panel constructed in Section 1.2.3 to perform empirical analysis. I estimate the following regression:

$$\Delta y_{m,j}(\omega) = \beta_0 + \beta_1 SI_{m,j} x_m + \beta_2 \mathbf{Z}_{m,j}(\omega) + \iota_m + \varepsilon_{m,j}(\omega). \tag{1.17}$$

For the dependent variable $\Delta y_{m,j}(\omega)$, I separately use log changes in domestic sales, ordinary exports, and production costs for firm ω between 2005–2010. I measure skill intensity $SI_{m,j}$ using the share of college-educated workers in total employment in region m and industry j from ASM 2004.[34] I focus on 2-digit industries to be consistent with my calibration. $SI_{m,j}x_m$ captures exposure to the college expansion for firms in region m and industry j, as guided by analytical results in Section 1.4. I instrument $SI_{m,j}x_m$ with $SI_{m,j}x_m^*$. Controls $\mathbf{Z}_{m,j}$ include: (1) log output value, log employment, log fixed capital, and dummies of firm registration types (e.g., SOE) in 2005; and (2) input and output tariff reductions due to WTO. Finally, ι_m captures region-specific trends,[35] and hence my identification of β_1 relies on within-region different responses of firms across industries.

I use export prices as a proxy for production costs[36] that cannot be directly observed, because prices and production costs are perfectly aligned in my model. I construct changes in export prices, using the weighted average of changes in firm-level export prices for each 6-digit HS product that they exported in both 2005 and 2010. The weights are firm-level export shares across 6-digit HS products in 2005.

[34] ASM 2004 does not distinguish between R&D and non-R&D workers, whereas the measure of skill intensities aims to capture skill intensities of production. I have experimented with adjusting $SI_{m,j}$ by deducting the industry-level relative amount of full-time R&D workers to employment, drawn from Firm Census Assembly 2004. As the relative amount of full-time R&D workers to college-educated workers was only 5% for overall manufacturing in 2004, I obtain similar results as in Table 1.1.

[35] By using a first difference for the dependent variable, I naturally control region-specific fixed effects.

[36] I use free-on-board (FOB) prices, which do not include freight costs.

Table 1.1: College Expansion and Sales Growth, 2005–2010

Dep Var:	Δlog(ordinary exports)		Δlog(domestic sales)		Δlog(export prices)	
Geographic level	provincial (1) 2SLS	city-level (2) 2SLS	provincial (3) 2SLS	city-level (4) 2SLS	provincial (5) 2SLS	city-level (6) 2SLS
Exposure to CE	3.796*** (0.717)	3.679*** (0.721)	1.820*** (0.421)	2.006*** (0.420)	-0.645*** (0.229)	-0.628*** (0.230)
Obs	10,162	10,136	40,540	40,460	8,450	8,425
R-squared	0.047	0.067	0.067	0.077	0.022	0.037
First-stage F	410.38	722.33	451.34	694.12	402.01	690.83
Inferred θ	3.1	3.5	3.1	3.5	3.1	3.5
Inferred σ	6.9	6.9	6.9	6.9	6.9	6.9

Note: This table provides estimates from regressions in equation (1.17), separately treating regions as cities and provinces. "CE" is short for "college expansion." I control dummies for firm registration types (e.g., SOE), log employment, log fixed capital, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

Table 1.1 presents two sets of regression results, separately treating regions as cities and provinces. This is motivated by that city-level shocks allow for more variation, whereas I will use province-level shocks to discipline model parameters, as my model will be calibrated to the provincial level due to the data availability. Regardless of the geographic level, the results show that with larger exposure to the college expansion, a firm's export prices decreased, and its ordinary exports and domestic sales both increased. In particular, ordinary exports responded more strongly to the college expansion than domestic sales. Guided by Result (i) in Proposition 3, I can use these estimates to discipline between-industry and within-industry elasticities of substitution (θ and σ):

$$-\frac{\beta_{1,\text{ordinary exports}}}{\beta_{1,\text{export costs}}} = \hat{\sigma} - 1, \quad -\frac{\beta_{1,\text{domestic sales}}}{\beta_{1,\text{export costs}}} = (\hat{\sigma} - 1)(1 - \bar{\Pi}_{CC}) + (\hat{\theta} - 1)\bar{\Pi}_{CC}.$$

According to China's Input-Output Table in 2005, $\bar{\Pi}_{CC} \approx 0.8$ is the average share of China's expenses devoted to domestic goods across 2-digit manufacturing industries. The resulting θ and

Table 1.2: Dependent Variable: Changes in R&D Status between 2005–2010

Dep var:	Δ R&D status					
	(1) 2SLS nonexporter	(2) 2SLS ord. exporter	(3) 2SLS nonexporter	(4) 2SLS ord. exporter	(5) 2SLS all firms	(6) 2SLS export share<0.4
Exposure to CE	0.441***	0.513***	0.331***	0.529***	0.457***	0.418***
	(0.103)	(0.150)	(0.095)	(0.170)	(0.098)	(0.097)
Exposure to CE $\times$ export share					0.058	2.545**
					(0.416)	(1.205)
Obs	31,139	11,669	26,325	10,162	42,808	40,093
R-squared	0.016	0.038	0.012	0.041	0.022	0.022
First-stage F	428.58	413.47	456.99	410.38	224.76	224.28

Note: This table provides estimates from regressions in equation (1.17), treating regions as provinces. "CE" is short for "college expansion." I control dummies for firm registration types (e.g., SOE), log employment, log fixed capital, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Columns (1) and (2) focus on firms that were nonexporters and ordinary exporters in 2005, respectively. Columns (3) and (4) focus on firms that did not switch export status between 2005 and 2010, respectively. In Columns (5) and (6), the interaction term is instrumented by the interaction between $SI_{m,j}x_m^*$ and the export share. In Columns (5) and (6), I also control initial export shares, and I allow the coefficients on initial export shares to be different across regions to capture region-specific export growth rates. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

σ are 3.1 (3.5) and 6.9 (6.9) based on provincial (city-level) shocks.[37]

Interaction between Innovation and Exports

I next investigate how the college expansion affects firms' innovation and the interaction between innovation and exports. I perform the same regression in equation (1.17), but use changes in R&D status (1 if R&D is positive and 0 otherwise) as the dependent variable.

In Columns (1)–(2) of Table 1.2, I run the regressions separately for firms based on their export status in 2005. I only report the results treating regions as provinces, as city-level results are very similar. I find that larger exposure to the college expansion induced more innovation, especially among ordinary exporters, confirming the interaction between exports and innovation in Proposition 4. To avoid firm entry/exits associated with changes in innovation returns, Columns

[37]My estimates are comparable to Broda & Weinstein (2006), where the average elasticity of substitution for varieties from different countries within 3-digit SITC industries is 6.8 between 1972–1988 (Table IV).

(3)–(4) report the results for firms that did not switch export status between 2005–2010. The results are similar to Columns (1)–(2).[38]

In Column (5), I perform the regression for all firms, but add the interaction between exposure to the expansion and firms' share of ordinary exports in total sales in 2005. The effect of the college expansion on innovation did not appear to be significantly amplified by initial export shares. One reason is that very export-intensive Chinese firms tend to be small and unproductive (Lu 2010), thus unlikely to pay fixed costs to innovate.[39] I thus restrict the sample to firms with export shares lower than 0.4 (75% percentile of export shares among exporters) in Column (6), avoiding extremely export-intensive firms. The estimates show that firms with larger initial share of exports performed more innovation in response to the college expansion, confirming Result (i) in Proposition 4.

Robustness Checks

I briefly describe my robustness checks and other tests, with details in Appendix A.4.2.

Alternative Instruments. I also explore different ways of constructing the instrument $SI_{m,j}x_m^*$. First, as Chinese firms may change labor composition in advance of future sales growth, I use U.S. Population Census 1990 to construct industry-level college employment shares $SI_{m,j}$. Second, considering that the college distribution in 1982 may reflect the current government's regional policies, I use the distribution of colleges in 1948 (when there was ongoing civil war) to develop a different measure of historic college resources x_m^*. Third, I also build on China's relocating university departments in the 1950s—which arose due to political reasons (Glaeser & Lu 2018)—to construct another instrument for regional college resources x_m^*. I employ these alternative instruments in the regressions and find quantitatively similar results as in Tables

[38]Columns (3)–(4) produce a larger difference in the coefficients between ordinary exporters and nonexporters than Columns (1)–(2). One reason is that nonexporters in 2005 had more export entry in response to the expansion, which led to more innovation and higher coefficient in Column (1).

[39]Using the 2005 ASM, I also find that after controlling industry and city fixed effects, firms with extremely high export shares were smaller in size and less innovative than firms with lower export shares.

1.1–1.2, and the implied within-industry and between-industry elasticities are $6.4 \sim 13.3$ and $1.7 \sim 4.6$.

Alternative Data Construction. First, to avoid firms' switches of exporting products, I utilize 6-digit HS products exported in both 2005 and 2010 to construct changes in exports. Second, I use the 2005–2007 data to perform all the regressions, for which I show that my results are not due to different datasets (ASM and SAT). Third, I only use exporting firms to estimate how changes in domestic sales responded to the college expansion, because my use of export prices only applies to exporters. I employ these new data construction in the regressions and find quantitatively similar results as in Tables 1.1–1.2, and the implied within-industry and between-industry elasticities are $6.3 \sim 7.4$ and $2.0 \sim 4.9$.

1.6 Model Estimation

To quantitatively investigate the impact of China's college expansion, I calibrate my model to 33 industries, 30 Chinese provinces, and a constructed Rest of World in 2000–2018. My 33 industries include 30 2-digit manufacturing industries, agriculture, mining, and services (see Appendix Table A.10). In this section, I briefly discuss the model extension to incorporate processing exports, the data sources, calibration processes, and the model fit.

1.6.1 Incorporating Processing Exports

In the quantitative model, I assume that each manufacturing industry in a Chinese region also hosts many processing exporters. Production- and trade-related variables and parameters are now qualified by $m(k)$ for a Chinese region $m \in \mathcal{C}$, with $k \in \{\mathcal{O}, \mathcal{P}\}$ indexing export regimes (ordinary or processing). For ease of description, I denote the set of China's regions and export regimes by $\tilde{\mathcal{C}} = \{m(k)\}_{m \in \mathcal{C}, k \in \{\mathcal{O}, \mathcal{P}\}}$. Processing exporters are modelled analogously as ordinary firms in Section 1.3.2, and the main differences between two export regimes are tariff treatments, domestic market access, and value added shares. Processing exporters do not invest in R&D. See Appendix A.5.1 for details.

1.6.2 Data

I briefly discuss the data sources used in the calibration, with details in Appendix A.5.3.

Provincial Output and Exports. For each province and industry, I obtain manufacturing output in 2000–2012 from ASM, and processing and ordinary exports from the matched ASM-Customs Database.[40] As processing output cannot be sold domestically, processing exports from customs data are total output for processing exporters. Therefore, for each province and industry, the difference between total output and processing exports is the output of ordinary production. I obtain provincial production in agriculture, mining, and services by provinces between 2000–2012 from input-output tables.

Imports and Tariffs. I obtain imports by 8-digit HS products, export regimes, and provinces from China's Customs Transactions Database in 2000–2016. I aggregate these data by 33 industries to obtain imports and exports for each province-industry-regime. To capture tariff changes in the model, I also draw tariffs by 4-digit HS products from UNCTAD TRAINS Database, and compute the weighted-average tariffs for China's exports and imports by 33 industries in each year.

Inter-provincial Trade Flows by Industries and Regimes. I construct China's inter-provincial bilateral trade flows by industries and export regimes using China's regional input-output table in 2007. I deflate these trade flows to the year 2005, using growth rates of China's industrial output between 2005 to 2007. I use these inter-provincial trade flows to calibrate inter-provincial trade costs.

[40] As the match between ASM and Customs Database is imperfect, for each province, I adjust the value of processing (ordinary) exports in the matched ASM-Customs Database proportionally to match the total value of processing (ordinary) exports in customs data.

China's Firm Distribution. I obtain the number of firms by provinces and industries from Firm Census 2004, 2008, and 2013, and divide the number of firms in each province-industry into two export regimes (ordinary or processing), using the relative number of two types of firms in the matched ASM-Customs Database 2000–2012. I interpolate and extrapolate the data for the missing years between 2000–2018 using the linear trend.

China's Labor Market Data. I obtain employment by ages, provinces, and education levels in 2000 and 2005 from micro-level Population Census. The data in 2005 also provide individual-level wages. I adjust workers of education levels lower than high school to the equivalents of high-school grads, using their relative wages in 2005. I adjust college grads with part-time degrees to the equivalents of college grads with regular degrees, using their relative wages from Xu et al. (2008). I use inter-provincial migration flows provided by Population Census 2000 to inform migration costs.

I obtain the number of college grads by province between 2000–2014 from Statistical Yearbooks and extrapolate these data to later years using the regional distribution of grads in 2014 and changes in the total amount of college grads. Because most data I use do not distinguish between college-educated workers with regular degrees and part-time degrees, I take into account college grads with part-time degrees (adjusted to equivalents of college grads with regular degrees) to target the data moments. I infer the amount of new noncollege entrants between 2000–2018 from changes in the total labor force and the number of college grads. Due to the lack of data, I set the geographic and education distribution of new noncollege entrants to be the same as that in Population Census 2000.

Foreign Data. I obtain foreign output by industry between 2000–2011 from the World Input-Output Table Database, and convert foreign output to 33 industries. I obtain the amount of foreign college-educated and noncollege people by age between 2000–2018 from Barro & Lee (2013) and adjust these numbers proportionally to match each year's employment from the World

Bank. I adjust noncollege workers to the equivalents of high-school grads (12 years of schooling) by assuming a 10% return to one-year schooling. Due to the lack of firm data, I assume that in 2005, for each industry, the ratio of foreign firm numbers to China's firm numbers is equal to the relative output ratio. I then use employment growth to obtain firm numbers in Foreign for all other years.

1.6.3 Calibration Procedure

My model cannot be directly solved by the "Exact Hat" approach, because of the dynamic nature of the model especially due to firm innovation, which is the focus of this study. In what follows, I briefly describe my calibration procedure, with details, parameter values, and targeted moments provided in Appendix A.5.4. I will use subscript u to specify whether parameters are specific to export regimes in China.

I consider several sets of parameters to be time-variant: the amount of new college-educated and noncollege workers $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{C,F\}}$; productivity growth $\{g_{u,j,t}\}_{u\in\{\tilde{C},F\}}$; productivity of research goods $\{A_{u,r,t}\}_{u\in C}$; international trade costs $\{d_{u,F,j,t}, d_{F,u,j,t}\}_{u\in\tilde{C}}$; the amount of exogenous firm entrants $\{N_{u,j,t}\}_{u\in\{\tilde{C},F\}}$ (or entry costs $\{f^{e}_{u,j,t}\}_{u\in\{\tilde{C},F\}}$ under endogenous entry of firms); and the schedule of R&D tax incentives $\zeta_t(\cdot)$.

I first set some pre-determined parameters. A period in the model is one year. I set $T = 45$ years for the length of the working life (aged 20–64),[41] the discount rate $\beta = 0.95$, and migration elasticity $\nu = 2$ of annual frequency from Caliendo, Dvorkin & Parro (2015). I calibrate input-output linkages $\{\gamma^{L}_{u,j}, \gamma^{j'}_{u,j}\}_{u\in\{\tilde{C},F\}}$ using China's and the World Input-Output Tables in 2005. I obtain the amount of new college-educated and noncollege workers across years $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{C,F\}}$ directly from the data. The schedule of R&D tax incentives $\zeta_t(\cdot)$ is drawn from Chen et al. (2018).[42]

[41] I consider that noncollege workers start jobs at age 20, and college-educated workers start at age 23.

[42] Before 2008, firms with R&D intensity larger than 5% are qualified to enjoy a reduction in profit tax rates from 33% to 15%. After 2008, firms are qualified to reduce profit tax rates from 25% to 15% with R&D intensity: (1)

I then calibrate other parameters in three steps. First, as shown in Section 1.3.4, given labor and firm distributions,[43] my model is a static trade model. Thus, I exploit these distributions in 2005 and calibrate production-related parameters $\{\gamma_j, \gamma_r, \alpha_{j(k)}, \beta_a^H, \beta_a^L, \frac{\sigma_\varepsilon^2}{1-\rho_\varepsilon^2}\}$, trade costs $\{d_{u,u',j}, d_{F,u,j,2005}, d_{u,F,j,2005}, f_{u,F,j}, f_{F,u,j}\}_{u,u' \in \tilde{C}}$ and operation costs $\{f_{u,j}\}_{u \in \{\tilde{C},F\}}$ to target relevant parameters in 2005 (with rich data). For instance, marketing costs $\{f_{u,F,j}, f_{F,u,j}\}_{u \in \tilde{C}}$ are informed by the share of exporters in each province-industry or foreign industry. International variable trade costs $\{d_{F,u,j,2005}, d_{u,F,j,2005}\}_{u \in \tilde{C}}$ are disciplined by export and import shares in each Chinese province-industry-regime, and I obtain variable trade costs in other years after accounting for China's import and export tariff changes.

In the second step, given observed firm distributions in the data, I simulate my dynamic model over time with only workers' migration decisions. I assume that China's internal migration costs $\{\tau_{u,u',a}^I\}_{u,u' \in C}$ are zero if workers stay in the current province. For movers, migration costs are a function of age, distance, and contiguity. I also model a destination-specific term in migration costs, capturing that moving to a destination that is not birthplace (with limited access to Hukou) incurs welfare losses (Fan 2019). Thus, I group workers based on education types, current locations of residence, and birthplaces.[44] Given the labor distribution in the initial year (2000), I choose parameters in migration costs and elasticities of substitution (ρ_x and ρ_a) to target the migration pattern in 2000 as well as moments regarding the college premium. In particular, the destination-specific term is informed by the share of in-migrants in a province's employment.

Finally, I calibrate the parameters regarding productivity $\{g_{u,j,t}, N_{u,j,t}, \sigma_\varepsilon, \delta, \delta_p, \rho_\varepsilon\}_{u \in \{\tilde{C},F\}}$ and innovation $\{\chi, \sigma_\eta, \phi_{1,j}, \phi_{2,j}, A_{u,r,t}\}_{u \in C}$ to target related moments between 2000–2018. Given the firm distribution in the initial year (2000), I calibrate firms' productivity drifts $\{g_{u,j,t}\}_{u \in \{\tilde{C},F\}}$

larger than 6% if their sales are smaller than 50 million RMB; (2) larger than 4% if their sales are between 50–200 million RMB; or (3) larger than 3% if their sales are larger than 200 million RMB.

[43] The number of firms across regions, industries, and export regimes is directly observed in the data. I choose the productivity in each region-industry-regime to match the output level.

[44] I save on notation for birthplaces in the formula. The birthplace information is from Population Census 2000. Due to the lack of data, I set the distributions of birthplaces for new college-educated and noncollege workers between 2000–2018 to be the same as in Population Census 2000.

to match changes in output over time. The amount of new firms $\{N_{u,j,t}\}_{u\in\{\tilde{C},F\}}$ is disciplined by changes in the number of firms. I focus on Chinese manufacturing industries' innovation and set other industries' R&D expenses as given by the data. For each China's manufacturing industry, fixed and variable costs of innovation $\{\phi_{1,j},\phi_{2,j}\}$ are informed by the share of R&D firms and the R&D intensity in 2005. I assume aggregate research productivity to be region-specific with a common time trend $A_{u,r,t} = \bar{A}_{u,r}a_t$. $\bar{A}_{u,r}$ is informed by the share of R&D firms by province in 2005, and the trend a_t matches aggregate manufacturing R&D intensity in 2000–2018.

In the alternative scenario with free entry of firms, directly applying equation (1.10) faces two challenges quantitatively. First, China has experienced very fast growth in the number of manufacturing firms, which indicates unrealistically large entry costs. Second, as shown by Kucheryavyy et al. (2017), industry-level free entry of new firms may lead to corner solutions. Appendix Section A.5.4 discusses how I modify equation (1.10) to deal with these two challenges and compute entry costs $\{f^e_{u,j,t}\}_{u\in\{\tilde{C},F\}}$ that generate the same amount of entrants as $\{N_{u,j,t}\}_{u\in\{\tilde{C},F\}}$.

1.6.4 Model Fit

Figure 1.5 shows that my model can replicate the pattern of China's innovation surge and export skill upgrading in the data. Panel (a) presents the time-series pattern of manufacturing R&D intensity. As I targeted the overall trend of manufacturing R&D intensity using changes in aggregate research productivity, my model can replicate the data well. Panel (b) reports the time-series pattern of the share of sales in high skill-intensity industries[45] for domestic sales and ordinary exports. Even though I did not directly target domestic sales and ordinary exports, my model predicts the similar skill upgrading pattern as in the actual data. In particular, relative to domestic sales, China's ordinary exports experienced massive skill upgrading after the college

[45] As my model is calibrated to 2-digit manufacturing industries, I use 2-digit industries to define high skill-intensity industries, which are industries with skill intensities above the average across all 2-digit manufacturing industries. Industry-level skill intensities are still computed from ASM 2004.

expansion. Appendix Figure A.5 shows that my model can also replicate changes in the share of processing exports.

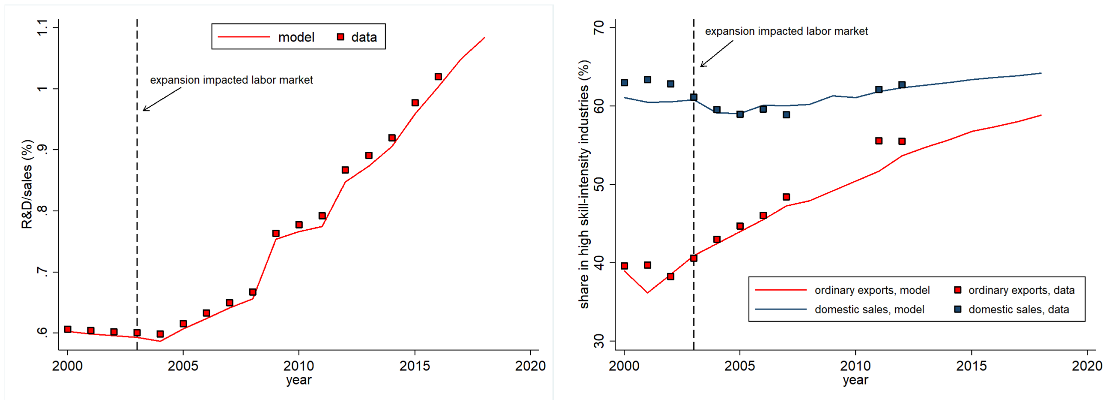
Figure 1.6 presents the untargeted distribution of exporting and R&D activities among manufacturing firms in 2005. Panel (a) shows that my model can replicate the shares of R&D firms and exporters across firm size percentiles. Panel (b) presents the share of R&D firms among nonexporters and exporters by different firm size percentiles, measuring the interaction between exports and innovation. My model can reconcile with observed differences in R&D activities between exporters and nonexporters pretty well.

Figure 1.7 shows that my model can match observed changes in employment by provinces and education levels between 2000–2010. In Appendix A.6, I also estimate college wage premiums for different age groups following Card & Lemieux (2001). In the 2000s, the model and the data both predict a decline of the college premium for young workers, and an increase of college premium for old workers. In the model, the former pattern is due to a large inflow of young college grads due to the college expansion, and the latter pattern is driven by the fast growth of manufacturing firms' sales.

Finally, Appendix Table A.1 compares the model-generated and observed responses of province-industry-level exports, domestic sales, and R&D activities to the college expansion between 2005–2010, using regression (1.17) and the instruments constructed in Section 1.5. I find that the model-generated responses are quite close to observed responses.

1.7 The Quantitative Impact of China's College Expansion on Innovation and Exports

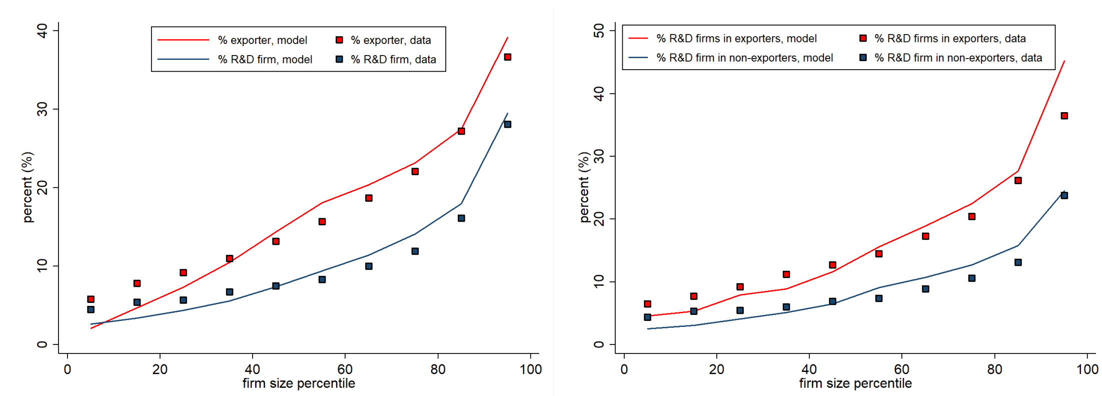
In this section, I quantify how the college expansion contributed to China's innovation surge and export skill upgrading. I also study the role of trade openness in helping China accommodate this policy shock and analyze the costs and benefits of this policy change.



(a) R&D sales/sales

(b) Export Skill Upgrading

Figure 1.5: Innovation and Skill Upgrading, in Model and Data



(a) Share of R&D Firms and Exporters

(b) Innovative Activities by Export Status

Figure 1.6: Exporting and R&D Activities by Firm Size, in Model and Data

Note: Firm size percentiles are computed based on rankings of firm sales within each province-industry pair.

To quantify the impact of China's college expansion, I simulate the scenario of "no college expansion" ("no CE"). Instead of using observed college enrollments in Figure 1.1, I set the number of newly admitted students to grow at 3.8% annually after 1999 (previous policy goal) and accordingly change the flow of college grads after 2003. Relative to the baseline economy, the number of college-educated workers would be 62 million lower in 2018 (8% of employment) in counterfactual exercises. I maintain the employment growth in the data, and thus new high-school grads would replace the "missing" college-educated grads.[46] In all years, I treat the final good in

[46] To isolate the effects of the expansion of regular college education, I keep each year's enrollments in part-time colleges unchanged in all simulations. This restriction will be discussed in Section 1.7.5.

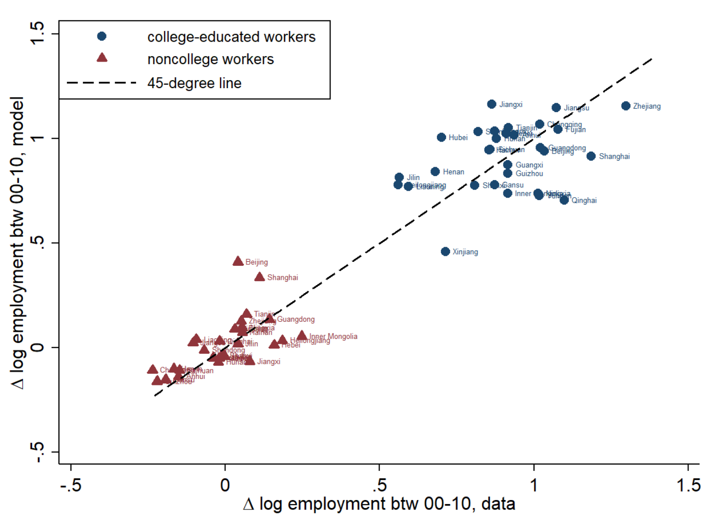


Figure 1.7: Changes in Employment between 2000–2010, in Data and Model

Note: The data on employment by education levels and provinces are from Population Census 2000 and 2010.

China as the numeraire,[47] and trade is balanced for each Chinese province and Foreign.

1.7.1 Innovation Surge

Figure 1.8a presents the impact of the college expansion on China's manufacturing innovation. When the number of new firms is fixed, the college expansion accounted for $\frac{0.33 \text{ p.p.}}{0.48 \text{ p.p.}} = 69\%$ of increases in manufacturing R&D intensity between 2003–2018. Figure 1.8b further reports the contributions of the college expansion to manufacturing output growth through changes in innovation and composition of college-educated/noncollege labor. I isolate the effects of innovation by simulating the calibrated equilibrium using firms' research intensity from the scenario of "no CE."[48] Similarly, I isolate the effects of labor composition by recomputing the calibrated equilibrium with the same firm distributions but new labor composition from the scenario of "no CE." Figure 1.8b shows that through combined effects of innovation and labor

[47] I normalize the GDP-weighted average price of final goods across Chinese regions to be 1. I also experimented with foreign GDP as the numeraire except for autarky, and the results are similar.

[48] I use research intensity i (specific to firms of different productivity levels, research efficiency, and demand shifters) from the scenario of "no CE" to recompute productivity evolution in equation (1.6) in the calibrated equilibrium. I keep all other components of productivity evolution as unchanged.

composition, China's college expansion accounted for a third of manufacturing output growth after 2015.[49]

It is worth noting the differential effects of China's college expansion through labor composition and innovation. Although the college expansion still produces positive effects on manufacturing output through increases in the proportion of high-skill workers, the rapid accumulation of college-educated workers faces declining marginal returns, and thus the positive effects will be reversed. In fact, marginal products of new college grads were already 5% lower than high-school grads of the same age in 2018.[50] On the other hand, the increasing stock of college-educated workers raises R&D intensity, speeding up annual productivity growth persistently. Figure 1.8b shows that higher innovation due to the college expansion accounted for 8% of manufacturing output growth in 2018, and the contribution of the college expansion through innovation will become more considerable with China's rapid increases in innovation levels (Wei et al. 2017).

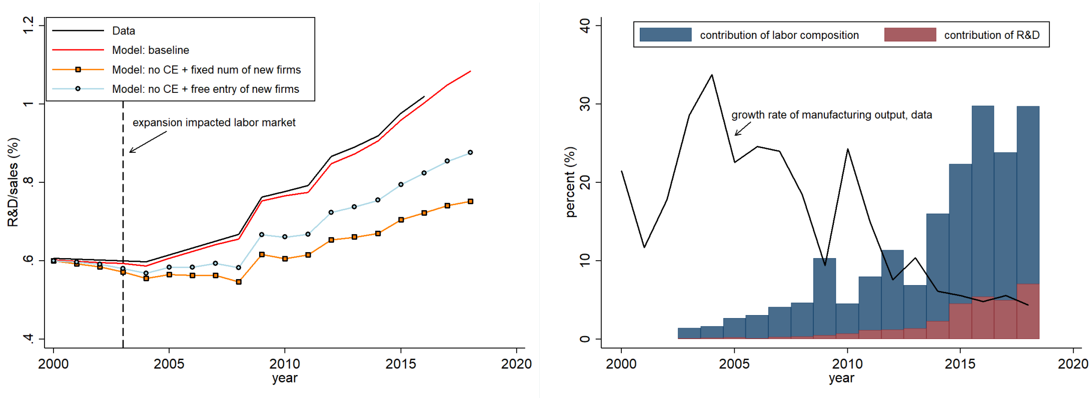
Figure 1.8a also reports the results when the number of new firms is endogenous for China's manufacturing industries.[51] Allowing for free entry of firms reduced the contribution of the college expansion to manufacturing innovation to $\frac{0.21\text{ p.p.}}{0.48\text{ p.p.}} = 43\%$ between 2003–2018. This was because with reduced R&D costs, the college expansion also produced more firm entry especially in highly skill-intensive industries, thus discouraging innovation due to reduced revenues (innovation returns) per firm.[52]

[49]Figure 1.8b shows that China's growth rate of manufacturing output was very high in the 2000s, mainly due to policy reforms, including the development of private enterprises (Song et al. 2011), loosening of migration barriers (Tombe & Zhu 2019), and embrace of globalization (Feenstra & Wei 2010). Favorable demographic transitions have also contributed to China's' growth (Wei et al. 2017).

[50]The college expansion still produced positive effects on manufacturing output growth in 2018, as the effects of this large-scale policy shock are inframarginal.

[51]I keep the number of new firms as constant in other industries and Foreign.

[52]By equation (1.14), if a firm performs R&D, its optimal R&D expenses are a convex function of innovation returns. Thus, reduced innovation returns per firm would decrease aggregate R&D.



(a) Manu R&D/sales

(b) Decomposition of Effects

Figure 1.8: Effects of China's College Expansion on Manufacturing Innovation

Note: The data on manufacturing output growth come from China's Statistical Yearbooks and are adjusted for CPI. Because there are changes in statistical methods after 2015 due to tax reforms, I use growth of manufacturing value added as a proxy for growth of manufacturing output.

1.7.2 Export Skill Upgrading

Figure 1.9 reports the impact of China's college expansion on skill upgrading of ordinary exports. With the college expansion, the share of ordinary exports in high skill-intensity industries increased by 18 percentage points, from 40.9% in 2003 to 58.9% in 2018. If the number of new firms is fixed, this increase dropped to 12.1 percentage points in the absence of the college expansion; therefore, the contribution of the college expansion to skill upgrading of ordinary exports was $\frac{18-12.1}{18} = 33\%$. Allowing for free entry of manufacturing firms further increased the contribution to $\frac{18-8}{18} = 56\%$, because more firm entry in highly skill-intensive industries reinforced China's export skill upgrading.

Appendix Figure A.6 shows that China's college expansion explained 12–27% of the decline in the share of processing exports between 2003–2018. Despite low skills of processing exports, more than half of China's processing exports are in industry "Computer, Electronic and Optical Equipment,"[53] whose processing exporters have higher skill intensities than ordinary firms in a third of manufacturing industries. Therefore, after China's college expansion, reallocation

[53] Appendix Section A.2.2 shows that processing exports are less skill-intensive than ordinary exports in the same industry. The share of processing exports in industry "Computer, Electronic and Optical Equipment" was 53% in 2003 and increased to 60% in 2011.

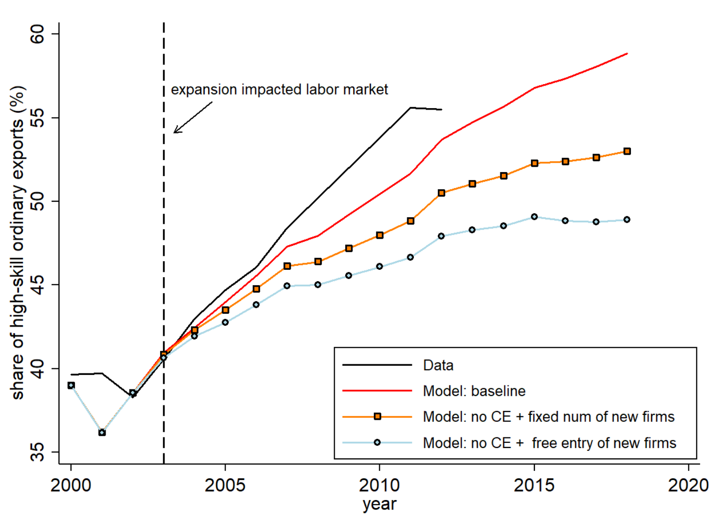


Figure 1.9: Effects of the College Expansion on the Share of High-skill Ordinary Exports

effects from low to high skill-intensity industries within ordinary exports were stronger than from processing to ordinary exports.

1.7.3 Amplification Effects of Trade Openness

To explore the effects of trade openness, I simulate the impact of the college expansion in autarky with trade costs between China and Foreign going to infinity. In the autarkic economy with the college expansion, I recalibrate time trends of aggregate research productivity such that manufacturing R&D intensity in each year is identical to the baseline calibration (Figure 1.5a).[54] I keep all other parameters at their baseline levels.

Table 1.3 presents the impact of China's college expansion on production, innovation, and labor income in 2018, under different assumptions about firm entry and with and without trade openness. I highlight two main findings. First, when the number of new firms is fixed, the college expansion increased China's GDP and manufacturing output in 2018 by 10.30% and 11.79% respectively. In contrast, when the number of new firms is endogenous, these two increases

[54] As I focus on level changes in manufacturing R&D intensity, I need levels of manufacturing R&D intensity in each year to be identical in the calibrated equilibrium with and without trade openness.

Table 1.3: Effects of the College Expansion on Output, R&D, and Labor Income in 2018

	Output and Innovation			Labor Income	
	GDP	manu output	manu R&D/sales	avg wage	log(col premium)
	Panel A: Exogenous Number of New Firms				
Baseline	10.30%	11.79%	0.33 p.p.	9.90%	-0.57
Autarky	9.65%	10.81%	0.28 p.p.	9.31%	-0.59
Amplification effect of trade (% from autarky to baseline)	6.8%	9.1%	17.9%	6.4%	-3.4%
	Panel B: Free Entry of New Firms				
Baseline	18.40%	24.37%	0.21 p.p.	17.50%	-0.55
Autarky	17.27%	22.10%	0.17 p.p.	16.60%	-0.58
Amplification effect of trade (% from autarky to baseline)	6.6%	10.3%	23.5%	5.5%	-5.2%

Note: Panel A–B impose different assumptions about firm entry for China's manufacturing industries. The college premium is the average wage of college-educated workers relative to the average wage of high-school grads.

were 18.40% and 24.37% respectively. The larger effects under endogenous entry of new firms were driven by more firm entry especially in highly skill-intensive industries, as shown in Figure 1.10. More notably, Figure 1.10 also shows that free entry of firms appears to be a reasonable assumption, as model-generated changes in the number of firms due to the college expansion varied across industries of different skill intensities in a similar way as in the actual data.[55]

Second, trade amplified the effects of the college expansion on GDP, output and innovation. The amplification effects of trade openness on GDP and manufacturing output in 2018 were 5–10%, as trade shifted industry composition and reduced the diminishing returns of additional college-educated workers. Thus, trade openness also tamed the negative impact of the college expansion on the college premium by 3–6%. The amplification effects of trade on innovation were much larger (15–25%), as exporters were intensively engaged in innovative activities. Moreover, Figure 1.11 shows that the college expansion always increased R&D intensities in more skill-intensive industries, especially among exporters, confirming the interaction between exports and

[55]When the number of new firms is fixed, changes in the number of firms due to the college expansion still had a positive yet much smaller slope with regard to skill intensities than the actual data. The positive slope was because the college expansion reduced firm exits in more skill-intensive industries.

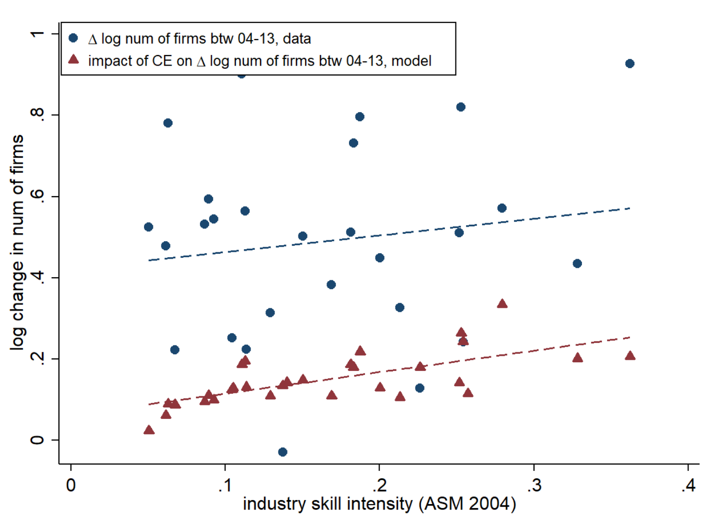


Figure 1.10: Changes in the Number of Firms, in Data and Model with Free Entry

Note: This graph shows changes in the number of firms in the data and the impact of the college expansion on the number of firms in the model (under the assumption of endogenous entry), between 2004–2013 and across 2-digit manufacturing industries. The data are from Assembly of Firm Census 2004 and 2013. Because of a change in China's industry classifications between 2004–2013, I use the 3-digit industry with one-to-one correspondence between industry classifications in two years to construct changes in the number of firms in the data.

innovation found in Figure 1.4.

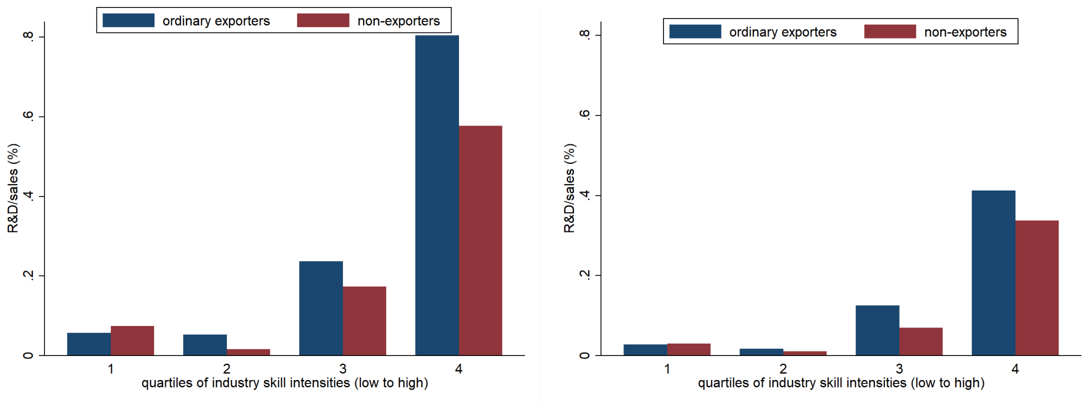
1.7.4 Costs and Benefits of China's College Expansion

China's college expansion does not come at no costs. First, the expansion of college education leads to higher education expenses, which could otherwise be used as consumption or other types of investments.[56] Moreover, new college grads could have entered the labor market earlier if they had not attended colleges. Hence, the college expansion incurs implicit costs—production losses of additional enrollments—which are not accounted for in my counterfactual exercises that maintain the employment growth in the data.

In each year, I compute increases in education expenses by multiplying additional enrollments[57] with average education expenses (including tuition and government subsidies) per

[56] Although my model does not directly model education expenses, college-educated workers' consumption can be thought of partially being spent on education.

[57] I assume that it takes 4 years for newly admitted students to graduate, and therefore additional enrollments include all increases in the number of newly admitted students within the last 4 years.



(a) Fixed Num of New Firms (b) Free Entry of New Firms

Figure 1.11: Effects of China's College Expansion on Firms' R&D Intensities in 2018

Note: This graph shows the impact of the college expansion on R&D intensities. I divide industries into quartiles based on their skill intensities. I compute R&D intensities separately for exporters and nonexporters in each quartile. The impact of the college expansion is the difference of R&D intensities in the observed equilibrium and in the counterfactual exercise without the college expansion.

college enrollment from China's Education Statistical Yearbook. I compute implicit costs by multiplying additional enrollments with average marginal products of high-school grads (aged less than 23) in the baseline equilibrium.

Figure 1.12 plots the results. The additional education expenses of China's college expansion represented roughly 1% of GDP in the 2010s, which were relatively small compared with the loss of production (2–3% of GDP in the 2010s). Figure 1.12 also finds that the increase in yearly GDP driven by the college expansion started to exceed education and implicit costs of the college expansion in 2006–2009, with exact years depending on the model's assumption about firm entry.

1.7.5 Robustness Checks of Quantitative Analysis

I discuss several robustness checks of my quantitative analysis. In these checks, I recalibrate time trends of aggregate research productivity such that manufacturing R&D intensity in each year is identical to the baseline calibration (Figure 1.5a). I keep all other parameters at their

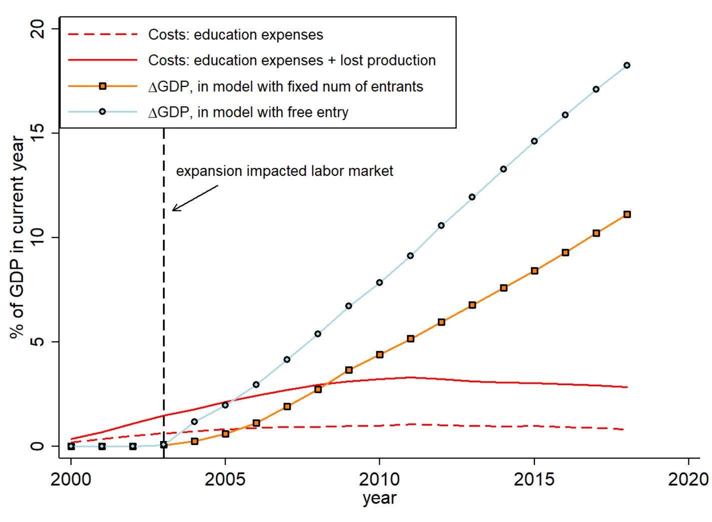


Figure 1.12: Costs and Benefits of China's College Expansion

baseline levels unless otherwise specified.[58]

Incorporating R&D Misreporting. Chinese firms often reclassify non-R&D costs as R&D to obtain tax subsidies (e.g., Chen et al. 2018, König et al. 2018). The college expansion may ease firms to categorize wage bills of non-R&D college-educated workers as R&D.

I first provide empirical evidence, adopting the approach in Chen et al. (2018) who show that firms manipulate non-R&D administrative costs and find a discontinuous drop in firms' non-R&D admin costs around the threshold of R&D incentives. I explore whether the drop varies across industries of different skill intensities by estimating a regression:

$$\begin{aligned} y(\omega) =& \beta_0 + \beta_1 D + \beta_2 SI_j D + [\beta_3 + \beta_4 D](Z(\omega) - c) + [\beta_5 + \beta_6 D](Z(\omega) - c)^2 \\ &+ [\beta_7 + \beta_8 D](Z(\omega) - c)^3 + \beta_9 SI_j + \varepsilon(\omega) \end{aligned} \tag{1.18}$$

$y(\omega)$ is the ratio of non-R&D admin expenses to R&D expenses required to attain the tax incentive (see footnote 42). The dummy variable D equals 1 if the firm satisfies the threshold of R&D. The parameter β_1 captures the drop in non-R&D admin expenses at the threshold, and the parameter

[58]The baseline economy in robustness checks still matches the export skill upgrading in Figure 1.5b well.

Table 1.4: Misreporting of R&D across Industries, 2009–2011

	Data		Model
	(1)	(2)	(3)
R&D threshold	-0.275***	-0.187**	-0.189***
	(0.058)	(0.086)	(0.003)
R&D threshold × industry skill intensity		-0.405*	-0.405***
		(0.217)	(0.020)
Obs	22,608	22,608	30
R-squared	0.028	0.028	0.946
Avg % R&D misreported (firms at the threshold)	27.5%	27.5%	27.6%

Note: Columns (1)–(2) present the results from regression (1.18). I restrict the sample to firms within 2 percentage points of the required R&D threshold following Chen et al. (2018). Columns (3) uses the model-generated data and regresses industry-level reclassification rates of non-R&D costs between 2009–2011 on skill intensities. Average R&D misreporting rates are computed for firms at the threshold. Standard errors are clustered by industry. Significance levels: * 10%, ** 5%, *** 1%.

β_2 shows how the drop relies on the firm's affiliated-industry skill intensity. I control a cubic function of differences between firms' R&D intensities $Z(\omega)$ and the threshold c, as well as industry-level skill intensities SI_j to allow non-R&D expenses to differ across industries. I use SAT 2009–2011 for estimation and still measure skill intensity SI_j from ASM 2004. I focus on 2-digit manufacturing industries.

Column (1) of Table 1.4 shows that firms at the threshold on average misreported 27.5% of the required R&D expenses from non-R&D admin costs.[59] Column (2) of Table 1.4 finds that the drop in non-R&D admin costs at the threshold increased with industry-level skill intensities. To test the robustness of my model, I interpret this result as reflecting that larger wage bills to college-educated workers can facilitate R&D misreporting.

In the model, I assume that Chinese firms can reclassify non-R&D costs as up to a portion $(k_1 + k_2 SI_{u,j,t})$ of required R&D expenses to attain the tax incentive, where $SI_{u,j,t}$ is the share of payments to college-educated labor in total labor bills for province-regime $u \in \tilde{\mathcal{C}}$ and industry j.

[59] My estimate is close to the findings in Chen et al. (2018) who find that in 2008–2011, the misreporting percentage was 23.3% for large sales firms, 32.9% for medium sales firms, and 26.9% for small sales firms.

Figure 1.13: Effects of the College Expansion on Manufacturing R&D (with Misreporting)

I also assume that firms above the threshold do not misreport R&D, because misreporting in this case brings no benefits but risks of being caught.

I calibrate k_1 and k_2 in three steps. First, I simulate the baseline equilibrium with a set of k_1 and k_2. Second, for firms at the threshold in industry j, I compute reclassification rates of non-R&D costs, using the difference between actual and reported R&D as a share of required R&D expenses to attain the tax incentive. Finally, I regress industry-level reclassification rates between 2009–2011 on a constant and same industry-level skill intensities as in Column (2) of Table 1.4. I iterate with these steps until the intercept and the slope from the regression match the coefficients in Column (2) of Table 1.4. I find that with $k_1 = 0.17$ and $k_2 = 0.42$, the model-generated data match the pattern of reclassification of non-R&D costs across industries, as shown in Column (3) of Table 1.4.

Figure 1.13 presents the impact of China's college expansion on R&D, in the model with R&D misreporting and a fixed number of new firms. I highlight three findings. First, China's R&D expenses were not as extraordinary as in the data, as only 77% of reported manufacturing R&D was actually spent in 2018. Second, the college expansion still accounted for $\frac{0.27 \text{ p.p.}}{0.48 \text{ p.p.}} = 56\%$ of increases in China's manufacturing reported R&D/sales between 2003–2018. Third, the

Table 1.5: The Impact of the College Expansion on Export Skills and Innovation, 2003–2018

	Δ% high-skill ordinary exports		Δmanu R&D intensity	
Assumption of new firms	fixed num	free entry	fixed num	free entry
(1) Baseline model	33%	56%	69%	43%
(2) With R&D misreporting	29%	51%	56%	35%
(3) With expansion of part-time edu	34%	60%	70%	41%
(4) Without intranational regions	37%	65%	75%	49%
(5) Changes in migration costs	35%	59%	72%	46%

Note: The contributions are computed in the same way as in Section 1.7. For the model with R&D misreporting, R&D intensity is the ratio of reported R&D to sales.

college expansion also induced more R&D misreporting. Only 81% of the increase in China's manufacturing reported R&D intensity between 2003–2018 was driven by actual increases.[60]

Incorporating Expansion of Part-time College Education. The number of grads from part-time colleges also experienced a threefold expansion after 1999 (see Appendix A.2), whereas my earlier analysis did not account for this expansion. Now, in the counterfactual exercise of "no CE," I consider new student enrollments in part-time education to grow at the same annualized rate of 3.8% as enrollments in regular education after 1999. Because enrollments in part-time education were relatively small, Table 1.5 shows that considering the expansion of part-time college education only slightly changed the impact of the college expansion on export skill upgrading and innovation between 2003–2018.[61]

Abstracting from China's Intranational Regions. I considered multiple Chinese regions with trade and migration networks, as I used cross-regional variation to discipline structural

[60]With the college expansion, reported and actual R&D intensities grew by 0.48 and 0.42 percentage points between 2003–2018, respectively. Without the college expansion, these two intensities grew by 0.21 and 0.20 percentage points between 2003–2018, respectively. Therefore, only $\frac{0.42-0.2}{0.48-0.21} = 81\%$ of the increase came from actual costs. As a result, the yearly contribution of China's college expansion to manufacturing output growth through innovation dropped by 36% between 2003–2018, compared to the model without R&D misreporting (Figure 1.8b).

[61]Considering expansion of part-time college education further reduced the college premium, thus reinforcing export skill upgrading. However, it also generated negative income effects, as additional part-time grads were already much less productive than noncollege workers of the same age in later years. Thus, the impact of the college expansion on innovation remained quite similar to the baseline results.

parameters. To show that incorporating multiple regions within China is necessary, I recalibrate the model following the same steps in Section 1.6, except for no intranational regions within China.[62] Table 1.5 finds that abstracting from China's intranational regions increased the overall impact of the college expansion on innovation and export skill upgrading. This indicates that the geographic distribution of new college grads was unfavorable for aggregate productivity, confirming the mismatch between college enrollments and regional development levels discussed in Section 1.1.

Reductions in Migration Costs. I calibrated the destination-specific term in migration costs to match the share of in-migrants across provinces in 2000 and remain constant over time. Tombe & Zhu (2019) find reductions in China's internal migration costs driven by the Hukou reform after 2000. Thus, I now assume that after 2000, the destination-specific term has experienced proportional changes annually. For each destination province, I calibrate annual changes of migration costs in the 2000–2005, 2006–2010, and 2011–2015 period to match changes in the share of in-migrant population in the same period.[63] I set migration costs to remain unchanged after 2015.

I find that the average reduction in the destination-specific term of migration costs was 65% between 2000–2015 (weighted by migrant population), consistent with Hao et al. (2020) who also find a substantial reduction in between-province migration costs in the same period.[64] Table 1.5 shows that reductions in migration costs amplified the impact of the college expansion on innovation and export skills, as new college grads could more easily relocate toward more productive regions.

[62]I still use the between-industry and within-industry elasticities of substitution estimated from IV regressions using province-level variation.

[63]I compute the share of in-migrant population based on people's current province and province of residence 5 years ago, obtained from Population Censuses 2000, 2005, 2010, and 2015. Due to data limits, I consider changes in migration costs to be identical for both college-educated and noncollege workers at each destination province.

[64]Hao et al. (2020) find the average reduction in between-province migration costs to be 60% in 2000–2015. However, my results are not directly comparable to Hao et al. (2020) who employ a static Roy-Frechét model and have different parametric assumptions about migration costs from mine.

1.8 Conclusion

This paper studies how China's massive expansion of college education affects exports and innovation. I develop a multi-industry general equilibrium model, featuring skill intensity differences across industries and heterogeneous firms' exporting and innovation choices. I empirically validate my model mechanisms about exports and innovation, using regional distribution of historic college endowments to disentangle labor supply from demand shocks. I apply the resulting reduced-form estimates to discipline the key structural parameters that determine export expansion strength. The calibrated model shows that the college expansion could explain a large portion of China's innovation surge and export skill upgrading between 2003–2018. I also find that trade openness amplified the impact of this policy shock on production and innovation.

This paper shows that the college expansion contributed to China's innovation through increases in the supply of college-educated workers and the interaction between trade and innovation. Arguably, the expansion of college education could benefit innovation through other channels, such as increases in the number of entrepreneurs or faculty's research output. A fruitful area for future study is whether these other channels are present in the data and quantitatively important.

1.9 Acknowledgements

Chapter 1 is currently being prepared for submission for publication. It is sole authored by the dissertation author.

Chapter 2

China's Export Surge and the New Margins of Trade

From 1980 to 2005, the share of global trade of "Made in China" goods grew from 0.8% to 13%. While a large number of literature has examined the consequences of China's export surge (see Autor et al. 2016), fewer papers have focused on the sources causing China's export surge. In this paper, we quantify the relative contributions of several factors to China's export surge.

We build a multi-sector spatial general equilibrium model featuring heterogeneous firms' and workers' location choices. We account for Chinas export surge between 1990 and 2005 in light of three policy changes: changes in Chinas import tariffs, changes in tariffs imposed against Chinas exports, and changes in barriers to internal migration in China. Theoretically, we decompose the aggregate trade elasticity into four margins of firm adjustments and show that each margin has an analytic expression. Two adjustments are the standard *intensive* and *extensive margins* of trade (Chaney 2008). The other two are the location switching of firms, referenced as the *new-firm margin*, and the choice of firms between processing and ordinary export regimes, referenced as the *export-regime margin*.[1] Empirically, we find support for the *new-firm* and *export-regime margins* by using provincial and sectoral variation on the changes in the number of firms in response to the changes in the scale of migrant employment and the changes in import tariffs respectively. Finally, we use our empirical estimates to discipline our model parameters and evaluate the importance of each margin in accounting for China's export surge.

Our model has three main components. First, each firm draws a vector of correlated productivities across foreign countries, Chinese provinces, and export regimes (processing or ordinary). The second component is the inter-sectoral input-output linkages (Caliendo & Parro 2015). The third component is that Chinese workers with heterogeneous location preferences and migration costs sort into provinces and sectors. In this setting, a policy shock generates four types of firm adjustments. For instance, a reduction in China's import tariffs lowers the costs of

[1] Export processing is the process where firms import raw materials or intermediate inputs from abroad and export the final goods after some processing (Feenstra & Hanson 2005). Processing firms are not allowed to sell output domestically.

intermediate inputs and attracts more firms to locate in China (the *new-firm margin*). Further, ordinary export production is subject to nominal import tariffs, whereas imported intermediate materials are duty-free for processing export production. Import tariff reductions thus induce switching from processing to ordinary regime (the *export-regime margin*). Moreover, the reduced costs of intermediate inputs incentivize existing exporters to export more (the *intensive margin*) and lead to some previously non-exporting firms to begin exporting (the *extensive margin*).

We derive analytic results that decompose the aggregate trade elasticity into four margins. The *intensive margin* and the *extensive margin* replicate the exact formula in Chaney (2008). We show that the *new-firm margin* is determined by the correlation of firms' productivity draws across locations, and the *export-regime margin* depends on the correlation of firms' productivity draws between processing and ordinary regimes. This analytic result is important, as it guides our empirical strategy to discipline the parameter values for the *new-firm* and *export-regime margins*. It also guides our parameter restrictions for our quantitative exercises to decompose the export impact into four margins of firm adjustments.

We assemble a dataset from various Chinese sources to show that the *new-firm* and *export-regime margins* are prominent in the time period of this study. First, we validate the *new-firm margin* by showing that between 1990 and 2005, the rise in migrant employment strongly increased the number of firms across provinces and sectors. To address the endogeneity issues, we construct a Card-type instrument for changes in migrant employment in each province and sector by exploiting historical patterns of location and sector sorting for workers from different provinces of origin. Second, to validate the *export-regime margin*, we use provincial import penetration and sectoral input-output linkages to construct changes in production costs resulting from import tariff reductions (WTO). We instrument potentially endogenous tariff changes with maximum tariff levels under the WTO agreement, extending the strategy developed in Brandt et al. (2017). We explore cross-sectoral variation to find that decreases in import tariffs led to a rise in the relative number of ordinary firms to processing firms.[2]

We rely on the reduced-form estimates to discipline the two key model parameters that govern the *new-firm* and *export-regime margins* using an indirect inference approach. Specifically, we choose the correlation of productivity draws across locations to target our reduced-form estimate on the extent to which the number of firms responded to migration shocks. We choose the correlation of productivity draws between ordinary and processing regimes to target our reduced-form estimate on the response of the relative number of ordinary to processing firms to import tariff changes.

We combine detailed transaction-level customs data, firm-level data, international and intranational trade data, and micro-level population census data to account for China's export surge due to the three policy changes mentioned above. Our quantitative model includes 29 sectors, 2 export regimes (processing and ordinary), 30 Chinese provinces, and 36 foreign countries. We measure changes in tariffs on China's imports, tariffs on China's exports, and internal migration barriers. After that, we perform two sets of counterfactual exercises. In the first set of exercises, we introduce each shock to our model, one at a time. With these exercises, we quantify the extent to which each shock promoted Chinas aggregate export growth between 1990 and 2005. In the second set of exercises, we re-introduce each shock to our model under parameter restrictions based on the analytic decomposition. With these exercises, we decompose the export growth resulting from each shock into four margins of firm adjustments.

We find that the three policies combined accounted for 29% of China's export growth between 1990 and 2005. More notably, the *new-firm margin* was important in explaining China's export surge: if we held the number of firms constant, the portion of China's export surge explained by the three shocks combined would drop to 16%. This difference suggests that the emergence of new firms resulting from (trade and migration) barrier reductions explained 13% of

[2]This channel was first studied in Brandt & Morrow (2017) who focused on how the value share of exports organized through ordinary trade responded to tariff changes. In contrast, in order to discipline our model parameter on firm adjustments of export regimes, we use the relative number between ordinary and processing exporters as the dependent variable.

China's export surge. Individually, reductions in Chinas import tariffs explained 13%, whereas changes in foreign tariffs on China's exports and reductions in internal migration barriers each accounted for around 8% respectively. We also find that each shock had differential impacts on processing and ordinary exports: import tariff reductions operated primarily by boosting ordinary exports, whereas the reductions in migration barriers and in foreign tariffs on China's exports both favored processing exports.

Our paper relates to the quantitative trade and spatial equilibrium literature that studies the impact of goods and labor market integration (e.g., Allen & Arkolakis 2014, Redding & Rossi-Hansberg 2017, among others). On the topic of Chinas internal migration and trade, Tombe & Zhu (2019) analyze its impact on aggregate productivity, and Fan (2019) studies its distributional impact.[3] Both papers adopt multi-sector Eaton-Kortum (EK) models where the scale of the economy does not change with migration or trade shocks. We model firm location choices to allow for the number of firms to respond endogenously to economic shocks. Relative to these two papers, the endogenous number of firms in our model amplifies the impact of trade and migration barrier reductions on China's aggregate economic outcomes. We build upon Arkolakis et al. (2018) (ARRY hereafter) to model firm location choices, instead of firm entry. This is because the model with firm location choices allows arbitrary non-negative values on the elasticity of firm switching with respect to the size of local population, and we discipline the elasticity using reduced-form estimates.[4] We also incorporate firm sorting into ordinary and processing regimes to distinguish the differential tariff treatments between the two regimes (Branstetter & Lardy 2006). In this aspect, our paper relates to Brandt et al. (2018), who build an EK model with ordinary and processing regimes to quantify the welfare losses of restricting processing output

[3]Also see Ma & Tang (2020) and Zi (2020).

[4]We do not choose a model with firm entry as our benchmark approach as it imposes strong restrictions on the relationship between the number of firms and population size. As shown in Arkolakis et al. (2012), among the broad class of trade models, the free-entry condition implies the number of firms responds one-to-one to local population. In Appendix B.5, we also use an alternative model with firm entry as a robustness check. As we extend the ARRY model to a nested-CES demand system, our paper relates to the quantitative trade literature with non-CES demand systems (Adao et al. 2017, Lind & Ramondo 2018).

from selling domestically. The main difference of our approach is that we decompose export growth into multiple margins of adjustments.

Recent papers find that the decline of trade barriers and China's WTO accession had a significant contribution to China's productivity growth (Yu 2015, Brandt et al. 2017). One important source behind the rapid productivity growth is the massive number of new firms (Brandt et al. 2012). Khandelwal et al. (2013) find that the elimination of export quota boosted export growth, which was mainly due to the entry of new firms. These previous papers primarily use reduced-form approach. With a general equilibrium setting, we complement the literature by quantifying the role of new firms induced by trade barrier reductions in explaining the export growth. A recent working paper by Brandt & Lim (2019) also accounts for China's export growth. Our approach differs from theirs in two main aspects. First, they focus on changes in productivity, demand, and labor and firm-entry costs between 2000 and 2013, whereas we study migration and tariff barrier changes. Second, they calibrate their model to analyze evolution of China's export growth. We focus on Chinas export growth between 1990 and 2005 and use empirical estimates to discipline the degree of firm adjustments to barrier reductions.[5]

This paper proceeds as follows: Section 2.1 presents facts to motivate our analysis; Section 2.2 presents our model; and Section 2.3 decomposes the aggregate trade elasticity into multiple margins. Section 2.4 validates the *new-firm* and *export-regime margins*. Section 2.5 discusses our data sources and measures policy shocks. Section 2.6 presents the quantitative results, and Section 2.7 concludes.

2.1 Motivating Facts

We describe the magnitude of the tariff changes we analyze. We also present facts to motivate the importance of internal migration in manufacturing employment and the importance

[5] We choose the time window between 1990 and 2005 because of data availability.

of the growing number of firms and their potential contribution to China's export growth.

There has been a dramatic decline in the world's Most-Favored-Nation (MFN) tariffs since the Uruguay Round in 1991 (Caliendo, Feenstra, Romalis & Taylor 2015). As China joined the WTO and gained the Most-Favored-Nation (MFN) status in foreign countries, the data show a decline in tariffs levied by foreign countries on Chinas exports between 1990 and 2005 (see Appendix Figure B.3).[6] The decline in China's import tariffs was even more prominent, which on average declined from over 40% to less than 10%. Substantial heterogeneity emerged in import tariff reductions across sectors (see Appendix Figure B.4). China's import tariff reductions were only applied to ordinary producers, whereas processing firms had enjoyed duty-free imported intermediate materials since 1987. Therefore, we distinguish Chinese firms by processing and ordinary export regimes in the model.

2.1.1 Migrants' Employment and Manufacturing Exports

We define migrants as individuals whose *Hukou* is not registered in the province where they are currently working. We measure migrants' employment shares using micro-level data from the 2005 Population Census. The left-hand panel of Figure 2.1 presents cross-sectional data in 2005 on the share of inter-provincial migrants in total manufacturing employment against manufacturing export-output ratios for each province. It is evident that provinces where migrants comprised larger portions of manufacturing employment were more export-oriented and accounted for higher shares of national exports (export volumes are reflected by circle size). Two noteworthy provinces are Guangdong and Shanghai, where migrants accounted for 55.6% and 40.1% of provincial manufacturing employment.

While yearly data on the provincial level of internal migration and export growth are difficult to obtain, Appendix B.2 provides additional evidence for the timing of provincial

[6] There have also been significant declines in non-tariff trade barriers, which are not captured by the tariff data. Examples are the reduction in uncertainty as China gained permanent MFN status (Handley & Limão 2017), and the elimination of export intermediaries (Bai et al. 2017).

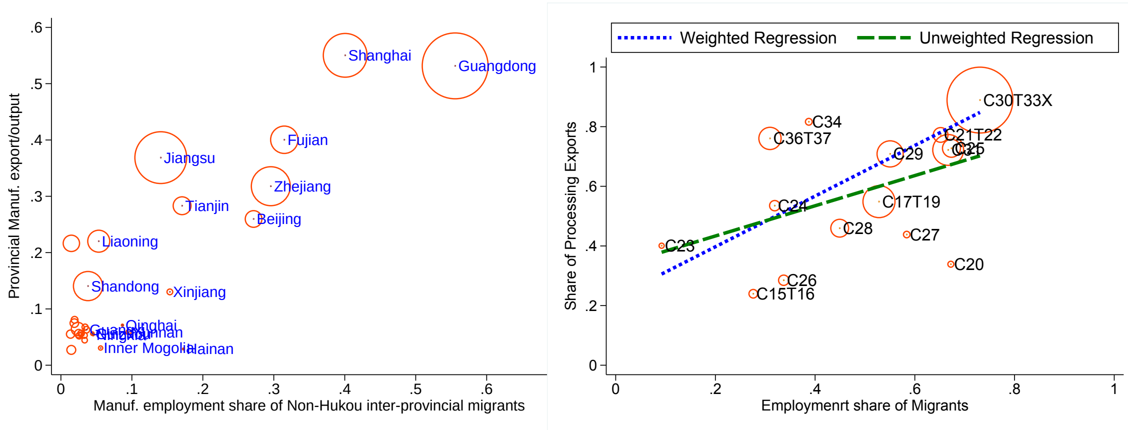


Figure 2.1: Migrants Manufacturing Employment Shares against Provincial Export-Output Ratios (left-hand); Migrants' Sectoral Employment Shares against Processing Export Shares across Manufacturing Sectors—Guangdong Province (right-hand)

Notes: The circle size of the left-hand panel measures provincial export volume. The circle size of the right-hand panel reflects provincial processing export volume in each sector. Sectors are labelled using International Standard Industrial Classification (ISIC) Revision 3 codes (see Appendix Table B.1). Fitted lines from an export-weighted regression (in blue) and an unweighted regression (in green) confirm a strong positive correlation.

migration and exports at three time points, 1990, 2000, and 2005. We find evidence that the massive migration to coastal provinces started no later than the surge in Chinese exports. The timing suggests agglomeration economies at coastal provinces arose from internal migration. We model these agglomeration forces as external economies of scale (Ethier 1982), where the provincial and sectoral TFP increases with their employment.

The right-hand panel plots migrants sectoral employment shares (x-axis) against the share of processing exports in total sectoral exports (y-axis) in Guangdong Province. Migrants employment shares were higher in processing-oriented manufacturing sectors than in sectors that were less concentrated in processing exports.

2.1.2 The Number of Firms and Manufacturing Exports

Figure 2.2 plots annual export growth against annual growth rates of the number of manufacturing firms for each province between 1990 and 2005. It shows that provinces where

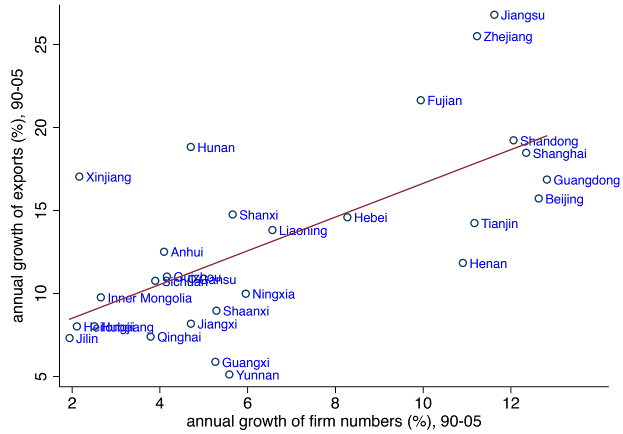


Figure 2.2: Provincial Annual Growth of Exports and the Number of Firms

Notes: The number of firms in 1990 and 2005 are obtained from the Industrial Statistical Yearbook and the Firm Census, respectively. We use the 2004 Firm Census to measure the number of firms in 2005, as it provides full coverage of manufacturing firms.

the number of manufacturing firms expanded faster also experienced stronger export growth. Although rapid increases in the number of firms are partially due to reduced barriers to firm entry, reductions in tariffs and migration barriers also lead to the emergence of new firms.[7] Therefore, reductions in tariffs or migration barriers affect aggregate exports not only through the *intensive* and *extensive margins* of trade, as in Chaney (2008), but also by attracting more firms to locate in China and driving firms to switch between processing and ordinary regimes.[8] Motivated by this, we build firm sorting across locations and across regimes into a Melitz-Chaney model.

[7]This fact is consistent with the recent finding in Khandelwal et al. (2013), where trade liberalization led to a rapid expansion in the number of Chinas manufacturing firms.

[8]Because processing and ordinary producers face differential tariff treatments, China's reductions in import tariffs affect aggregate exports by causing firms to switch between processing and ordinary regimes. Also note that migrants' sectoral employment shares differ between processing- and ordinary-oriented sectors. Therefore, reductions in migration barriers would differentially affect processing and ordinary producers and cause firms to switch between these two export regimes.

2.2 A Spatial Equilibrium Model with Firms' Location Choices

We build a multi-sector spatial general equilibrium model with heterogeneous firms' and workers' location choices. The world has a total number M_s of potential intermediate-good producers (firms) in each sector s.[9] We treat each foreign country as a single region. In China, we consider provinces as regions, and in each province we further consider processing and ordinary export regimes. Firms decide in which country to produce and whether to export; if located in China, firms also choose a combination of province and export regime.[10] In China, workers are imperfectly mobile across provinces and sectors, but are perfectly mobile between processing and ordinary firms within each province-sector pair. In foreign countries, we simply assume that workers are perfectly mobile across sectors.

We use index $l(m)$ to denote a combination of province l and export regime $m \in \{\mathcal{O}, \mathcal{P}\}$, where $\mathcal{O}$ and $\mathcal{P}$ denote ordinary and processing regimes respectively. We use j or n to index foreign countries. For ease of description, we mostly present our model based on China's provinces and export regimes. We discuss the setup for foreign countries when a distinction arises. All proofs are provided in Appendix B.1.

2.2.1 Final-good Producers

In province l and regime m, non-tradable final goods are produced using a Dixit-Stiglitz production function

$$Q_{l(m),s} = \left(\sum_j \int q_{j,l(m),s}(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega + \sum_{l'} \int q_{l'(\mathcal{O}),l(m),s}(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}},$$

[9]Idea-based growth literature (e.g., Jones 1995, Kortum 1997) typically assumes that the total number of ideas scales with population. In our model, the population is constant in the quantitative analysis, and therefore we assume that the number of potential producers is constant.

[10]We do not distinguish between export regimes in foreign countries.

where $q_{j,l(m),s}(\omega)$ is the quantity of intermediate goods ω shipped from foreign country j to $l(m)$, and $q_{l'(O),l(m),s}(\omega)$ is the quantity sourced from domestic ordinary producers in province l'. Since processing producers must sell their output overseas, the summation combines intermediate goods sourced from all foreign countries and domestic ordinary producers in all China's provinces. $\sigma > 1$ is the elasticity of substitution across varieties. The final good can be either consumed by households or used as raw materials to produce intermediate goods. The price index of the final good in $l(m)$ and sector s is

$$P_{l(m),s} = \left(\sum_j \int p_{j,l(m),s}(\omega)^{1-\sigma} \mathrm{d}\omega + \sum_{l'} \int p_{l'(O),l(m),s}(\omega)^{1-\sigma} \mathrm{d}\omega \right)^{\frac{1}{1-\sigma}}.$$

Foreign producers can source from processing and ordinary regimes of China. The production function in foreign country n and sector s is

$$Q_{n,s} = \left(\sum_j \int q_{j,n,s}(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega + \sum_{l'} \sum_{m'} \int q_{l'(m'),n,s}(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}}.$$

The price index in country n and sector s is

$$P_{n,s} = \left(\sum_j \int p_{j,n,s}(\omega)^{1-\sigma} \mathrm{d}\omega + \sum_{l'} \sum_{m'} \int p_{l'(m'),n,s}(\omega)^{1-\sigma} \mathrm{d}\omega \right)^{\frac{1}{1-\sigma}}.$$

2.2.2 Intermediate-good Producers

Production Technology

Firms with productivity $\phi_{l(m),s}$ employ $L_{l(m),s}$ efficiency units of labor and $Q_{l(m),s,k}$ units of raw materials (final goods) from sector k to produce $q_{l(m),s}$ units of output, according to the following production function

$$q_{l(m),s} = \phi_{l(m),s} L_{l(m),s}^{\lambda^L_{l(m),s}} \prod_k Q_{l(m),s,k}^{\lambda^k_{l(m),s}}, \tag{2.1}$$

where $\lambda^L_{l(m),s}$ is the share of workers' value added, and $\lambda^k_{l(m),s}$ is the share of expenses on raw materials from sector k. We assume $\lambda^L_{l(m),s} + \sum_k \lambda^k_{l(m),s} = 1$.

The implied unit cost of the input bundle is

$$c_{l(m),s} = \left(\frac{w_{l(m),s}}{\lambda^L_{l(m),s}}\right)^{\lambda^L_{l(m),s}} \prod_k \left(\frac{P_{l(m),k}}{\lambda^k_{l(m),s}}\right)^{\lambda^k_{l(m),s}}.$$[11]

Two of the three policies we analyze would affect exports directly through the unit cost. First, decreases in barriers to labor mobility would reduce wages $w_{l(m),s}$. Second, the decline in import tariffs would change the price index $P_{l(m),k}$ for ordinary producers by lowering the prices of imported inputs. However, it has no direct impact on the price index for processing producers who have faced no import tariffs since 1987.

In each sector, each firm draws a vector of productivities, $\left\{\vec{\phi}_{l(m),s}, \vec{\phi}_{j,s}\right\}$, across China's provinces and regimes, and across foreign countries from a multivariate Pareto distribution with the following cumulative distribution function (CDF) (Arkolakis et al. 2016):

$$F\left(\vec{\phi}_{l(m),s}, \vec{\phi}_{j,s}\right) = 1 - \left[\sum_l \left(\sum_m A_{l(m),s} \phi_{l(m),s}^{-\frac{\theta}{1-\rho}}\right)^{\frac{1-\rho}{1-\gamma}} + \sum_j A_{j,s} \phi_{j,s}^{-\frac{\theta}{1-\gamma}}\right]^{1-\gamma}, \tag{2.2}$$

with support defined on values greater than $\left[\sum_l \left(\sum_m A_{l(m),s}\right)^{\frac{1-\rho}{1-\gamma}} + \sum_j A_{j,s}\right]^{\frac{1-\gamma}{\theta}}$.

The parameter ρ captures the correlation of productivity draws between processing and ordinary regimes, while the parameter γ captures the correlation across locations. Each correlation parameter takes a value between 0 and 1, with values closer to 1 indicating a stronger correlation. These two correlation parameters govern the *new-firm* and *export-regime margins* of the aggregate trade elasticity, which will be shown in Section 2.3.

We assume $\theta > \sigma - 1$. A larger θ corresponds to a smaller productivity dispersion across the continuum of firms. As the timing of migration and export growth suggests a story of

[11] The unit cost of the input bundle is common to all firms in province l and export regime m.

agglomeration economies (discussed in Section 2.1), we assume $A_{l(m),s} = \bar{A}_{l(m),s} L^{\alpha}_{l(m),s}$ with α governing the agglomeration externality.

Firm's Problem

Firms face fixed marketing costs of exporting and two types of variable trade costs—iceberg trade costs and *ad valorem* tariffs following Costinot & Rodríguez-Clare (2014). They solve a sequential optimization problem. In the first stage, for each destination market n, firms choose where to locate by minimizing the unit cost of exporting to destination n. In the second stage, given location and regime choices, firms decide whether to export to destination n and the optimal price if exporting. We solve the firms optimization problem through backward induction.

Optimal Price: Under monopolistic competition, firms choose the optimal price to maximize profits if they were to produce in $l(m)$ and export to foreign country n,

$$\pi(\phi_{l(m),s}) = \max_{p_{l(m),n,s}} \left\{ \frac{p_{l(m),n,s} q_{l(m),n,s}}{\tilde{t}_{i,n,s}} - q_{l(m),n,s} \frac{c_{l(m),s} d_{l(m),n,s}}{\phi_{l(m),s}} - c_{n,s} f_{n,s} \right\},$$

subject to the quantity demanded, $q_{l(m),n,s} = \left[p_{l(m),n,s} \right]^{-\sigma} E_{n,s} P^{\sigma-1}_{n,s}$, where $E_{n,s}$ is destination n's total expenditure in sector s. The expression, $\tilde{t}_{i,n,s} = 1 + t_{i,n,s}$, incorporates the export tariff levied by foreign country n on Chinese goods and is constant across all provinces and regimes. Firms also need to pay fixed marketing costs in terms of input bundles of destination n, denoted as $c_{n,s} f_{n,s} > 0$.[12] The optimal price is set with a markup $\frac{\sigma}{\sigma-1}$ over the marginal cost of selling to country n

$$p_{l(m),n,s} = \frac{\sigma}{\sigma - 1} \tilde{t}_{i,n,s} \frac{c_{l(m),s} d_{l(m),n,s}}{\phi_{l(m),s}}.^{13} \tag{2.3}$$

[12] $f_{n,s}$ is the fixed cost in units of input bundles at destination n. Although our model remains tractable by considering $f_{n,s}$ to be specific to l and m, we assume that $f_{n,s}$ is the same across l and m. This is because the l and m components in fixed costs are over-identified and can be absorbed into $A_{l(m),s}$ in our calibration.

[13] Alternatively, we can also quantify the impact of China's elimination of trading rights on export growth by incorporating a commission rate charged by export intermediaries into $\tilde{t}_{i,n,s}$. However, we do not pursue this exercise as the commission rate is unobserved (Bai et al. 2017).

Exporting Decisions: Firms will only export from $l(m)$ to destination n if the profit is positive. Given the demand and the optimal price in equation (2.3), the zero-profit productivity cutoff above which the firm would export from $l(m)$ to destination n is

$$\phi^*_{l(m),n,s} = \frac{\sigma}{\sigma-1} c_{l(m),s} d_{l(m),n,s} \tilde{t}_{i,n,s}^{\frac{\sigma}{\sigma-1}} \left(\frac{\sigma c_{n,s} f_{n,s}}{E_{n,s}} \right)^{\frac{1}{\sigma-1}} \frac{1}{P_{n,s}}. \tag{2.4}$$

In related papers that model firms' location choices in the spatial equilibrium, Serrato & Zidar (2016) and Fajgelbaum et al. (2018) assume zero fixed costs. Here we allow for positive fixed costs, and therefore our model captures firms' decisions on whether to export to given markets (the *extensive margin* of trade).[14] Another point to note from equation (2.4) is that by modeling revenue tariffs, the zero-profit productivity cutoff is more responsive to tariff changes than to changes in iceberg costs.

Firm's Location and Regime Choices: We define a cost-adjusted productivity, which relates to the inverse unit cost of exporting to destination n, as follows

$$\widetilde{\phi}_{l(m),n,s} = \frac{\phi_{l(m),s}}{c_{l(m),s} d_{l(m),n,s} \tilde{t}_{i,n,s}}. \tag{2.5}$$

Choosing where to locate by minimizing the unit cost to serve destination n is equivalent to choosing the highest cost-adjusted productivity:

$$Y = \arg\max_{l(m),j} \left\{ \vec{\widetilde{\phi}}_{l(m),n,s}, \vec{\widetilde{\phi}}_{j,n,s} \right\},$$

where Y is a discrete random variable denoting firms' location and regime choices. We omit subscript n and s, but we are aware that Y is destination- and sector-specific.

[14] Without fixed marketing costs, every firm makes positive profits and exports to every market under monopolistic competition.

Firm Sorting and the Distribution of Maximum Productivity

Definition. ***(The Maximum of Cost-adjusted Productivity)*** *Let Z be a continuous random variable such that*

$$Z = \max_{l(m),j} \left\{ \vec{\tilde{\phi}}_{l(m),n,s}, \vec{\tilde{\phi}}_{j,n,s} \right\}.$$

According to the maximization problem regarding firms' location and regime choices, Z is the equilibrium (cost-adjusted) productivity of all operating firms (after sorting into locations and regimes). Again, we omit subscript n and s, but we are aware that Z is also specific to each destination and sector. Assume that $f_{n,s}$ is large enough such that $\phi^*_{r,n,s} > c_{r,s} d_{r,n,s} \tilde{t}_{r,n,s} Z^* \ \forall \ r$, where Z^* is the lower bound of the support for Z. This restriction ensures that some firms would not serve market n from everywhere. We focus on $Z > Z^*$ and obtain the following proposition.[15]

Proposition 1. ***(The Marginal Density of*** Y ***and*** Z***)***

(a) Firm Sorting Probability: The probability density function of Y is

$$P\Big(Y = l(m)\Big) = \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}}, \tag{2.6}$$

$$P\Big(Y = j\Big) = \frac{\psi_{j,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}}, \tag{2.7}$$

where $\psi_{l(m),n,s} = A_{l(m),s}\Big(c_{l(m),s} d_{l(m),n,s} \tilde{t}_{i,n,s}\Big)^{-\frac{\theta}{1-\rho}}$, $\psi_{j,n,s} = A_{j,s}\Big(c_{j,s} d_{j,n,s} \tilde{t}_{j,n,s}\Big)^{-\frac{\theta}{1-\gamma}}$, $\Psi_{l,n,s} = \Big[\sum_m \psi_{l(m),n,s}\Big]^{\frac{1-\rho}{1-\gamma}}$. $\tilde{t}_{i,n,s}$ and $\tilde{t}_{j,n,s}$ include tariffs levied by destination n on Chinas and country j's exports, respectively.

(b) Z follows a univariate Pareto distribution with the following probability density function

$$f\Big(Z = z\Big) = \left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s} \right)^{1-\gamma} \theta z^{-\theta-1}. \tag{2.8}$$

[15]The density distribution at Z^* depends on the relative lower bounds of $\vec{\tilde{\phi}}_{l(m),n,s}$ and $\vec{\tilde{\phi}}_{j,n,s}$. As firms with Z^* are not actively operating, we do not consider them in the analysis.

(c) Y and Z are independent.

Part (a) states that the probability of firms' location and regime choices is determined by structural parameters (θ, ρ, and γ), firm-level TFP, trade costs, and production costs. Part (b) states that in each sector, the maximum of cost-adjusted productivity follows a univariate Pareto distribution. The scale parameter is captured by firms' market access to destination market n. Part (c) states that Y and Z are independent, implying that the distribution for the maximum of cost-adjusted productivity conditional on choosing each $l(m)$ or j still has the density defined in equation (2.8).[16] As a result, conditional on being located in $l(m)$, the unadjusted productivity, which differs from the cost-adjusted productivity by a scale $c_{l(m),s}d_{l(m),n,s}\tilde{t}_{i,n,s}$, also follows a Pareto distribution.

Corollary. *The unadjusted productivity for firms choosing r has a Pareto CDF function $G_{\phi|r} \equiv P\Big(\phi_{r,s} \leq z \mid Y = r\Big)$, $r \in \big\{l(m), j\big\}$:*

$$1 - \left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^{1-\gamma} \left(c_{r,s}d_{r,n,s}\tilde{t}_{r,n,s}\right)^{\theta} z^{-\theta}. \tag{2.9}$$

So far we have shown that the unadjusted productivity after firm sorting across location and regimes follows a univariate Pareto distribution. Therefore, we can derive aggregate trade shares and price indices similarly as in the Melitz-Chaney model, except for two key differences: (1) we need to keep track of the endogenous number of firms defined in equations (2.6) and (2.7), and (2) the scale parameter of the Pareto distribution is an endogenous variable that captures changes in market access resulting from firm sorting. The cumulative distribution function defined in equation (2.9) allows us to obtain the aggregate trade share and prices.

[16] Another implication is that $P\Big(Y = l(m)\Big)$ reflects not only the probability of location choices among exporting firms, but also the probability among all firms with $Z > Z^*$, since the independence property implies $P\Big(Y = l(m) \mid Z > Z^*\Big) = P\Big(Y = l(m) \mid Z > \widetilde{\phi}^*_{l(m),n,s}\Big)$.

2.2.3 Aggregate Trade Shares and Prices

The share of country n's expenditure in sector s that is spent on goods produced by $l(m)$ is

$$\Pi_{l(m),n,s} = \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{\Psi_{l,n,s}\tilde{t}_{i,n,s}^{\vartheta}}{\left[\sum_l \Psi_{l,n,s}\right]\tilde{t}_{i,n,s}^{\vartheta} + \sum_j \psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}}. \tag{2.10}$$

Analogously, the share of country n's expenditure in sector s that is spent on goods produced by foreign country j is

$$\Pi_{j,n,s} = \frac{\psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}}{\left[\sum_l \Psi_{l,n,s}\right]\tilde{t}_{i,n,s}^{\vartheta} + \sum_j \psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}}. \tag{2.11}$$

Equation (2.10) specifies the key factors that determine trade shares. Our counterfactual analysis quantifies the impact of changes in $c_{l(m),s}$ (resulting from internal migration or import tariff changes) and changes in export tariffs on China's export surge. We attribute the residual of export growth to $A_{l(m),s}$ and non-tariff trade costs $d_{l(m),n,s}$.

Another noteworthy point is that as a *macro-level* consequence of modelling revenue tariffs, the changes in export tariffs have an additional impact on aggregate trade, which is captured by $\vartheta = \frac{\sigma-1-\theta}{\sigma-1}$, rather than entering symmetrically into iceberg trade costs. We also obtain the aggregate price index in country n and sector s as

$$P_{n,s} = \left[\Theta M_s\left(\frac{c_{n,s}f_{n,s}}{E_{n,s}}\right)^{\vartheta}\left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^{-\gamma}\left(\left[\sum_l \Psi_{l,n,s}\right]\tilde{t}_{i,n,s}^{\vartheta} + \sum_j \psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}\right)\right]^{-\frac{1}{\theta}}, \tag{2.12}$$

where $\Theta = \sigma^{\frac{\sigma-\theta-1}{\sigma-1}}\left(\frac{\theta}{\theta-\sigma+1}\right)\left(\frac{\sigma}{\sigma-1}\right)^{-\theta}$.

2.2.4 Workers' Preferences and Labor Markets

Preferences. Workers' preferences over final goods are $U = \prod_s C_s^{\beta_s}$, with $\beta_s > 0$ denoted as the expenditure share on the final good produced by sector s and $\sum_s \beta_s = 1$.

Chinese Labor Markets: Chinese workers are grouped based on the province of their *Hukou* registration, and we index group by g. Workers sort into provinces and sectors based on their idiosyncratic location preferences, following Tombe & Zhu (2019). Within each province and sector, workers are perfectly mobile between processing and ordinary firms, $w_{l,s} = w_{l(\mathcal{P}),s} = w_{l(\mathcal{O}),s}$. Each worker supplies one unit of labor.

Specifically, a worker chooses provinces and sectors by maximizing $\tau_{g,l,s} \times a_{g,l,s} \times V_{l,s}$. $\tau_{g,l,s}$ represents migration frictions which act as proportional adjustments to real expenditure.[17] Migration frictions are modelled as group-destination-sector-specific because Section 2.1.1 suggests that there was a large degree of heterogeneity in migrants' employment shares across provinces and sectors.[18] Preferences over locations $a_{g,l,s}$ are drawn independently across l and s from a Fréchet distribution with CDF $G(a) = \exp\left(-a_{g,l,s}^{\kappa}\right)$, where a larger shape parameter κ corresponds to a smaller degree of heterogeneity in location preferences across workers. $V_{l,s} = \frac{w_{l,s}}{P_l}$ is the real wage per efficiency unit in l and s, where P_l is the aggregate price index in province l.[19]

With Fréchet-distributed location preferences, we obtain the closed-form solution for the fraction of group g workers in province l and sector s:

$$\Lambda_{g,l,s} = \frac{\tau_{g,l,s}^{\kappa} V_{l,s}^{\kappa}}{\sum_{l',s'} \tau_{g,l',s'}^{\kappa} V_{l',s'}^{\kappa}}. \tag{2.13}$$

Parameter κ governs the elasticity of labor supply with respect to real wages. We define $L_{g,l,s} = L_g \Lambda_{g,l,s}$ as efficiency units of labor provided by group g to province l and sector s.

Foreign Labor Markets: Each foreign country n has a fixed population L_n. We consider a single labor market in each foreign country, where labor is perfectly mobile across sectors, and

[17]The assumption that migration costs are proportional adjustments to real expenditure is commonly exploited in the literature; for example, see Borjas (1987), Chiquiar & Hanson (2005), Caliendo et al. (2017), and Galle et al. (2017). One interpretation is that migrants may enjoy fewer working/leisure hours because of more time spent traveling (Bryan & Morten 2015).

[18]In provinces such as Guangdong and Zhejiang, migrants were disproportionately employed in manufacturing sectors, whereas in Shanghai and Beijing, migrants were disproportionately employed in the hotel & restaurant service and retail sectors.

[19]As workers only consume the final goods from ordinary production, $P_l = \prod_s \left(P_{l(\mathcal{O}),s}/\beta_s\right)^{\beta_s}$.

w_n denotes the wage rate in country n.

2.2.5 Market Clearing Conditions

Assuming that profits are spent by managers on input bundles,[20] and tariff revenues are rebated to local workers, the market clearing condition for final goods in Chinese provinces is:

$$E_{l(m),s} = \beta_s I_{l(m)} + \sum_k \lambda^s_{l(m),k} \left((1-\eta) \sum_r \frac{\Pi_{l(m),r,k} E_{r,k}}{\tilde{t}_{l(m),r,k}} + \eta \sum_r \frac{\Pi_{r,l(m),k} E_{l(m),k}}{\tilde{t}_{r,l(m),k}} \right), \tag{2.14}$$

where $\eta = \frac{\theta-\sigma+1}{\sigma\theta}$ is the ratio of marketing costs to net-of-tariff trade flows. The left-hand side is the value of the final good produced in $l(m)$ and sector s.[21] The first term on the right-hand side is workers' consumption. Because processing goods cannot be consumed domestically, workers spend wages and tariff revenues on ordinary goods: $I_{l(O)} = \sum_g \sum_s w_{l,s} L_{g,l,s} + \sum_s \sum_r \frac{t_{r,l(O),s}}{\tilde{t}_{r,l(O),s}} \Pi_{r,l(O),s} E_{l(O),s}$ and $I_{l(\mathcal{P})} = 0$. The second term sums up the material costs spent by local establishments and the marketing costs incurred by firms selling to the local market.

The labor market clears for each China's province l and sector s separately:

$$\sum_m \lambda^L_{l(m),s} \left((1-\eta) \sum_r \frac{\Pi_{l(m),r,s} E_{r,s}}{\tilde{t}_{l(m),r,s}} + \eta \sum_r \frac{\Pi_{r,l(m),s} E_{l(m),s}}{\tilde{t}_{r,l(m),s}} \right) = \sum_g w_{l,s} L_{g,l,s}. \tag{2.15}$$

The left-hand side represents both ordinary and processing producers' expenses on labor. The right-hand side is the labor income in province l in sector s earned by workers from all labor groups.

In summary, given model fundamentals and parameters, Chinese provinces and sectors'

[20] This assumption allows us to directly use input-output tables to calibrate input-output parameters $\{\lambda^L_{l(m),s}, \lambda^k_{l(m),s}\}$; otherwise, we need to adjust input-output tables by firms' profit ratio to obtain $\{\lambda^L_{l(m),s}, \lambda^k_{l(m),s}\}$, and the profit ratio relies on structural parameters. As an alternative, we also experiment with the assumption that profits are spent by managers on consumption goods according to workers' preferences. This gives quantitatively similar results, which are available upon request.

[21] Since the final good is produced using only intermediate goods (either produced domestically or imported), the value of the final good equals its total expenditure on intermediate goods, $E_{l(m),s} = P_{l(m),s} Q_{l(m),s}$.

endogenous variables $\{\Pi_{l(m),n,s}, P_{l(m),s}, \Lambda_{g,l,s}, E_{l(m),s}, w_{l,s}\}$ satisfy conditions (2.10), (2.12), and (2.13)–(2.15). The equilibrium conditions for foreign countries can be obtained analogously.

2.3 Decomposing the Aggregate Trade Elasticity

This section obtains an analytic expression for each of the four margins: the *intensive*, *extensive*, *new-firm*, and *export-regime margins*. Again, we develop our argument by considering exports from $l(m)$ in China to foreign destination n. Recall that the aggregate trade flow from $l(m)$ to n in sector s is

$$X_{l(m),n,s} = M_s \cdot P\Big(Y = l(m)\Big) \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi) \, \mathrm{d}G_{\phi|l(m)} \right], \tag{2.16}$$

where $x_{l(m),n,s}(\phi)$ denotes the sales from $l(m)$ to n in sector s by firms with productivity level ϕ. ϕ^* is the zero-profit productivity cutoff defined in equation (2.4).[22] $G_{\phi|l(m)}$ is given in equation (2.9), which represents the equilibrium productivity distribution among firms that choose $l(m)$. The gravity equation (2.16) resembles the one in a Melitz-Chaney model, except for two differences: (1) The number of firms $P\Big(Y = l(m)\Big)$ choosing location $l(m)$ to serve n is endogenous, and (2) the scale parameter of the unadjusted productivity distribution defined in equation (2.9) is also endogenous. We rewrite equation (2.16) as

$$X_{l(m),n,s} = M_s R \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi) \, \mathrm{d}G_{\phi} \right],$$

[22] $x_{l(m),n,s}(\phi)$ is firm's sales to n, and we write it as

$$x_{l(m),n,s}(\phi) = \Big(\frac{\sigma}{\sigma - 1}\Big)^{1-\sigma} \Big(c_{l(m),s} d_{l(m),n,s} \tilde{t}_{i,n,s}\Big)^{1-\sigma} \Big(\phi_{l(m),s}\Big)^{\sigma-1} E_{n,s} P_{n,s}^{\sigma-1}.$$

where $G_\phi = 1-\phi^{-\theta}$ and $R = P\Big(Y = l(m)\Big)\Big(c_{l(m),s}d_{l(m),n,s}\tilde{t}_{i,n,s}\Big)^{\theta}\Big(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\Big)^{1-\gamma}$. Taking the derivative with respect to $d_{l(m),n,s}$ and applying the Leibniz rule, we have

$$\frac{\partial X_{l(m),n,s}}{\partial d_{l(m),n,s}} = \underbrace{M_s R \int_{\phi^*}^{+\infty} \frac{\partial x_{l(m),n,s}(\phi)}{\partial d_{l(m),n,s}}\, \mathrm{d}G(\phi)}_{\text{Intensive Margin}} \underbrace{- M_s R\, x_{l(m),n,s}(\phi^*) G'(\phi^*) \frac{\partial \phi^*}{\partial d_{l(m),n,s}}}_{\text{Extensive Margin}}$$
$$+ \underbrace{\frac{\partial R}{\partial d_{l(m),n,s}} M_s \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi)\, \mathrm{d}G(\phi)\right]}_{\text{Export-regime and New-firm Margins}}$$

In our model, firms first choose a location and an export regime, and then decide whether to export and the optimal volume of exports. The first two terms on the right-hand side reflect the *intensive* and *extensive margins* of firm adjustments respectively, given that firms have chosen $l(m)$. In the third term, the derivative $\frac{\partial R}{\partial d_{l(m),n,s}}$ captures the consequences of firm sorting. We break down the third term into the *new-firm* and *export-regime margins* and obtain an analytic expression of the trade elasticity as follows:

$$\underbrace{\Big(\sigma - 1\Big)}_{\text{Intensive Margin}} + \underbrace{\Big(\theta - \sigma + 1\Big)}_{\text{Extensive Margin}} + \underbrace{\frac{\theta\gamma}{1-\gamma}\left(1 - \frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}}}_{\text{New-firm Margin}} + \underbrace{\frac{\theta\rho}{1-\rho}\left(1 - \frac{M_{l(m),s}}{M_{l,s}}\right)}_{\text{Export-regime Margin}}, \tag{2.17}$$

where $M_{l,s}$ is the number of firms choosing province l in sector s, and $M_{l(m),s}$ is the number of firms choosing province l and regime m in sector s. Three comments are in order. First, despite an endogenous number of firms, the *intensive and extensive margins* in our model have the exact formula as in Chaney (2008). This implies identical *intensive* and *extensive margins* of trade among incumbents and entrants. This result is due to the independence between location choice Y and productivity Z: after firms choose their locations and regimes, the shape parameter of the productivity distribution among firms located in $l(m)$, captured by θ, is unchanged.

Second, the *new-firm margin* increases with γ, and the *export-regime margin* increases with ρ. Since γ and ρ take values between 0 and 1, the *new-firm margin* and *export-regime margin* can take any arbitrary non-negative values which offer flexibility to match the empirical regularity. [23] Third, equation (2.17) guides our parameter restrictions to decompose Chinas aggregate export growth into four different margins of adjustments using a general equilibrium model. For example, the *new-firm* and *export-regime margins* are absent when $\rho = \gamma = 0$.[24]

2.4 Empirical Analysis

We provide empirical validation for the *new-firm* and *export-regime margins* of firm adjustments in our data. In Section 2.4.1, we validate the *new-firm margin* by estimating the impact of an increase in the supply of migrant workers on the number of firms across provinces and sectors between 1990 and 2005. In Section 2.4.2, we explore cross-sectoral variation to validate the *export-regime margin* by estimating the impact of changes in production costs (induced by import tariff changes) on the relative number of ordinary to processing exporters. Section 2.4.3 uses the reduced-form estimates to discipline the values of the structural parameters ρ and γ, using an indirect inference procedure.

2.4.1 Internal Migration and Firms' Location Choice

We estimate the following reduced-form regression:

$$\Delta M_{l,s} = \beta_0 + \beta_1 \Delta N^m_{l,s} + \gamma x_{l,s} + \varepsilon_{l,s}. \tag{2.18}$$

The dependent variable is growth in the total number of firms (processing and ordinary) in province l and sector s between 1990–2005, $\Delta M_{l,s} = (M_{l,s,2005} - M_{l,s,1990}) / \left(\frac{1}{2} M_{l,s,2005} + \frac{1}{2} M_{l,s,1990}\right)$,

[23] $\left(1 - \frac{M_{l,s}}{M_s}\right)$ and $\left(1 - \frac{M_{l(m),s}}{M_{l,s}}\right)$ take values between 0 and 1.

[24] Our counterfactual experiments that involve internal migration shocks or import tariff reductions would affect firms' costs of production, $c_{l(m),s}$. Since $c_{l(m),s}$ and $d_{l(m),n,s}$ are symmetric in our gravity equation, the decomposition results in equation (2.17) can be applied to analyze these two shocks. Since export tariffs have an asymmetric effect from iceberg costs, export tariffs have an additional elasticity captured by ϑ.

where $M_{l,s,t}$ is the number of firms in province l and sector s at year t. This way of defining growth follows from Davis & Haltiwanger (1992) and allows growth rates to lie in the closed interval $[-2,2]$, which avoids extreme values. We obtain the number of firms in 1990 and 2005 from the Industrial Statistical Yearbook and the Firm Census, respectively. We cluster industries to 16 aggregated manufacturing sectors (see Table B.1). The independent variable is the changes in the migrant share in province l and sector s between 1990 and 2005, computed as $\Delta N^m_{l,s} = (N^m_{l,s,2005} - N^m_{l,s,1990}) / \left(\frac{1}{2}N_{l,s,2005} + \frac{1}{2}N_{l,s,1990}\right)$. Here $N^m_{l,s,t}$ and $N_{l,s,t}$ are the number of migrant workers and the total number of workers in province l and sector s at year t, respectively. We obtain these variables from Chinas Population Census in 1990 and 2005. $x_{l,s}$ is the province and sector control variables.

The OLS regression in equation (2.18) tends to be biased because an unobserved local productivity or policy shock could attract more firms and migrant workers. To deal with this endogeneity issue, we construct a Card-type instrument to predict exogenous labor supply shifts as follows

$$\Delta \widetilde{N}^m_{l,s} = \sum_g \Delta N_g^{-l,-s} \times \Lambda_{g,l,s,t_0},$$

where $\Delta N_g^{-l,-s}$ is the change in the total number of group g migrants between 1990 and 2005, excluding those who migrated to province l and sector s. As in Section 3.4, we group Chinese workers based on the province of their *Hukou* registration. Λ_{g,l,s,t_0} is the share of workers choosing province l and sector s in the year t_0 among those who migrated.[25] We find that the instrument $\Delta \widetilde{N}^m_{l,s}$ (in units of millions of people) strongly predicts the actual migration pattern $\Delta N^m_{l,s}$, with the coefficient of 0.525 and the standard error of 0.046.[26]

The Card-type instrument, while widely used, is subject to criticism. One concern is that it may be invalid if regional labor demand shocks are persistent (Borjas et al. 1997). Helpfully,

[25]We use the 1990 Population Census to measure internal migration in the initial year, based on workers' current province of residence and province of residence in the year 1985.

[26]For all regressions results, we cluster standard errors by province.

Table 2.1: The Impact of Internal Migration on the Number of Firms

	OLS (1)	**2SLS** (2)	**2SLS** (3)	**2SLS** (4)
	Dep Var: Growth in Num of Firms, 90–05			
Δmigrant share	1.018***	0.987***	0.957***	0.750***
	(0.225)	(0.327)	(0.274)	(0.182)
Controls	No	No	Yes	Yes
Sector FE	No	No	No	Yes
First-stage F		76.42	58.29	63.24
Obs	420	420	420	420
R-squared	0.233	0.232	0.457	0.544

Notes: This table presents the results from estimating regression (2.18) across provinces and sectors. The instrument is the Card-type instrument to predict exogenous labor supply shifts (measured in units of millions of people). The controls include: 1) log labor productivity in 1990; 2) changes in non-tariff barriers, FDI restrictions, and input and output tariffs between 1990 and 2005, from Brandt et al. (2017). Regressions are weighted by firm numbers in each province-sector pair in 1990. Standard errors are in parenthesis and clustered by province. Significance levels: 10% * 5% ** 1% ***.

we find that our instrument $\Delta\widetilde{N}^m_{l,s}$ is uncorrelated with labor productivity in 1990 and labor productivity growth between 1990 and 2005 across provinces and sectors. Our IV analysis is thereby immune to productivity shocks that may drive migration.

Column (1) of Table 2.1 presents the estimate based on the OLS regression. We find a strong and positive association: provinces and sectors that experienced faster growth in the number of migrants also experienced a rapid growth in the number of firms. The IV regression in Column (2) reports a slightly lower β_1 estimate than the OLS result. The upward bias in the OLS regression likely reflects that fast-growing regions or sectors attracted more migrants and firms. Column (3) shows that our IV estimate is robust to adding control variables including: 1) log labor productivity in 1990; 2) changes in non-tariff barriers, FDI restrictions, and input and output tariffs between 1990 and 2005. Column (4) further controls for sector fixed effects,[27] and the within-sector variation delivers a smaller estimate.

[27]We do not control province fixed effects because changes in the migrant share mainly came from between-province variation, as a result of different *Hukou* policies (Kinnan et al. 2018).

2.4.2 Import Tariffs and Firms' Export-Regime Choices

Because imported materials for processing exports are duty-free, we expect ordinary exporters to benefit more from import tariff reductions due to China's WTO accession compared to processing exporters. Thus, we estimate the following reduced-form regression:

$$\Delta M_{l(m),s} = b_0 + (b_1 + b_2 \mathbf{1}_O) \sum_k \lambda_{l,s}^k IP_{l,k} \left(\frac{1 + t_{k,2005}}{1 + t_{k,2000}} - 1 \right) + \gamma x_{l,s} + \varepsilon_{l,s}, \tag{2.19}$$

where the dependent variable is the changes in the number of exporters in province l and sector s between 2000 and 2005, $\Delta M_{l(m),s} = (M_{l(m),s,2005} - M_{l(m),s,2000}) / \left(\frac{1}{2} M_{l(m),s,2005} + \frac{1}{2} M_{l(m),s,2000}\right)$, separately for ordinary and processing regimes $m \in \{\mathcal{O}, \mathcal{P}\}$. We obtain the number of processing and ordinary exporters across provinces and manufacturing sectors by linking the China's Annual Survey of Industrial Firms with Customs Database for 2000 and 2005.[28]

The independent variable measures province-sector-level changes in production costs resulting from import tariff reductions. $IP_{l,k}$ is the share of imports in the total expenditure of sector k in province l.[29] t_k is China's tariff rate imposed on imports in sector k, therefore $\left(\frac{1+t_{k,2005}}{1+t_{k,2000}} - 1\right) < 0$ captures changes in import costs due to tariff reductions. The tariffs are drawn from the UNCTAD Trade Analysis and Information System (TRAINS).[30] $\lambda_{l,s}^k$ is the share of sector s's production costs spent on materials from sector k, obtained from the input-output tables in 2005. In our independent variable, reductions in production costs were larger if the province intensively used foreign inputs (high $IP_{l,k}$) or that sector intensively used materials that had large tariff reductions (high $\lambda_{l,s}^k$ or low $\frac{1+t_{k,2005}}{1+t_{k,2000}}$). $\mathbf{1}_O$ is a dummy variable for ordinary exporters. The parameter of interest is β_2, with $\beta_2 < 0$ capturing that ordinary exporters would benefit more

[28] We follow Yu (2015) and Dai et al. (2016) to match these two datasets. The match is based on variables such as firm name, telephone number, and zip code. We compute the number of ordinary (processing) exporters as the total number of firms that perform ordinary (processing) exports, weighted by the share of ordinary (processing) exports in their sales.

[29] We compute import shares using the trade matrix in 2005.

[30] The raw data on tariffs are based on 6-digit HS products from each origin country to China. We use the trade volume as weights to aggregate China's import tariffs into our 16 manufacturing sectors (Table B.1).

Table 2.2: The Impact of WTO on the Number of Ordinary and Processing Exporters

	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
	Dep Var: Growth in Num of Firms, 00–05			
Δcosts due to import tariffs	-0.619	-1.545	3.127	-8.719**
	(9.118)	(9.617)	(9.577)	(3.766)
Δcosts due to import tariffs	-13.517	-12.741	-18.211**	-18.928*
$\times$ 1{ordinary exporters}	(10.383)	(9.945)	(7.829)	(9.857)
Controls	No	No	Yes	Yes
Province FE	No	No	No	Yes
First-stage F		2126.46	3423.86	1901.03
Obs	751	751	751	751
R-squared	0.354	0.354	0.426	0.664

Notes: This table presents the results from estimating regression (2.19) across provinces, sectors and export regimes. All regressions include a dummy variable for export regimes. The instruments are the change in maximum tariffs (as specified in the main text) and its interaction with the ordinary regime. The controls include: 1) changes in non-tariff barriers, FDI restrictions, and output tariffs between 2000 and 2005, from Brandt et al. (2017); 2) initial openness levels measured by the ratio of exports to output in 2000. Regressions are weighted by firm numbers in each province-sector-regime pair in 2000. Standard errors are in parenthesis and clustered by province. Significance levels: 10% * 5% ** 1% ***.

from tariff reductions relative to processing exporters.

Tariff changes between 2000 and 2005 may have been endogenous, as policymakers could change import tariffs selectively in favor of less competitive domestic sectors. We construct an instrument for the changes in applied tariffs by using the maximum tariff levels under the WTO agreement, following Brandt et al. (2017),

$$x^*_{l,s} = \sum_k \lambda^k_{l,s} IP_{l,k} \left(\frac{1+t^{WTO}_{k,2005}}{1+t^{WTO}_{k,2000}} - 1 \right), \tag{2.20}$$

where $t^{WTO}_{k,2000}$ and $t^{WTO}_{k,2005}$ refer to specified maximum tariff levels in the WTO agreement. We find that this instrument strongly predicts actual production cost changes due to tariff reductions, with the coefficient of 1.161 and the standard error of 0.038.

This instrument helps resolve the endogeneity issue because tariff rates in WTO agreements were mostly fixed by 1999 and thus unlikely to be affected by firms performance after

2000. Moreover, as shown by Brandt et al. (2017), there is little room for policy discretion of tariffs after WTO, and China's tariff cuts after WTO are uncorrelated with most initial industry-level characteristics. In line with Brandt et al. (2017), we find that our instrument constructed from WTO tariff cuts is uncorrelated with the number of processing (ordinary) exporters across provinces and industries in 2000.

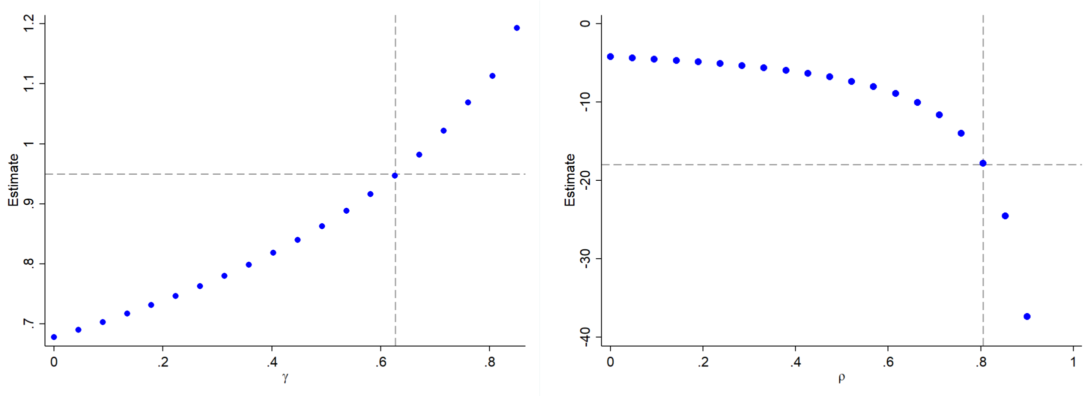
Our OLS and IV regressions in Columns (1)–(2) of Table 2.2 find that, for sectors that enjoyed larger cost reductions after WTO, the number of ordinary exporters grew faster relative to the number of processing exporters. Column (3) also controls for: 1) changes in non-tariff barriers, FDI restrictions, and output tariffs between 2000 and 2005; and 2) initial openness levels measured by the ratio of exports to output in 2000. After including controls, the results are quantitatively similar and become statistically significant. Column (4) further controls for province fixed effects, and the within-province variation delivers a similar estimate.

2.4.3 Linking Reduced-Form Estimates to Structural Parameters

We use an indirect inference approach (Gouriéroux & Monfort 1996) to jointly search structural parameters ρ and γ to target our reduced-form estimates in Column (3) of Tables 2.1 and 2.2. We provide the details of the procedure in Appendix B.4.

Figure 2.3 plots the one-dimensional relationship between the reduced-form estimates (using model-generated data) and the structural parameters, namely β_1 and γ on the left-hand panel and b_2 and ρ on the right-hand panel. Both panels show a monotonic relationship which corroborates the trade elasticity decomposition given in equation (2.17): a higher γ corresponds to greater firms' location adjustments when a province-sector receives more migrants; and a higher ρ indicates that firms switch more towards ordinary regime when import tariffs decrease. Our indirect inference approach yields estimates of $\gamma = 0.63$ and $\rho = 0.81$, both of which are comparable to those in the previous literature.[31]

[31] Brandt et al. (2018) find the correlation of productivity draws between export regimes to be 0.71. ARRY find the



(a) Estimate of β_1 in in Regression (2.18) (b) Estimate of b_2 in Regression (2.19)

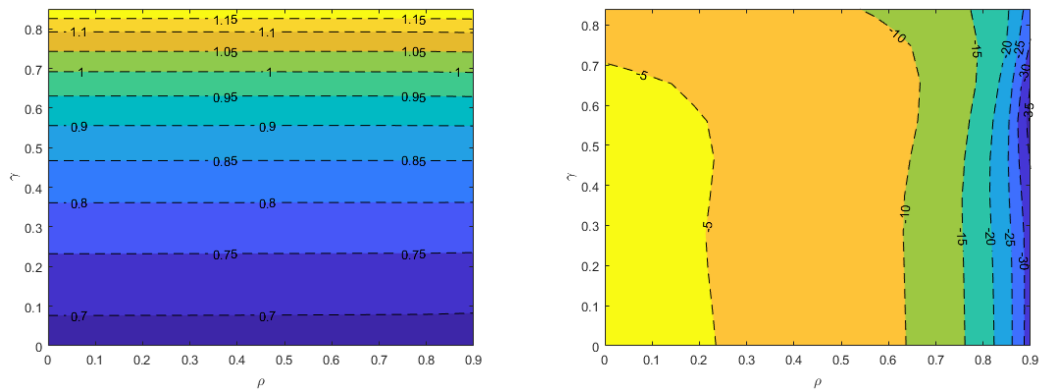
Figure 2.3: Estimates from Migration and Tariff Regressions using Model-Generated Data
This graph replicates Column (3) of Tables 2.1 and 2.2. The left-hand figure varies γ from 0 to 0.85 in the counterfactual exercise with changes in migration barriers, holding all other parameters at their baseline levels. The vertical line represents the value of $\gamma = 0.63$, in which the estimate produced by the model-generated data (0.95) matches the estimate in Column (3) of Table 2.1. The right-hand figure varies ρ from 0 to 0.9 in the counterfactual exercise with changes in import tariffs, holding all other parameters at their baseline levels. The vertical line represents the baseline value of $\rho = 0.81$, in which the estimate produced by the model-generated data (-17.8) matches the estimate in Column (3) of Table 2.2.

We show further evidence that each structural parameter is indeed identified from the related margins of firm adjustments discussed in Section 2.3, i.e., the *new-firm margin* for γ and the *export-regime margin* for ρ. Figure 2.4 plots the structural parameters ρ and γ on the horizontal and vertical axes, respectively. The value of each contour line, in the left-hand panel, is the reduced-form estimate of firm responses to migration, and in the right-hand panel, is the reduced-form estimate on the responses of the relative number of ordinary to processing exporters to the import tariff reductions. All reduced-form estimates are based on model-generated data. The pattern in the left-hand panel shows that the reduced-form estimate on firm responses to migration is only responsive to γ but not to ρ. We find an opposite pattern on the right-hand panel—the estimate on the relative number of exporters is mostly responsive to ρ but not to γ.

2.5 Quantitative Analysis

Chinas manufacturing exports increased by a factor of 11.8 in real terms between 1990 and 2005, equaling an annual growth rate of 17.8%. The growth rate was faster in coastal

correlation of productivity draws across countries to be 0.55.



(a) Estimate of β_1 in Regression (2.18) (b) Estimate of b_2 in Regression (2.19)

Figure 2.4: Estimates from Migration and Tariff Regressions using Model-Generated Data

provinces (see Appendix Figure B.5). We decompose this observed export increase into four sources including: 1) changes in the costs of intermediate inputs due to import tariff changes; 2) changes in export tariffs; 3) changes in labor costs ($w_{l(m),s}$) due to internal migration; and 4) the composite of changes in TFP ($\bar{A}_{l(m),s}$) and iceberg trade costs ($d_{l(m),n,s}$), which we match to the residual of the observed export increase.

We calibrate our model to 29 sectors, 30 Chinese provinces, 35 foreign countries and a constructed rest of the world. Our 29 sector categories are aggregated based on the 2-digit International Standard Industrial Classification (ISIC Rev 3), including 16 tradable sectors and 13 non-tradable sectors. We express the equilibrium system in proportional changes (see Appendix B.1.6) and solve the model using the Exact Hat Algebra approach. Noting that the Exact Hat Algebra approach can compare between any two equilibria, we match our model to the year 2005, for which we have high-quality data to measure provincial imports from and exports to foreign countries.[32] The interpretation of our counterfactual exercise is what level of China's exports in 2005 would be if tariffs and migration frictions were to stay at the level in 1990.

Given parameter values of $\{\theta, \rho, \gamma, \kappa, \sigma, \alpha, \beta_s, \lambda^L_{r,s}, \lambda^k_{r,s}\}$, we introduce China's import and

[32] Previous papers mostly calibrate models to the initial year (e.g., Caliendo & Parro 2015, among others). See Adao et al. (2017) who calibrated their model to the final year of their study. The interpretation of the counterfactual results differs by the choice of the year used to calibrate the model.

export tariff changes, and changes in migration frictions into the model, individually. We set $\widehat{\bar{A}}_{r,s} = \widehat{f}_{n,s} = \widehat{M}_s = \widehat{d}_{r,n,s} = \widehat{L}_g = \widehat{L}_n = 1$ and solve $\{\widehat{\Pi}_{l(m),n,s}, \widehat{\Pi}_{j,n,s}, \widehat{P}_{r,s}, \widehat{\Lambda}_{g,l,s}, \widehat{E}_{r,s}, \widehat{w}_{l,s}, \widehat{w}_n\}$ from the system of equations in changes, $r \in \{l(m), j\}$. We treat the U.S. GDP as the numeraire, and trade is balanced for all counterfactual exercises.[33] In the rest of this section, we discuss the data sources, measurement of three policy shocks, and other model parameters.

2.5.1 Data

Our counterfactual exercises require data on: intranational and international trade flows; firms' location probability $\{\frac{M_{l(m),s}}{M_s}\}$; inter-provincial migration rates $\{\Lambda_{g,l,s}\}$; sectoral output $\{X_{r,s}\}$; and labor income in both China $\{w_{l,s}L_{g,l,s}\}$ and foreign countries $\{w_n L_n\}$. We summarize the data sources we use below and provide detailed descriptions in Appendix B.3.

Provincial Imports and Exports by Sectors and Regimes: China's Customs Transactions Database has information on whether a firm is engaged in exporting processing activities. We aggregate firms' transaction-level import and export volume to the provincial level by processing and ordinary regimes and by 29 sectors. We thus obtain trade flows between China's provinces and foreign countries by processing and ordinary regimes in the year 2005.

Provincial Gross Output by Sectors and Regimes: Since processing production is not allowed to be sold domestically, we use the total amount of processing exports from China's Customs Transactions Database to measure processing output. We then measure province-sector gross output from input-output tables in the year 2007 (the closest available year to 2005), and deflate output using the growth rate of China's sectoral output between 2005 to 2007. The difference between gross output and the overall processing exports (which also equal processing output) reflects the gross output in ordinary production.[34]

[33] Instead of assuming balanced trade, an alternative approach is to assume the aggregate trade deficit as a fixed share of the world GDP (Caliendo & Parro 2015).

[34] China's regional input-output tables in 2007 are obtained from Liu et al. (2012). We match the 2-digit Chinese Standard Industrial Classification Code (CSIC) used in China's regional input-output tables with the 2-digit ISIC

Inter-provincial Trade Flows by Sectors and Regimes: Again, since processing production is not allowed to be sold domestically, sectoral inter-provincial trade flows from regional input-output tables reflect domestic sales from ordinary producers. We compute the amount of domestic sales to processing producers at each destination and sector, by using data from input-output tables, processing exports, and processing imports. The rest of domestic sales are sold to ordinary final-good producers. We further assume that processing and ordinary final-good producers at each destination and sector have identical expenditure shares on goods from each domestic origin.[35] This assumption allows us to construct trade flows between province-regime-sectors.

Trade Flows Between Foreign Countries and the Allocation of Firms: We measure bilateral trade flows between foreign countries using the STAN Bilateral Trade Database and measure sectoral gross output of each foreign country using OECD Input-Output Database. We also measure imports from the rest of the world by subtracting the imports from each country that we consider from the total import volume from the world.[36] For the distribution of firms, we obtain firms' choice probability according to equilibrium conditions on firms' choice probability and trade shares given in equations (2.6) – (2.11).

Labor Market Variables: We use the 2005 Chinese Population Survey to measure Chinas internal migration flows, wages, and sectoral employment. For the year 2005, we define China's internal migrants as those who work in a province other than the place of their *Hukou* registration. Since the variable on the province of *Hukou* registration is unavailable in the 1990 data, we define a worker as a migrant if their province of residence 5 years ago differs from their current province of residence.[37] We have a total of 30 groups defined by province of origin and measure the

code, using the concordance in Dean & Lovely (2010).

[35] This is because we do not have details on whether each trade flow (from an origin) is sold to ordinary or processing producers in the destination. The assumption of proportionality is typical in the trade literature (e.g., Johnson & Noguera 2016).

[36] Similarly, we measure exports to the rest of the world by subtracting the exports to each country that we consider from the total export volume to the world.

[37] Given that internal migration was under strict control before 1990, respondents' province of residence in 1985 tended to be their home province. Moving out of the *Hukou* area was initially tightly controlled by the government.

migration stock for each origin-destination-sector pair. We consider one aggregate labor group for each foreign country, and extract data from the IPUMSInternational and Luxembourg Income Study (LIS) to measure employment and wages in foreign countries.

2.5.2 Measuring Policy Shocks

Measuring Import and Export Tariff Changes: We obtain China's nominal import tariff rates and export tariff rates levied by each country in 1990 and 2005 at each sector, from the UNCTAD TRAINS database.[38] We use the trade volume as weights to aggregate the reported tariffs based on 6-digit HS products into our 29 sector categories. We apply changes in export tariffs between 1990 and 2005 to both processing and ordinary firms and apply changes in import tariffs only to ordinary firms. We keep the tariff structure between foreign countries unchanged. Therefore, our accounting exercises are only based on the realized China-related tariff structure changes.

Calibrating Migration Friction Changes: Following exactly from Tombe & Zhu (2019), we calibrate changes in migration costs to match changes in origin-destination-sector migration shares:

$$\widehat{\tau}_{g,l,s} = \frac{\widehat{V}_{l_g,s}}{\widehat{V}_{l,s}} \left(\frac{\widehat{\Lambda}_{g,l,s}}{\widehat{\Lambda}_{g,l_g,s}}\right)^{\frac{1}{\kappa}}.$$

The calculation assumes that the costs of staying in home province (denoted as l_g) remain unchanged, and we measure $\widehat{V}_{l,s}$ as changes in province-sector real wages from the China Labor Statistical Yearbook. Calibrating migration costs requires a value of migration elasticity. We assign $\kappa = 1.5$ following Tombe & Zhu (2019).[39] Using the calibrated migration cost

According to China's 1982 Population Census, only 0.6% of China's total population in 1982 resided out of their *Hukou* county.

[38]When the data are missing in the year 1990 or 2005, we use the data in the nearest available year to supplement the missing value.

[39]In an earlier version of this paper, we estimate κ by relating changes in migration shares of each origin-destination-sector pair between 1990 and 2005 to changes in wage rates. To address workers' non-random location and sector choices, we construct a model-based instrument following Allen et al. (2015) and Adao et al. (2018). We find a value of κ around 2.8.

changes, we present the migrant-population-weighted average over all origin provinces, for the aggregate manufacturing sector in Appendix Figure B.6 and for all sectors in Appendix Figure B.7. Unsurprisingly, the migration costs were reduced more if the destinations were the coastal provinces and major cities, such as Beijing, but reduced less if the destinations were inland provinces.

The calibrated change in migration costs reflects several sources. First, it picks up the changes in the institutional barriers (*Hukou* system) on labor mobility in China. China assigns a *Hukou* to each household to regulate the geographic area in which a Chinese citizen is eligible to reside, work, and obtain public benefits. Moving out of the *Hukou* area was initially tightly controlled by the government and the regulation began to relax in the 1980s. The effect of the *Hukou* reform was more dramatic in coastal destinations and major cities (Tombe & Zhu 2019), which is consistent with our calculation where the migration costs changed more for coastal destinations. Until 2003, many cities had eliminated the requirement for temporary residence certificates, but migrants were still denied most of the access to social welfare in the destination city. Second, the emergence of China's railway has significantly reduced travel costs, and our calibrated cost changes also capture the changes in travel costs.

2.5.3 Other Parameter Values

There are nine additional sets of parameter values we need to calibrate to solve the model. We calculate β_s, the share of income spent on sector s, as the ratio of total consumption on goods from sector s across all countries and provinces to the world total income. We match the 2005 China's Annual Survey of Industrial Firms (ASIF) with the 2005 Customs Database to compute sectoral value added shares $\lambda^L_{l(m),s}$ for processing and ordinary firms. We draw cost shares of inputs $\lambda^k_{l(m),s}$ from China's input-output tables, and rescale value added shares for processing and ordinary firms such that the export-weighted average of value added shares in each sector matches the one in the input-output tables. We obtain foreign countries' value added shares $\lambda^L_{n,s}$

Table 2.3: Other Parameter Values

Parameter	Definition	Source	Value
σ	Elasticity of substitution across varieties	Head & Mayer (2014)	4
θ	Trade elasticity	Simonovska & Waugh (2014)	4
$\lambda^L_{l(m),s}$	Value added share (China)	ASIF, Customs, China I/O Table	
$\lambda^k_{l(m),s}$	Intermediate input share (China)	ASIF, Customs, China I/O Table	
$\lambda^L_{n,s}$	Value added share (foreign)	OECD I/O Table	
$\lambda^k_{n,s}$	Intermediate input share (foreign)	OECD I/O Table	
β_s	Sector consumption share	OECD I/O Table	
α	Agglomeration elasticity	Combes & Gobillon (2015)	0.05
κ	Labor supply elasticity	Tombe & Zhu (2019)	1.5

and cost shares of intermediate inputs $\lambda^k_{n,s}$ from OECD input-output tables.[40] We summarize the values and sources of other parameters in Table 2.3.

2.5.4 Model Fit

Before taking our model to perform counterfactual exercises, we compare our model-predicted changes in province-sector employment by processing and ordinary regimes to those in the data. We introduce the changes in China's export and import tariffs between 2000 and 2005 into our model and calculate the changes in employment resulting from the tariff changes. Using the merged ASIF-Customs data for 2000 and 2005, we measure the actual changes in the overall province-sector employment by processing and ordinary exporters.[41]

Table 2.4 reports the regression results of the model-generated and actual changes in province-sector employment on tariff changes separately by processing and ordinary exporters. Although all coefficients only reflect the raw correlation between tariff and employment changes, we take the similarity between the model and the data as suggestive evidence that our model is able to capture the heterogeneity in province-sector employment changes.

[40]We calculate $\lambda^k_{n,s}$ as the ratio of intermediate inputs from sector k to total output in sector s for each country, and then take the average over all countries. We calculate the value added share as $\lambda^L_{n,s} = 1 - \sum_k \lambda^k_{n,s}$.

[41]We compute firms' ordinary (processing) employment using their total employment and the share of ordinary (processing) exports in their total sales.

Table 2.4: Province-Sector-Level Employment and Tariff Changes between 2000 and 2005

Dependent variable	Changes in employment ordinary exporters		Changes in employment processing exporters	
	data	model	data	model
Panel A: import tariff changes between 2000–2005				
import tariff changes	-1.680*	-2.133***	-3.971***	-3.311***
	(0.854)	(0.346)	(1.397)	(0.548)
Obs	380	380	306	299
R-squared	0.012	0.113	0.044	0.111
Panel B: export tariff changes between 2000–2005				
export tariff changes	-7.054***	-10.375***	-10.403**	-11.788***
	(2.530)	(0.425)	(3.990)	(0.884)
Obs	380	380	306	299
R-squared	0.012	0.243	0.029	0.137

Notes: Changes in tariffs are defined as $\frac{1+t_{k,2005}}{1+t_{k,2000}}$, where $t_{k,t}$ is the tariff rate at time t for sector k. As changes in export tariffs are destination-specific, we use the average change of export tariffs across all destination markets as independent variables in the regression. Changes in employment are defined following Davis & Haltiwanger (1992). We perform the regressions across 30 provinces and 16 manufacturing sectors. Regressions are weighted by the initial employment size in year 2000. Standard errors are in parenthesis and clustered by province. Significance levels: 10% * 5% ** 1% ***.

2.6 Quantitative Effects of Trade and Migration Policies in China

We first show the extent to which each policy promoted China's export surge between 1990 and 2005. After that, we decompose the impact of the policies into four different margins of trade, and we present the quantitative results on how each policy affected the number of China's exporting firms. Finally, we show that our model predictions align with empirical evidence on firm relocation. Appendix B.5 presents additional quantitative results using an alternative model with firm entry.

2.6.1 China's Export Surge

We introduce the three measured policy changes (tariffs on imports, tariffs on exports, and internal migration barriers) to our model individually and attribute the residual of the observed export growth to changes in $\bar{A}_{l(m),s}$ and $d_{l(m),n,s}$.

Aggregate Impact on Exports: Panel A of Table 2.5 shows the impact of each shock on annual export growth rates in percentage points. The last column shows the average annual growth rate between 1990–2005. On the national level, reductions in migration barriers led to a 1.29 p.p. increase in annual export growth rate and accounted for $\frac{1.29}{17.8} \approx 7.2\%$ of the overall export growth during this period. Reductions in import tariffs caused a 2.30 p.p. increase in annual export growth rate and accounted for $\frac{2.30}{17.8} \approx 12.9\%$ of the overall export growth. Changes in export tariffs resulted in a 1.48 p.p. increase in annual export growth rate and accounted for $\frac{1.48}{17.8} \approx 8.3\%$ of the overall export growth. $\frac{12.73}{17.8} \approx 71.5\%$ of China's export surge was explained by changes in $\bar{A}_{l(m),s}$ and $d_{l(m),n,s}$.

Panel B of Table 2.5 reports the results for Chinas three major exporting provinces, Guangdong, Shanghai, and Jiangsu. These three provinces combined accounted for about 70 percent of China's overall exports in 2005. Reductions in migration barriers led to the most notable export increases in Guangdong and Shanghai, causing an increase of 4.00 p.p. in annual export growth in Guangdong and of 2.36 p.p. in Shanghai. They explained $\frac{4.00}{17.1} \approx 23.4\%$ and $\frac{2.36}{18.4} \approx 12.8\%$ of the entire export growth between 1990 and 2005 for these two provinces respectively. These results are consistent with the fact documented in Section 2.1 that a large fraction of manufacturing employment in Guangdong and Shanghai were supplied by internal migrants in 2005.

Because provinces differed in their sector composition, the impact of reductions in import and export tariffs varied systematically across provinces in each case. We find that the impact of changes in import and export tariffs was slightly larger in Guangdong, where these changes caused an increase of $2.34 + 1.90 = 4.24$ p.p. in annual export growth. In Shanghai and Jiangsu, changes in import and export tariffs led to an increase of $1.75 + 1.26 = 3.01$ and $1.83 + 1.63 = 3.46$ p.p. in annual export growth respectively.

Table 2.5: The Impact of Policies on Annual Export Growth Rates, in Percentage Points

	Migration	Import Tariff	Export Tariff	Residual	Annual Growth Rate
	Panel A: Impact on national exports				
China	1.29	2.30	1.48	12.73	17.8
	Panel B: Impact on provincial exports				
Guangdong	4.00	2.34	1.90	8.86	17.1
Shanghai	2.36	1.75	1.26	13.03	18.4
Jiangsu	0.38	1.83	1.63	22.86	26.7

Notes: In each counterfactual, we obtain proportional changes of exports denoted as $\widehat{\text{export}} = \frac{\text{export volume observed in 2005}}{\text{export volume in counterfactual}}$. We then calculate each value in columns 2–4 as $\left(\widehat{\text{export}}^{\frac{1}{15}} - 1\right) \times 100$.

Processing and Ordinary Exports: We break down China's export increases by processing and ordinary regimes and display the results in Table 2.6. We highlight three findings below.

First, changes in migration barriers had a larger impact on processing exports than on ordinary exports at the national level. Reductions in migration barriers caused a 1.48 p.p. increase in annual growth of processing exports, in comparison with a 1.05 p.p. increase in annual growth of ordinary exports. Although the domestic value added share was higher in ordinary production than in processing production (Kee & Tang 2016), the larger impact on processing exports was primarily driven by the fact that migrants employment shares were much larger in processing-oriented sectors than in sectors that were less concentrated in export processing. Driven by this fact, we find that reductions in migration barriers had a larger impact on processing exports than on ordinary exports in Guangdong, in line with Guangdong's large migrant employment in processing-oriented sectors (documented in Section 2.1.1). However, in Jiangsu and Shanghai, we find that the impact on ordinary exports was larger than on processing exports.[42]

Second, import tariff reductions had a larger impact on ordinary exports than on processing exports at both the national and provincial levels. This is consistent with the fact that ordinary production was impacted by reductions in nominal tariffs, whereas the imported materials for

[42]This result is driven by higher value added shares in ordinary production than in processing production.

Table 2.6: The Impact of Policies on Annual Export Growth Rates by Processing and Ordinary Trade, in Percentage Points

	Processing Share (2005)	**Migration**		**Import Tariff**		**Export Tariff**	
		Ordinary	Processing	Ordinary	Processing	Ordinary	Processing
		Panel A: Impact on national exports					
China	54.7%	1.05	1.48	2.67	2.03	0.55	2.32
		Panel B: Impact on provincial exports					
Guangdong	73.5%	3.51	4.20	2.90	2.13	0.38	2.59
Shanghai	57.2%	2.93	2.02	3.26	0.93	0.42	1.89
Jiangsu	66.7%	0.43	0.35	2.55	1.51	0.38	2.35

Notes: We calculate percentage points as $\left(\widehat{\text{export}}^{\frac{1}{15}} - 1\right) \times 100$, where $\widehat{\text{export}}$ is the proportional changes of export volume between the observed equilibrium and the counterfactual.

processing exporters were previously duty-free and thus unaffected by these reductions in nominal tariffs. On the national level, import tariff reductions caused a 2.67 p.p increase in annual growth rate of ordinary exports. Differing from the partial equilibrium approach in Brandt & Morrow (2017), our general equilibrium approach also predicts a 2.03 p.p. increase in annual growth of processing exports due to reductions in import tariffs. This difference is due to input-output linkages and equilibrium wage changes in response to import tariff reductions (similar to Ossa 2014).

Third, the impact of export tariff reductions operated mostly through promoting processing exports. On the national level, export tariff reductions caused a 2.32 p.p. annual growth rate of processing exports, in comparison to a 0.55 p.p. annual growth rate of ordinary exports. We find similar patterns in Guangdong, Shanghai, and Jiangsu. The results are driven by the fact that relative to ordinary producers, processing producers were more concentrated in sectors that experienced large export tariff reductions.

2.6.2 The Margins of Trade

We next break down the impact of each policy into four margins. In Table 2.3, we introduce three different sets of parameters for θ, γ, and ρ to isolate the effect of these margins of trade, while holding all other parameter values at their baseline levels. We calibrate all the versions of our model to the year 2005. We first set $\theta \equiv \sigma - 1 = 3$, $\gamma = 0$, and $\rho = 0$ and introduce each shock individually. This exercise examines the impact of policies on exports due to the *intensive margin* of trade. We then use the second set of parameters of $\theta = 4$, $\gamma = 0$ and $\rho = 0$ and introduce shocks individually. This exercise is used to quantify the *intensive* and *extensive margins* of trade. Note that the results from this exercise are equivalent to the ones predicted by a multi-sector Melitz-Chaney model with exogenous entry. Comparing the results under the second set of parameters ($\theta = 4$) with the results under the first set of parameters ($\theta = 3$), we isolate the *extensive margin* of trade. We then implement the third set of parameters $\theta = 4$, $\rho = 0.81$, and $\gamma = 0$. By changing ρ to 0.81 from 0, we isolate the effect of the *export-regime margin*. Finally, comparing the results of the third set of counterfactuals with our baseline results shown in Table 2.5, we isolate the impact on exports due to the *new-firm margin*.

For each set of parameters, Table 2.7 reports the impact of each policy on annual export growth rates in terms of percentage points. The first three rows report the impact of migration shocks, import tariff reductions, and export tariff reductions, respectively. The last row reports the combined impact of all three policies, by simply presenting a sum of the values in each column. A noteworthy result is that comparing column (3) with column (4), the *new-firm margin* of the three policies combined triggered a $5.07 - 2.87 \approx 2.20$ p.p. annual increase in China's exports and accounted for $\frac{2.20}{17.8} \approx 12.4\%$ of the overall national export growth. In other words, holding the number of firms constant in each province, the combined contribution of the three policies to Chinas export growth would drop from 28.5% to 16.1%. We present provincial results in Appendix Table B.4.

Next, in Figure 2.5, we decompose the impact of each policy on exports into four margins

Table 2.7: The Impact of Policies on National Annual Export Growth Rates by Different Margins of Trade, in Percentage Points

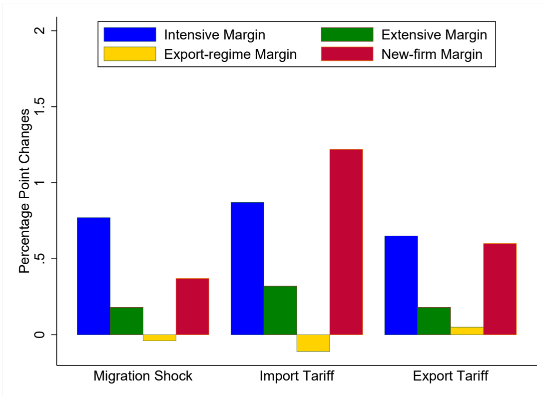
Policy Shock	Intensive Margin $\theta=3$, $\gamma=0$, $\rho=0$ (1)	Intensive & Extensive Margin $\theta=4$, $\gamma=0$, $\rho=0$ (2)	Intensive, Extensive & Regime Margin $\theta=4$, $\rho=0.81$, $\gamma=0$ (3)	All Margins $\theta=4$, $\rho=0.81$, $\gamma=0.63$ (4)
Migration Shock	0.77	0.95	0.91	1.29
Import Tariff	0.87	1.19	1.08	2.30
Export Tariff	0.65	0.83	0.88	1.48
Combined Policies	2.29	2.97	2.87	5.07

Notes: We calculate percentage points as $\left(\widehat{\text{export}}^{\frac{1}{15}}-1\right)\times 100$, where $\widehat{\text{export}}$ is the proportional changes of export volume between the observed equilibrium and the counterfactual. Each value in the last row adds up the values of the first three rows along its column.

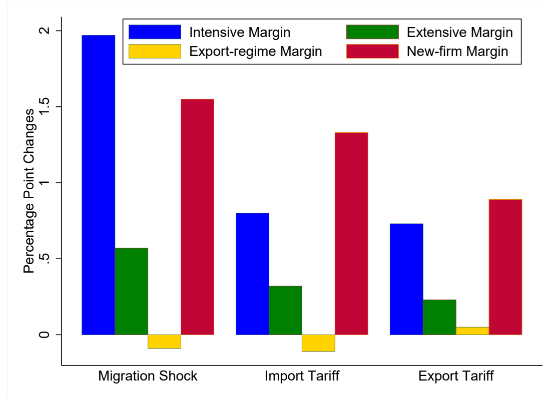
of trade. On the national level, presented in the upper left-hand Panel, the *new-firm margin* of trade (in red) had a pronounced impact on exports. This margin had the strongest impact in the case of import tariff reductions and caused a 1.22 p.p. annual increase in China's export growth. The migration-induced *new-firm margin* of trade was the smallest across all three policies, causing a 0.38 p.p. annual increase in national exports. The small impact of the *new-firm margin* resulting from internal migration suggests a strong offsetting effect due to firms' switching across provinces.[43]

For provinces, we find strong effects of the migration-induced *new-firm margin* in Guangdong, causing a 1.55 p.p. increase in annual export growth. The effect of the migration-induced *new-firm margin* was also substantial in Shanghai, leading to a 0.55 p.p. increase in annual export growth. However, we find small effects of the migration-induced *new-firm margin* in Jiangsu. As for import tariff reductions, the effects of the *new-firm margin* were substantial in all of Guangdong, Shanghai, and Jiangsu, causing a 1.33, 0.80, and 0.93 p.p. increase in annual export growth, respectively.

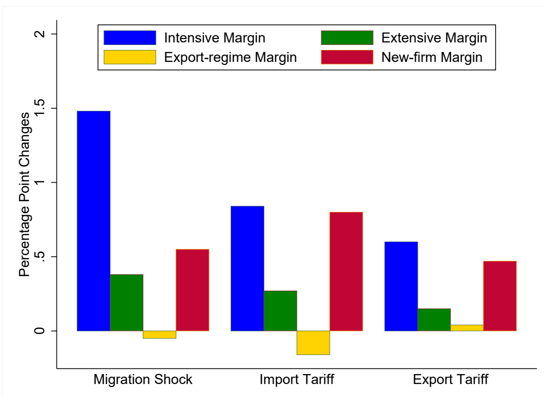
[43] We find that provinces which experienced a migration outflow or a relatively small migration inflow suffered a net outflow of firms.



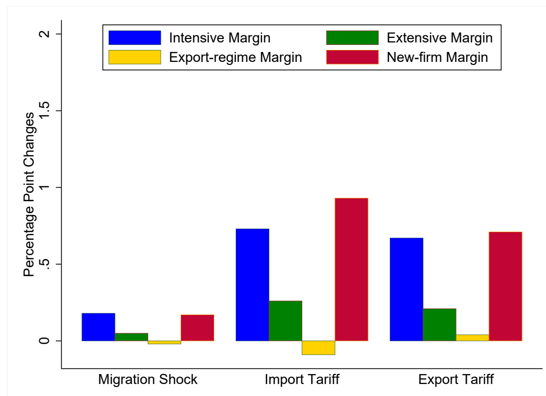
(a) China



(b) Guangdong



(c) Shanghai



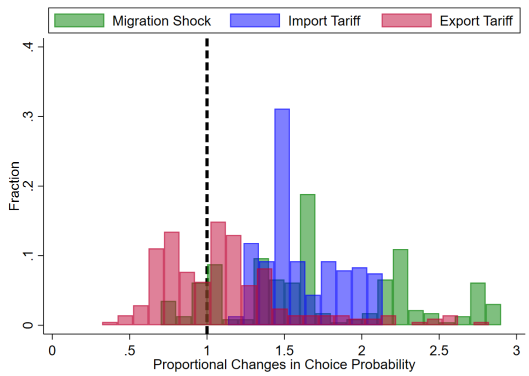
(d) Jiangsu

Figure 2.5: The Impact of Policies on Annual Export Growth Rates by Different Margins of Trade, in Percentage Points

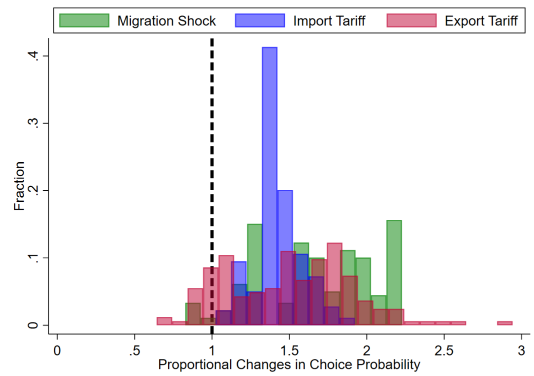
Notes: The intensive margin is obtained from Column (1) of Table 2.7. The extensive margin is obtained from the difference between Columns (2) and (1); the export-regime margin is obtained from the difference between Columns (3) and (2), and the new-firm margin is obtained from the difference between Columns (4) and (3).

2.6.3 The New-firm Margin

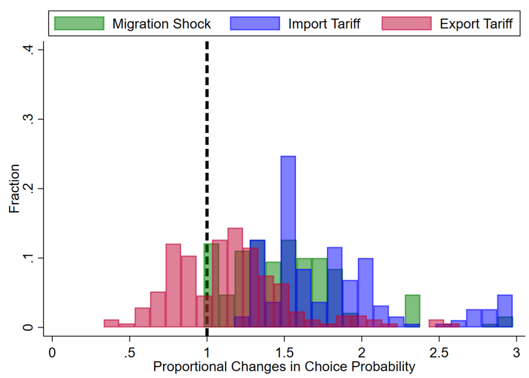
We further explore the extent to which each policy affected the number of exporting firms in China's coastal provinces. Figure 2.6 plots the histograms of $\widehat{P}\Big(Y = l(m)\Big)$, which are the proportional changes in firm's probability of choosing China's provinces and export regimes, across all foreign destinations and sectors. We plot the impact of migration shocks in green, the impact of import tariff reductions in blue, and the impact of export tariff reductions in red. Panels (a) and (b) show firms' likelihood of choosing ordinary and processing regimes in Guangdong respectively, while Panels (c) and (d) are for ordinary and processing regimes in Shanghai respectively. The vertical black dashed line indicates $\widehat{P}\Big(Y = l(m)\Big) = 1$.



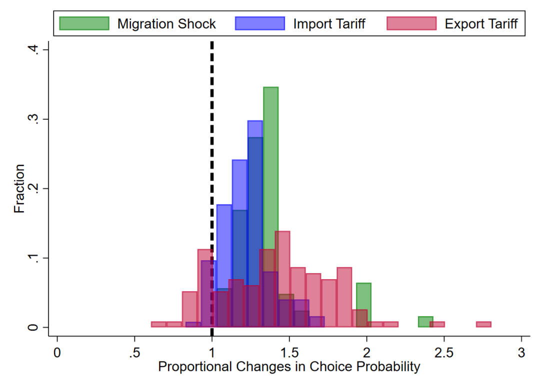
(a) Guangdong Ordinary Exporters



(b) Guangdong Processing Exporters



(c) Shanghai Ordinary Exporters



(d) Shanghai Processing Exporters

Figure 2.6: Changes in Firms' Probability to Choose China's Provinces and Export Regimes

Notes: The histogram is plotted across all foreign destinations and sectors where China's export volume was greater than 30 million US dollars. For the case of export tariffs, there are destination-sector pairs where $\widehat{P}\Big(Y = l(m)\Big)$ takes very large values (with probability density smaller than 0.05). We truncate the distribution such that $\widehat{P}\Big(Y = l(m)\Big)$ takes values smaller than 3.

One evident feature is that most areas of the histogram are located to the right of the vertical line, indicating that the policy changes attracted more exporting firms into China. We highlight some findings below. First, in both Guangdong and Shanghai, import tariff reductions had a stronger impact on attracting ordinary firms than processing firms, as the blue bars are more skewed to the right in Panels (a) and (c) in comparison with those in Panels (b) and (d), respectively. Second, reductions in migration barriers substantially attracted firms to relocate to Guangdong Province, and the impact was strong on both ordinary and processing exporters. Import tariff reductions appeared to be important in attracting ordinary firms to be located in Shanghai. Finally, export tariff changes had a relatively small impact on attracting firms to relocate to Guangdong and Shanghai. We plot the results for Zhejiang and Jiangsu provinces in Appendix Table B.8.

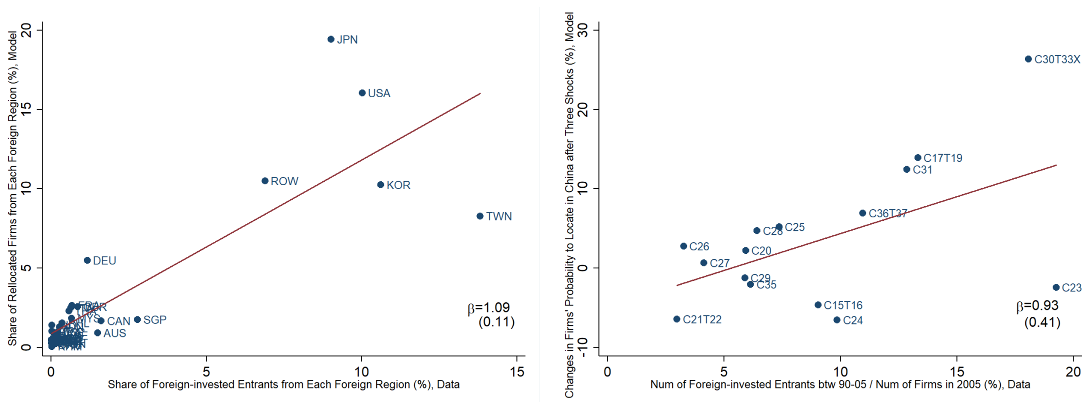
2.6.4 Evidence on Firms' Relocation

Although China has experienced a dramatic increase in foreign investments and inflows of production factories over the past 30 years, it is a challenge to distinguish between firm relocation and entry from our data. This section shows that our model-predicted origins of new firms align well with the data, which we take as suggestive evidence that our model can capture variation in the origin of new firms' majority owner.

We draw data from Chinese Ministry of Commerce to measure the number of new registered foreign-invested firms. Before 2016, all foreign-invested firms in China were required to obtain approval for registry and changes of business, and these requests were then publicized on the website. We collect all these raw data and use text analysis to identify information on firms' name, industry, and ownership structure.[44] Between 1990 and 2005, there were 102,072 new registrations of foreign-invested firms, which is similar to the 91,047 existing manufacturing foreign-invested firms in the Firm Census 2004.[45] Appendix Table B.5 presents the number of new foreign-invested firms between 1990 and 2005, ranked by sectors and places of origin. We identify the places of origin by the nationality of firms' majority owner.

[44] We keep manufacturing firms registered between 1990 and 2005 and define foreign-invested firms as firms with at least 30% foreign ownership. Our results are robust if we use thresholds of 0% or 50% to define foreign ownership. We do not use 50% as a threshold in the baseline results because for a long time, China requested individual firms' foreign ownership to be lower than 50% in many industries (e.g., automobile industry), especially before WTO accession.

[45] Across our 16 manufacturing sectors, the correlation between the number of foreign-invested entrants between 1990 and 2005 and the number of existing foreign-invested firms in 2004 is 0.95.



(a) Across Origins

(b) Across Sectors

Figure 2.7: Comparison of Model Predictions with Data on Foreign-invested Firms

We use our model to calculate the reduction in number of firms in each foreign region as a share of the increase in overall number of firms in China resulting from the reduction in trade and migration barriers. Panel (a) plots the model-predicted shares against the actual share of foreign-invested firms in China by origin between 1990–2005.[46] Panel (b) plots the model-predicted percentage changes in the number of firms by sectors against the observed changes.[47] Both plots show that our model can capture a reasonable amount of heterogeneity in terms of the origin of foreign firms, as well as at the sector level.

2.7 Conclusion

This paper quantifies how three policy reforms affected Chinese exports between 1990 and 2005. The rapidly increasing number of firms, which accompanied reductions in Chinese tariffs and internal migration costs, suggests that the entry of new firms induced by reductions in trade and migration barriers was an important source of China's export growth. We find that,

[46]We omit Hong Kong in the graph, as it invested hugely in mainland China because of its well-developed financial markets and shared border.

[47]We compute the change in firms' probability to locate in China for each destination-sector, normalized by the initial probability to locate in China. We use China's output sold to each destination-sector as weights to aggregate the changes to sectors. The negative change means that the sector experienced relocation of production from China to overseas resulting from the shocks.

together, the three policies explained around 29% of Chinas export surge between 1990 and 2005; holding the number of firms unchanged, the portion of Chinese export growth explained by the three policies combined would drop to 16%. In other words, overlooking the *new-firm margin* would cause substantial underestimation on the impact of these policy changes on China's export surge.

Differing from the standard Melitz model with endogenous firm entry, our model has an analytic trade elasticity decomposition for each margin of firm adjustment. While our empirical analysis validates that both the *new-firm* and *export-regime margins* exist in the data, it is our quantitative exercise and analytic trade elasticity decomposition that allow us to quantify the extent to which each policy reform impacted aggregate exports through each margin of firm adjustment. Because of the presence of the *new-firm* and *export-regime margins*, our model predicts a larger trade elasticity in response to trade costs than the standard trade model. The additional *new-firm margin* we analyze provides a potential channel to reconcile the small effects of trade liberalization predicted by standard trade models with the empirical evidence (e.g., Khandelwal et al. 2013, Feyrer 2019).

While our paper emphasizes the role played by the new firms in China's export surge, our decomposition results can be applied to several other questions in which the *new-firm margin* has the potential of playing an important role (e.g., transportation infrastructure). We look forward to address some of these questions in our future research.

2.8 Acknowledgements

Chapter 2 is currently being prepared for submission for publication and is couathored with Chen Liu. I would like to thank Chen Liu in particular for all the invaluable discussions. The dissertation author was a primary investigator of this material.

Chapter 3

Learning By Exporting and Wage Profiles: New Evidence From Brazil

3.1 Introduction

It is well-known that exporters are more productive than non-exporters. This could be driven by self-selection of the best firms into exporting activities, or by productivity improvements after exporting. In particular, Atkin et al. (2017) find that exporting improves firms' technical efficiency using a randomized experiment, and Loecker (2007) shows that firms' productivity gains after exporting may increase when firms export to high-income countries.[1] Whereas these existing studies mostly focus on firm-level outcomes, exporting may also impact workers. It is well-documented that workers earn higher wages in exporters than in non-exporters (Bernard & Jensen 1995). However, despite much attention to firm-level differences in life-cycle wage growth in recent studies (Herkenhoff et al. 2018, Jarosch et al. 2018, Gregory 2019),[2] little is known about how firms' exporting activities shape workers' life-cycle wage dynamics.

In this paper, we fill this gap. We rely on Brazilian linked employer-employee administrative data and customs records between 1994–2010, and assemble a long panel with detailed job information and firms' exporting activities. We document that workers' experience-wage profiles are steeper in exporters than in non-exporters. Aside from self-selection of better firms into exporting, we show that workers' experience-wage profiles are steeper when firms export to industrialized destinations. We discuss possible explanations and propose that this result is likely driven by faster human capital accumulation of workers in firms that export to advanced economies. To support our preferred hypothesis, we use the Enterprise Surveys and document that exporters are more likely to train workers than non-exporters, especially when they adopt foreign technology.

We begin our analysis by applying the standard approach to estimate workers' experience-wage profiles (Mincer 1974), regressing log hourly wage on dummies of experience bins, school-

[1]For more evidence on the comparison of productivity levels between exporters and non-exporters, see also Bernard & Jensen (1999), Aw et al. (2000), Van Biesebroeck (2005), Lileeva & Trefler (2010), and Aw et al. (2011).

[2]Herkenhoff et al. (2018) and Jarosch et al. (2018) study the effects of exposure to coworkers, and Gregory (2019) explores the impact of firm-specific human capital accumulation.

ing, time effects, and individual effects. The well-known challenge is that experience is collinear with time and individual fixed effects, making it impossible to separately identify experience and time effects. To solve this problem, we apply Heckman et al. (1998) approach (HLT) , following Lagakos et al. (2018). The centerpiece of this approach is to assume no experience effects in the final working years, in order to isolate time effects from returns to experience. Applying this approach and controlling for industry composition, we show that after 20 years of experience, workers wage growth is 78% in non-exporters and 96% in exporters, indicating a sizeable difference of 18 percentage points in life-cycle wage growth between exporters and non-exporters.

To understand what drives the difference in experience-wage profiles between exporting and non-exporting firms, we further construct firm-year-level experience-wage profiles based on the HLT method's assumption that old workers' wage growth purely comes from time effects. We obtain two main results. First, productivity proxies and firm fixed effects explain most of the differences in experience-wage profiles between exporters and non-exporters, hinting that exporters essentially provide higher returns to experience. Second, after controlling for firm size, labor composition, and firm fixed effects, workers life-cycle wage growth is higher in firms exporting to industrialized destinations than in non-exporters, whereas firms exporting to non-industrialized destinations do not enjoy similar increases. We also find that this increase in returns to experience materializes immediately following firms' entry into industrialized destinations, yet it does not show up before entry.

It is possible that destination-specific returns still originate from firms' selection into exporting, as firms may have workforce improvements prior to exporting. To lessen this concern, we conduct an event study using the 1999 currency devaluation episode, which led to a quasi-experimental surge in Brazilian firms' exporting activities. We focus on non-exporters prior to the devaluation shock. We find that firms exporting to industrialized destinations after this devaluation experienced a large jump in their experience-wage profiles after exporting, whereas firms exporting to non-industrialized destinations did not.

We discuss four possible explanations for our destination-specific effect: (1) selection of firms into different export destinations; (2) differential changes in labor composition; (3) job search and screening; and (4) human capital accumulation. Although we cannot entirely rule out other hypotheses, we construct a set of robustness checks and show that faster human capital accumulation when exposed to advanced destinations is the most likely hypothesis.

Anecdotal evidence, based on interviews to leading exporters in Latin America,[3] supports our hypothesis of human capital accumulation. These interviews show that exports to different types of markets imply very different hurdles. As Artopoulos et al. (2010) note, "successfully entering markets in developed economies with differentiated products requires potential exporters to make substantial efforts to upgrade the physical characteristics of their products and to make their marketing practices more sophisticated" (p. 6). With sophisticated technology and demanding customers, firms exporting to advanced destinations often need to invest in the capability of the workforce, in conjunction with specific training institutes or through on-the-job training provided by the firm.

We go beyond those exporters' experiences and provide direct evidence on the relationship between exporting, human capital accumulation and technology adoption, using the World Bank Enterprise Surveys for more than 100 countries. We find that exporters are more likely to offer on-the-job training than non-exporters, after controlling for firm size, industry, country, and year fixed effects. Therefore, human capital accumulation seems to drive at least a portion of the steeper experience-wage profiles in exporters. We also find that exporters which adopt foreign technology are more involved in training workers than exporters who do not. This indicates that destination-specific effects may originate from advanced knowledge that enhances human capital, in line with anecdotal evidence from interviews.

[3]The interviews were conducted by the Inter-American Development Bank under the project "The Emergence of New Successful Export Activities in Latin America," aiming to provide the experience of some leading exporters in Latin American countries. These studies include exporters in Brazil (Rocha et al. 2008), Argentina (Artopoulos et al. 2010), Chile (Agosin & Bravo-Ortega 2009), and Uruguay (Snoeck et al. 2009).

Our analysis of exporting and life-cycle wage growth has important aggregate implications. Through the lens of our empirical results, trade liberalization affects workers' life-cycle earnings growth by reallocating labor toward better firms and exposing workers to advanced destinations. This dynamic effect on workers' earnings, if overlooked, would lead researchers to underestimate the impact of trade liberalization on workers' welfare and income inequality. Moreover, the interaction between life-cycle wage growth and advanced destinations suggests that trade may disproportionately benefit workers' human capital in poor countries, providing support to export promotion policies in those economies.

This paper relates to several strands of the literature. We directly contribute to the large literature on learning by exporting. Recent research shows that through acquiring new knowledge from exporting, firms could improve their technical efficiency (Aw et al. 2000, De Loecker 2013, Atkin et al. 2017) or understanding of export demand (Albornoz et al. 2012, Morales et al. 2019). Few studies explore how workers may also acquire knowledge from exporting. Exceptions are Mion & Opromolla (2014) and Muendler & Rauch (2018) who find that employees' previous experience in exporting firms is valuable for their new employers' choices of export markets. In contrast with these studies, we look into how exporting activities affect workers' life-cycle wage growth within the firm. Our results indicate that exporting may enhance workers' human capital, especially with exposure to advanced export destinations.

Second, we make contact with research on trade and workers' earnings. Much empirical work finds wage differences between exporters and non-exporters but abstracts from experience effects (e.g., Bernard & Jensen 1995).[4] Our evidence shows that the exporter wage premium increases with workers' experience and relies on export destinations. A few recent studies explore how trade openness affects wage growth. Our paper relates to Dix-Carneiro (2014) who estimates industry-specific returns to experience in Brazil to study welfare gains of trade liberalization. Our

[4] The literature finds that the exporter wage premium is composed of differences in labor composition and wage premia for workers with identical characteristics, including Schank et al. (2007), Frias et al. (2009), and Krishna et al. (2014). These existing studies abstract from workers' experience effects.

results imply that between-firm labor reallocation and interacting with export destinations amplify the effects of returns to experience on gains from trade. Our paper also relates to Fajgelbaum (2019) who quantitatively finds higher wage growth in exporters, due to wage renegotiations and increased job surplus after exporting. Our evidence shows that human capital accumulation may also induce higher wage growth in exporters, especially when exposed to advanced destinations.[5]

Third, we relate to research on life-cycle wage profiles. The literature has shown that workers' life-cycle wage growth is heterogeneous across firms, due to factors such as job search (Bagger et al. 2014), coworkers (Herkenhoff et al. 2018, Jarosch et al. 2018), and firm-specific learning (Gregory 2019).[6] To our knowledge, our study is the first to empirically study the role of firms' exporting activities. Recent studies highlight the importance of life-cycle wage growth in accounting for cross-country income differences (Lagakos et al. 2018). Our results imply that incentivizing exporting in poor countries may reduce the cross-country income gap.

Finally, we connect with the literature on international knowledge diffusion. Many studies use macro aggregates, such as TFP and R&D, and empirically link trade with knowledge diffusion (e.g., Coe & Helpman 1995), as reviewed in Keller (2004). Our results highlight that workers human capital accumulation may reflect trade-induced knowledge flows. Recent theoretical papers also explore the relation between trade-induced knowledge diffusion and firm productivity growth (e.g., Alvarez et al. 2013, Perla et al. 2015, Sampson 2016, Buera & Oberfield 2020).[7] Alvarez et al. (2013) and Buera & Oberfield (2020) show that interacting with sellers from more productive countries induces larger knowledge diffusion in domestic markets, whereas our results imply that knowledge diffusion may also originate from exporting to more productive destinations.

[5]Fajgelbaum (2019) abstracts from human capital, and the effects of exporting on wage growth rely on wage renegotiations and export revenue. However, we find that export revenue cannot explain our destination-specific effects, suggesting that other factors also matter. Another difference is that Fajgelbaum (2019) abstracts from workers' age, and therefore wage growth may reflect common trends which do not exactly correspond to life-cycle wage growth studied in this paper.

[6]Besides firm-level factors, Islam et al. (2019) show that a lot of factors, such as sectors, occupations, and Internet penetration, are associated with returns to experience.

[7]See Lind & Ramondo (2019) for a review.

This paper is organized as follows. Section 3.2 describes our findings on experience-wage profiles for exporters and non-exporters, and highlights the interaction between wage profiles and export destinations. Section 3.3 exploits the Brazilian currency crisis to address the endogeneity issue of exporting. Section 3.4 discusses possible explanations for the destination-specific effect. Section 3.5 provides evidence on training and foreign technology adoption for exporters, using firm-level data from more than 100 countries. Section 3.6 concludes.

3.2 Experience-Wage Profiles and Exporting

In this section, we present a set of stylized facts on how exporting affects experience-wage profiles in Brazil. Section 3.2.1 describes the data, and Section 3.2.2 shows the cross-sectional pattern of experience-wage profiles. Section 3.2.3 discusses the identification challenges and provides our method to apply Mincer regressions to formally estimate experience-wage profiles. Sections 3.2.4 to 3.2.6 report our main findings on differences in experience-wage profiles between exporters and non-exporters, and highlight that experience-wage profiles are steeper when firms export to industrialized destinations.

3.2.1 Data

Our analysis focuses on Brazil, which constitutes a good case study for several reasons. First, Brazil has great data availability and quality, as this subsection shows. Second, the Brazilian case is typical of developing countries, especially in Latin America, and thus our analysis is relevant for policy making. Third, Brazilian exporters sell to a wide range of destinations, allowing the exploration of how export destinations shape experience-wage profiles. For example, in 2010, Brazil's exports were not only directed to high-income countries (10% of total exports sold to the U.S., 25% to Europe, and 4% to Japan), but also to middle-income and low-income countries (23% to Latin America, 15% to China, and 10% to Middle East and Africa). Appendix

C.1 describes details of the Brazilian economy, export trends, export products, and destination markets over our sample period.

We rely on the RAIS (Relao Anual de Informaes Sociais of Brazilian labor ministry MTE) database with comprehensive linked employer-employee information in Brazil between 1994–2010. It provides a complete depiction of workers employed in the Brazilian formal sector, because firms are mandated (by law) to annually provide workers' information to RAIS (Menezes-Filho et al. 2008).[8] Each datapoint represents a worker-firm-year observation, containing worker ID, firm ID, and workers information on schooling, age, hourly wage, occupations, and other demographic indicators. These data provide a great laboratory to study returns to experience in the Brazilian formal sector.

One limitation of the data is the absence of information about the informal sector. Therefore, appropriate caution is necessary to interpret our empirical findings from RAIS. Appendix C.2 discusses the characteristics of the Brazilian informal sector and shows that including informal workers in the sample may strengthen our empirical results.[9]

Because we are mainly interested in the interaction between experience-wage profiles and exporting, we restrict our empirical analysis to manufacturing industries, which are tradable and extensively studied in the firm literature. In addition, we focus on full-time male workers aged between 18–65 and employed in firms with the number of employees (including females and part-time workers) larger than 10.[10] If a worker has multiple records in a year, we select the

[8]The ministry of labor estimates that above 90% of formally employed workers in Brazil were covered by RAIS throughout the 1990s. The data collection is typically concluded by March following the year of observation (Menezes-Filho et al. 2008). One benefit of this data is that the reports are substantially accurate. This accuracy stems from the fact that workers' public wage supplements rely on the RAIS information, which encourages workers to check if information is reported correctly by their employers.

[9]Another important limitation is the possible inconsistency in correctly reporting the workers ID number (PIS). Firms may choose to fire and rehire a worker several times throughout any given year to allow the worker to withdraw unemployment benefits multiple times in a single year. This phenomenon may lead companies to incorrectly or repeatedly report a workers ID.

[10]The restrictions on full-time male workers follow Lagakos et al. (2018), due to large changes in female labor participation rate over time. According to the World Bank's estimates for those aged 15+ in Brazil, female labor force participation rate increased from 45% in 1994 to 54% in 2010, whereas male labor force participation rate changed from 81% to 77%. The restriction on firm size aims to avoid the issues of self-employment.

record with the highest hourly wage (Dix-Carneiro 2014). Under these restrictions, we obtain a sample of 71,748,105 observations between 1994–2010, including 16,629,730 unique worker IDs and 228,890 unique firm IDs.

We use firm IDs to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX (Secretaria de Comrcio Exterior) for the years 1994–2010, following Aguayo-Tellez et al. (2010). We define a firm as an exporter in a given year if the firm has at least one export transaction in that year. Moreover, we divide destinations into industrialized and non-industrialized regions based on the classification provided in Appendix C.3. The SECEX data for the years 1997–2000 also provide firm-level export quantity and value (U.S.$) by 8-digit HS products and destinations. This allows us to measure the structure of export destinations in more detail for these years, which will be used for robustness checks. We discuss more details of the data in Appendix Section C.3.

Table 3.1 describes characterizations of the RAIS database, based on worker-firm-year observations. On average, workers in exporters are slightly older and more educated, earn higher hourly wages, and tend to work in cognitive occupations, relative to non-exporters. Moreover, exporters are much larger in terms of employment size than non-exporters. These pieces of evidence are consistent with the exporter premium typically found in the literature (e.g., Bernard et al. 2003, Verhoogen 2008). Finally, 49% of workers in the sample stay in exporters, and therefore exporting activities are nontrivial in our sample.

Panel B of Table 3.1 also characterizes dynamic features of the database. Several features stand out. First, the average duration per worker-firm link is 2.78 years, with an average worker working for 1.55 firms in the database. The low duration of the average worker in the sample ($2.78 \times 1.55 = 4.31$ years) is driven by workers switching into industries other than manufacturing or the informal sector, and by young workers entering the workforce in later periods of the sample. Second, we find that 33% of jobs are destroyed after one year—either by workers' switching to another firm or exiting the database entirely. Finally, we also compute firms' transition matrix and

Table 3.1: Sample Statistics

Panel A: Cross-Sectional Characteristics

Observations (72 million)	Non-exporter		Exporter	
	Mean	S.D.	Mean	S.D.
workers' characteristics:				
age	31.97	9.72	32.78	9.39
schooling	8.23	3.46	9.06	3.77
log(hourly wage), Brazilian Real$	0.67	0.77	1.20	0.96
cognitive occupations (1 if yes)	0.20	0.40	0.25	0.43
share of workers in the sample	0.51	–	0.49	–
firms' characteristics:				
log(employment)	4.51	1.56	7.05	1.71
by destinations:				
industrialized regions	–	–	0.06	–
non-industrialized regions	–	–	0.19	–
both types of regions	–	–	0.75	–
log(exports per worker), U.S.$	–	–	8.09	2.31

Panel B: Dynamic Characteristics

Observations (72 million)	Mean	S.D.		Mean
duration of worker-firm links (years)	2.78	2.76		
num of firms per worker	1.55	0.96		
by worker: probability (t to t+1)				
same firm	0.67	–		
different firm	0.06	–		
exit	0.27	–		
by firm: probability (t to t+1)				
non-exporter: to non-exporter	0.84		exporter: to non-exporter	0.11
to exporter	0.05		to exporter	0.84
exit	0.11		exit	0.05

Note: Because Brazil experienced large inflation during the sample period, we adjust log(hourly wage) for inflation using 1994 as the baseline year. The inflation data are drawn from Penn World Table 9.0 (Feenstra et al. 2015). Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. The export value data are only available in 1997–2000, and hence log(exports per worker) are based on these four years. In computing firms' switching probabilities, we weight switching statuses between years t and $t+1$ by firm employment size at year t. This aims to be consistent with workers' and firms' statistics, which are computed based on firm-worker-year observations.

find that firms' statuses are stable, with 84% of exporters remaining exporters after one year.[11]

[11] The exit rates for manufacturing firms include the probability of them becoming nonmanufacturing firms or having employment size less than 10. In non-exporters' exit rates (0.11), 0.07 is due to becoming nonmanufacturing firms or having employment size less than 10. In exporters' exit rates (0.05), 0.02 is due to becoming nonmanufacturing firms or having employment size less than 10.

3.2.2 A First Glance at Experience-Wage Profiles

Using the raw data, we first show differences in experience-wage profiles between exporters and non-exporters in the cross section. We measure workers' potential experience as years elapsed since finishing schooling (min{age-18,age-6-educ}). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5-year experience bin $x \in X = \{1\text{–}5, 6\text{–}10, ..., 36\text{–}40\}$, separately for workers observed in exporting and non-exporting firms. Because we are interested in life-cycle wage growth, we normalize the value of the first experience bin (1–5 years of experience) to be 0 for each experience-wage profile. Finally, we average profiles across years to obtain experience-wage profiles for exporters and non-exporters, respectively.

In Table 3.2, we report the average log wage for workers with 36–40 years of experience relative to 1–5 years of experience (normalization). Column (1) in Panel A shows that, in exporters (non-exporters), the average log wage of workers with 36–40 years of experience is 0.74 (0.49) higher than workers with 1–5 years of experience.[12] This pattern holds in different time periods (Columns (2)–(3)). More notably, it is not caused by lower starting wages of workers in exporters. In the last two columns of Panel A, we recompute the average log wage of each experience bin relative to workers with 1–5 years of experience in non-exporters for any given year. We find that workers with 1–5 years of experience already have higher wages in exporters than in non-exporters. This gap grows larger as workers' experience increases.

In light of potential composition effects (exporters are larger and have better workforce), in Panels B to D of Table 3.2, we recompute the result in Column (1) of Panel A within the same workers' education levels, occupations, or firm size categories. Consistent with recent papers (Islam et al. 2019, Lagakos et al. 2018), we find that the experience-wage profile is steeper for

[12] Our results are comparable to Lagakos et al. (2018) who use Brazilian Population Census and document that the percent wage increase of 36–40 years of experience relative to 1–5 years of experience is around 60% (see Figure 1 in Lagakos et al. (2018)).

Table 3.2: Average Log Wage of Workers with 36–40 Yrs of Exp Relative to 1–5

	(1)	(2)	(3)	(4)	(5)
	Panel A: Aggregate profiles				
				Rel. to non-exporters' first bin	
	all	1994–2000	2001–2010	first bin	40 years of exp
Exporter	0.74	0.67	0.79	0.29	1.04
Non-Exp	0.49	0.48	0.51	0	0.50
Difference	0.25	0.19	0.28	0.29	0.54
	Panel B: Aggregate profiles by education level				
	illiterate	primary	middle school	high school	college
Exporter	0.22	0.69	0.84	1.29	1.43
Non-Exp	0.18	0.46	0.55	0.82	1.08
Difference	0.04	0.23	0.29	0.47	0.35
	Panel C: Aggregate profiles by occupation				
	professionals	technical	other white-collar	Skilled blue-collar	unskilled blue-collar
Exporter	1.10	0.99	0.52	0.57	0.23
Non-Exp	0.85	0.71	0.34	0.44	0.16
Difference	0.25	0.28	0.18	0.13	0.07
	Panel D: Aggregate profiles by firm size				
	10-50	50-100	100-500	500-1000	1000+
Exporter	0.55	0.61	0.69	0.77	0.81
Non-Exp	0.43	0.50	0.59	0.58	0.47
Difference	0.12	0.11	0.10	0.19	0.34

Note: This table reports the average log wage for workers with 36–40 years of experience relative to 1–5 years of experience (normalization). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5–year experience bin, separately for workers observed in exporters and non-exporters. We normalize the value of the first experience bin (1–5 years of experience) to be 0 for each experience-wage profile. Finally, we average profiles across years to obtain experience-wage profiles for exporters and non-exporters, respectively. Columns (4)–(5) of Panel A use the average log wage of workers with 1–5 years of experience in non-exporters as normalization.

workers with higher education levels (Panel B), in cognitive occupations (Panel C),[13] and in larger firms (Panel D). Moreover, we find that within all of these categories, workers have higher life-cycle wage growth in exporters than in non-exporters.

There are many identification problems with this first-pass attempt: for example, workers observed in exporters in a given year may have previously accumulated working experience in non-exporters in their earlier career. Nonetheless, the preliminary evidence from the raw data indicates that workers in exporters may have steeper experience-wage profiles than workers in non-

[13]Cognitive occupations refer to professionals, technicians, and other white-collar workers.

exporters. With this suggestive pattern in mind, we proceed to formally estimate experience-wage profiles.

3.2.3 Experience-Wage Profiles: Estimation Method

We estimate experience-wage profiles by Mincer regressions, following the labor literature (e.g., Deaton 1997, Lagakos et al. 2018). We restrict our sample to workers in the same firm for two consecutive years, as there may be imperfect portability of human capital across firms and wage gains/losses related to job separations. We estimate the following regression:

$$\Delta \log(w_{it}) = \sum_{x \in X} \phi_s^x D_{it}^x + \beta_s \Delta e_{it} + (\gamma_{st} - \gamma_{st-1}) + \varepsilon_{it}, \tag{3.1}$$

where i and t represent individuals and years respectively. The subscript s is the level of aggregation for estimating experience effects (e.g., industries, exporters and non-exporters), which will be specified in later implementation. $\Delta \log(w_{it})$ denotes log hourly wage growth from $t-1$ to t for an individual i within the same firm. By using a difference in log hourly wages within the same firm across two periods, we control for individual and firm fixed effects that affect wage levels, as in the employer-employee literature (e.g., Abowd et al. 1999, Card et al. 2013).[14]

D_{it}^x is a dummy variable that takes the value 1 if a worker's potential experience (min{age-18,age-6-educ}) is in group $x \in X = \{1\text{–}5, 6\text{–}10, ...\}$ at time t. The parameter ϕ_s^x measures wage growth for one year of experience accumulated in the experience group x. By avoiding a specific parametric function of experience effects, we allow returns of experience to nonparametrically differ across different stages of the life cycle.[15] We also control for changes in schooling, Δe_{it}, in all our regressions. In addition, γ_{st} represents time effects on wage levels at time t (e.g., TFP, price levels).

[14]Our setting also captures match-specific fixed effects affecting workers' wage levels.

[15]The nonparametric approach of modelling experience effects is commonly used (e.g., Lagakos et al. 2018). Given the large sample size of our data, we choose this approach that allows more precision. Another common way to model experience effects is to assume a quadratic functional form (e.g., De la Roca & Puga 2017).

Estimating Equation (3.1) faces the well-known collinearity problem regarding experience, individual effects, and time effects in the labor literature (Deaton 1997). This is easily seen as $\sum_x D_{it}^x = 1$ is perfectly correlated with the constant $(\gamma_{st} - \gamma_{st-1})$ for each aggregation level s and time t.[16] Intuitively, wage growth over time can be induced by experience or better aggregate economic conditions (e.g., TFP growth). Therefore, to disentangle returns to experience from aggregate trends, we must impose more structure into the model. First, we decompose time effects into trend and cyclical components:

$$\gamma_{st} = g_s t + e_{st}, \tag{3.2}$$

where g_s denotes linear time trends. Specially, we restrict cyclical components to average zero over the time period $\sum_t e_{st} = 0$ and to be orthogonal to the time trend $\sum_t e_{st} t = 0$. These two restrictions resolve the collinearity problem in Equation (3.1) and are also made in Deaton (1997) and Aguiar & Hurst (2013) in estimating life-cycle profiles.

To pin down the wage trend g_s, we adopt the HLT method in Lagakos et al. (2018). The method draws on the basic prediction of a large number of theories of life-cycle wage growth that there are little experience effects in the final working years.[17] Implementing the HLT approach requires assumptions on two parameters: the number of years with no experience effects, and the depreciation rate. Following Lagakos et al. (2018), we consider 10 years at the end of the working life (31–40 years of experience) with no experience effects and a 0% depreciation rate. We conduct our estimation of Equation (3.1) by iterating on g_s until individuals have no experience effects in the last 10 years of their working life.

[16] In other words, the current year and a person's entering year and initial experience pin down their potential experience. The person's entering year and initial experience are captured by individual effects.

[17] See Lagakos et al. (2018) for a detailed description of the method and Rubinstein & Weiss (2006) for a review of theories about life-cycle wage growth.

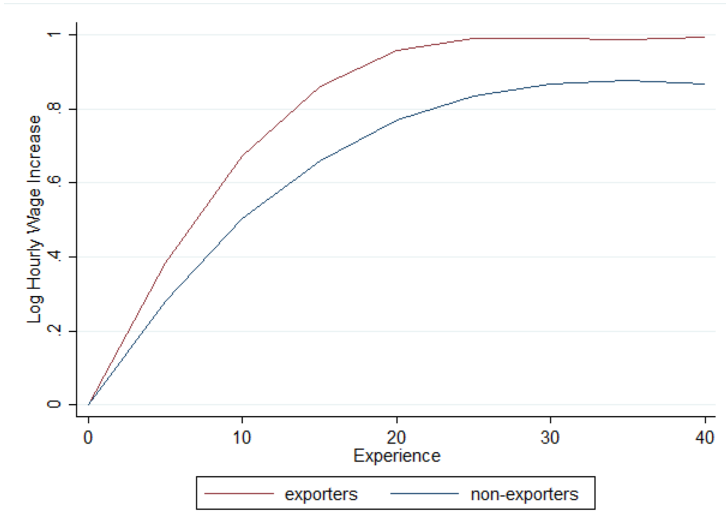


Figure 3.1: Returns to Experience in Exporters and Non-exporters

Note: This graph presents experience-wage profiles for exporters and non-exporters, by estimating Equation (3.1) separately for manufacturing workers in exporters and non-exporters between 1994–2010.

3.2.4 Experience-Wage Profiles and Export Status

We first apply Equation (3.1) to estimate experience-wage profiles separately for manufacturing workers in exporters and non-exporters between 1994–2010. Figure 3.1 presents the log wage growth with regard to potential experience, for a hypothetical person working for 40 years from the beginning of their career. Consistent with the cross-sectional evidence, we find that workers in exporters have a larger life-cycle wage growth: after 40 years of experience, their wage growth is 13 percentage points higher than workers in non-exporters.

Different reasons can explain this difference in experience-wage profiles between exporters and non-exporters. First, an important driver of the result could be industry composition. This is motivated by two well-established results in the literature: (1) different industries have different returns to experience (e.g., Islam et al. 2019); (2) trade induces industry specialization and labor reallocation, possibly driven by comparative advantage (e.g., Costinot et al. 2012) or home market effects (e.g., Head & Ries 2001). Therefore, if exporters are more concentrated in industries with higher returns to experience than non-exporters, exporters will also have steeper experience-wage profiles.

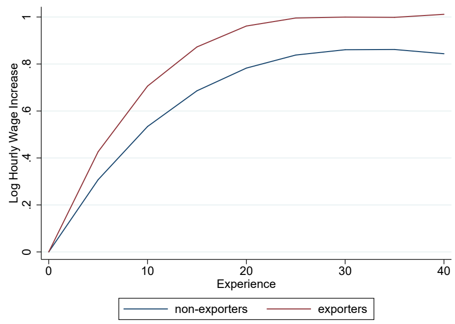
In Appendix Section C.4.1, we examine in detail the role of industry composition in driving the difference of experience-wage profiles between exporters and non-exporters. We find a large degree of heterogeneity in returns to experience across industries, indicating that trade-induced labor reallocation could potentially have a large impact on the aggregate returns to experience. However, for Brazil, exporters are more concentrated in industries with lower returns to experience than non-exporters, and therefore industry composition cannot explain the aggregate difference in returns to experience between exporters and non-exporters.[18]

As industry composition cannot explain our results, the difference in returns to experience between exporters and non-exporters must be driven by firm-level differences within industries. To explore this, we estimate Equation (3.1) separately for workers within exporters and non-exporters, for each 3-digit industry. For precision, we focus on industries with more than 0.1% of total employment and require at least 10 workers in each year-experience-bin (separately for exporters and non-exporters). This leaves us with 78 industries with estimated experience-wage profiles for both exporters and non-exporters, and these industries represent 96% of manufacturing employment in the sample.

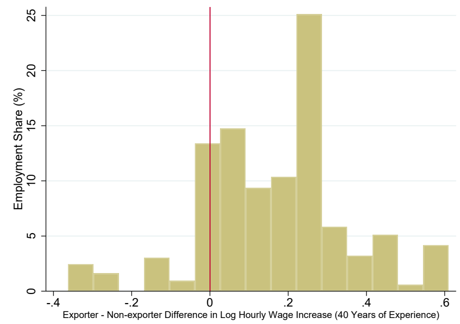
Figure 3.2a plots the (employment-weighted) within-industry experience-wage profiles for workers in exporters and non-exporters. To avoid effects of industry composition, we apply identical weights (total industry-level employment) to construct profiles for exporters and non-exporters. For a hypothetical person working for 40 years from the beginning of their career, the life-cycle wage growth is 16 percentage points higher in exporters than in non-exporters, and 71% of this difference is achieved within the first 5 years of experience.

Figure 3.2b shows the cross-industry distribution of within-industry differences in returns to 40 years of experience between exporters and non-exporters. We find that experience-wage

[18]We estimate experience-wage profiles separately for workers in each 3-digit manufacturing industry. We find that after 40 years of experience, workers' wage growth would be 2 percentage points lower in exporters than in non-exporters because of the difference in employment distributions across industries. This pattern is consistent with Brazil's comparative advantage in low-tech products (see Table 3.3 in Bonelli & Pinheiro (2008)) and that returns to experience may increase with technology levels (see Table 5 in Islam et al. (2019)).



(a) Within-industry Experience-wage Profile



(b) Distribution of Differences

Figure 3.2: Log Hourly Wage Increase by Exporters and Non-exporters

Note: This figure presents the results from estimating Equation (3.1), separately for workers within exporters and non-exporters in each 3-digit industry between 1994–2010. Panel (a) is the (employment-weighted) within-industry experience-wage profiles for workers in exporters and non-exporters, where the weight reflects industry-level employment. Panel (b) is the cross-industry distribution of within-industry differences in returns to 40 years of experience between exporters and non-exporters.

profiles are steeper in exporters than in non-exporters for 85% of industries, which account for 89% of manufacturing employment in the sample.

Therefore, within-industry factors drive the difference in experience-wage profiles between exporters and non-exporters. We documented in Table 3.1 that exporters are larger and have larger shares of cognitive and educated workers. The pattern in Figure 3.2a could partly reflect workforce composition and selection of firms into exporting. Moreover, additional benefits from exporting may occur due to increased revenues or interactions with destination markets. Thus, in the following subsection, we investigate how the difference in life-cycle wage growth between exporters and non-exporters is driven by differences in firms' characteristics, export status, and the interaction with different destination markets.

3.2.5 Firm-level Wage Profiles and Export Destinations

This subsection aims to understand plausible drivers of the differences in returns to experience between exporters and non-exporters. To make progress, we construct firm-year-level returns to experience in each experience bin as follows:

$$\phi_{\omega,t}^{x} = \frac{\sum_{i\in\omega} D_{it}^{x} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{x}} - \frac{1}{2}\left(\frac{\sum_{i\in\omega} D_{it}^{31-35} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{31-35}} + \frac{\sum_{i\in\omega} D_{it}^{36-40} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{36-40}}\right). \tag{3.3}$$

$\frac{\sum_{i\in\omega} D_{it}^{x} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{x}}$ represents the average individual-level log hourly wage growth between year $t-1$ and t, for workers in firm ω in both periods and in experience bin $x \in X = \{1–5,...,36–40\}$. The second term reflects the average of log wage growth for workers within firm ω and in the last two experience bins. This term aims to capture firm-specific wage trends, based on the same assumption of the HLT approach that there are no experience effects in the last 10 years of the working life.[19]

By applying Equation (3.3), we not only control for firm, individual, and match-specific fixed effects that affect workers' wage levels, but also capture time-variant conditions (e.g., TFP growth, and supply and demand shocks of products) that alter wages for all workers within the firm. For instance, if the firm raises all workers' wage by the same proportion due to increased revenue or upgraded technology after exporting, this effect will not show up in Equation (3.3). However, if the wage growth is relatively higher for young workers than old workers, this relative difference in wage growth is interpreted as reflecting returns to experience. Section 3.4 discusses possible causes for this difference and connects the empirical results with existing theory.

In Table 3.3, we regress firm-year-level returns to 20 years of experience on firm characteristics. The dependent variable corresponds to $5 \times \sum_{x\in\{1-5,...,16-20\}} \phi_{\omega,t}^{x}$. The variable refers to the hypothetical life-cycle wage growth of a worker staying in firm ω for 20 years from the beginning of their career, with returns to experience fixed at time t. This variable provides a measure of time-variant firm-level returns to experience. We choose to report returns to 20 years of experience, because many firms do not have workers in all experience bins. This choice is also

[19] If only one term of $\frac{\sum_{i\in\omega} D_{it}^{31-35} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{31-35}}$ and $\frac{\sum_{i\in\omega} D_{it}^{36-40} \Delta\log(w_{it})}{\sum_{i\in\omega} D_{it}^{36-40}}$ exists, we use the existing one to construct firm-specific wage trends.

Table 3.3: Firm-year-level Log Hourly Wage Increase (20 Years of Experience)

	(1)	(2)	(3)	(4)
Exporter, non-industrialized dests	0.212***	0.101***	-0.007	-0.020
	(0.014)	(0.014)	(0.023)	(0.023)
Exporter, industrialized dests	0.225***	0.114***	0.083**	0.071**
	(0.025)	(0.025)	(0.036)	(0.036)
Exporter, both types of dests	0.315***	0.097***	0.070***	0.046*
	(0.012)	(0.014)	(0.027)	(0.027)
Log(firm employment)		0.103***		0.085***
		(0.004)		(0.014)
Share of high-school grads		0.238***		0.045
		(0.019)		(0.042)
Share of cognitive occupations		0.310***		0.172***
		(0.027)		(0.057)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Obs	361,850	361,850	361,850	361,850
R-squared	0.014	0.017	0.299	0.299

Note: This table presents estimates from regressions of firm-year-level log hourly wage increase after 20 years of experience on firm characteristics for the period 1994–2010. The baseline group is non-exporters. The shares of high-school graduates and cognitive workers in the workforce are computed based on our restricted sample, from which we obtained our estimates of firm-year-level experience-wage profiles. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. Notably, our results are quantitatively very similar if we use our restricted sample (full-time male workers) to compute firm employment size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

motivated by Figure 3.2a showing that workers have little returns to experience after 20 years of experience.[20] To lessen the effect of extreme values, we truncate the sample by dropping the highest and lowest 1% of the dependent variable.

In Column (1) of Table 3.3, the independent variables are exporter dummies by destinations and a set of industry and year fixed effects. The baseline group is non-exporters. We find that after 20 years of experience, workers' wage increase is 21–31 percentage points higher in exporters than in non-exporters. These numbers are comparable in magnitude to the within-industry difference found from Mincer regressions (Figure 3.2a)—18 percentage points after 20 years of

[20]This result is partly due to our use of the HLT approach, which assumes zero experience effects in the 31–40 years of experience. Our results are robust to using other ranges of potential experience to construct dependent variables.

experience.

In Column (2), we further control for the shares of high-school graduates and cognitive workers in the firm's workforce. This allows us to capture labor composition effects, because cognitive and more educated workers have steeper experience-wage profiles (Islam et al. 2019, Lagakos et al. 2018). In addition, we control for firm employment size, which proxies for a firm's productivity level as productive firms hire more (Hopenhayn 1992). As expected, experience-wage profiles are higher in larger firms, or firms with more cognitive and educated workers. However, after including these controls, the resulting exporters' premium in returns to experience is almost halved. By taking coefficients of these controls in Column (2) of Table 3.3 and differences in controls between exporters and non-exporters shown in Table 3.4,[21] we find that firm size is the most important factor in explaining the drop in exporters' premium between Columns (1) and (2). For exporters exporting to both industrialized and non-industrialized destinations, firm size explains 76% of the difference $(0.315-0.097)$, the share of high-school graduates explains 14%, and the share of cognitive workers explains 10%.

The large effect of firm size suggests the importance of firm productivity in affecting firm-level returns to experience. However, firm size may not entirely reflect firm productivity, if labor markets are frictional (Meghir et al. 2015) or productivity partly reflects product quality (Lentz & Mortensen 2008). Considering this, we further control for firm fixed effects in Columns (3) and (4), capturing time-invariant unobserved firm productivity levels and other characteristics. By introducing firm fixed effects, we are using firms that switch export status to identify exporters' premium in returns to experience. Surprisingly, exporting to non-industrialized destinations now leads to insignificant changes in returns to experience, whereas exporting to industrialized destinations results in statistically significant and positive gains. Consistently, exporting to both types of destinations has positive (yet lower) gains than solely exporting to industrialized destinations. We find similar results when we add back other controls in Column (4), but

[21] We use the first four rows of Table 3.4.

Table 3.4: Difference in Firm Characteristics (Relative to Non-exporters)

	Log(emp)	Share of high-school grads	Share of cogn occs
without Firm FE:			
Exporter, non-industrialized dests	0.818 (0.006)	0.058 (0.001)	0.042 (0.001)
Exporter, industrialized dests	0.800 (0.010)	0.062 (0.002)	0.046 (0.002)
Exporter, both dests	1.610 (0.006)	0.126 (0.001)	0.069 (0.001)
with Firm FE:			
Exporter, non-industrialized dests	0.143 (0.004)	0.008 (0.001)	0.004 (0.001)
Exporter, industrialized dests	0.136 (0.007)	0.013 (0.002)	0.002 (0.001)
Exporter, both types of dests	0.264 (0.006)	0.021 (0.001)	-0.001 (0.001)

Note: This table presents coefficients on exporter dummies, from regressions of firm-year-level characteristics on exporter dummies by destinations and a set of year and industry fixed effects. The baseline group is non-exporters. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. Robust standard errors are in parentheses.

nonetheless these controls are less important in affecting exporters' premium in the presence of firm fixed effects.

In Appendix Table C.4, we exploit firm-level data on export value by destinations, which are available for the 1997–2000 period, for robustness. We measure a firm's exposure to industrialized destinations by a continuous variable: the share of exports to industrialized destinations in its total exports. We regress firm-year-level returns to 20 years of experience on an exporter dummy, the share of firms' exports to industrialized destinations, and identical controls as in Table 3.3. We also control for export value per worker, as destination-specific effects may originate from increased revenue due to exporting. We find that after controlling for firm fixed effects, labor composition, and firm size, exporter status and export value do not affect returns to experience, whereas higher shares of exports to industrialized destinations significantly increase returns to experience. Appendix Table C.5 finds similar results, using export-weighted GDP per capita across destinations as a measure of exposure to industrialized destinations.

Before providing a detailed review of plausible causes for destination-specific effects in Section 3.4, we show more supportive evidence for the existence of these effects.

3.2.6 Dynamics of Exporting to Industrialized Destinations

In this subsection, we construct an event study on the dynamics of experience-wage profiles. We study whether changes in returns to experience—due to exporting to industrialized destinations—materialize immediately when firms start exporting. In particular, we perform the following regression:

$$\begin{aligned} y_{\omega,t} = & \sum_{\tau=-4}^{\tau=-2} \beta_\tau 1\{industrial\}_{\omega,t^*+\tau} + \sum_{\tau=0}^{\tau=4} \beta_\tau 1\{industrial\}_{\omega,t^*+\tau} + \beta_{pre} \sum_{\tau\leq -5} 1\{industrial\}_{\omega,t^*+\tau} \\ & + \beta_{post} \sum_{\tau\geq 5} 1\{industrial\}_{\omega,t^*+\tau} + \mathbf{X}'_{\omega,t}\mathbf{b} + \theta_\omega + \psi_{j(\omega,t)} + \delta_t + \varepsilon_{\omega,t}. \end{aligned} \tag{3.4}$$

As before, the dependent variable is firm-year-level returns to 20 years of experience: $y_{\omega,t} = 5 \times \sum_{x\in\{1-5,\ldots,16-20\}} \phi^x_{\omega,t}$. In the regression, we control for firm fixed effects θ_ω, industry fixed effects $\psi_{j(\omega,t)}$, and year fixed effects δ_t. Firm-level controls $\mathbf{X}_{\omega,t}$ include the shares of high-school graduates and cognitive workers, firm size, and a dummy variable indicating whether the firm is exporting to a non-industrialized destination.

The β_τ parameters of primary interest are coefficients on indicators for time periods relative to the firm's first export entry into industrialized destinations ($\tau = 0$).[22] We exclude an indicator for the period immediately before the firm's export entry into industrialized markets, and hence the parameters represent changes in returns to experience relative to that period. The coefficients are identified by firms starting as non-exporters or exporters only to non-industrialized destinations and then turning to export to industrialized destinations in our sample period. For the β_τ parameters after entry, we also require that firms remain exporting to industrialized destinations, and therefore β_τ (for $\tau > 0$) is interpreted as changes in returns to experience for a firm that still exports to industrialized destinations in τ periods after first entry. We are aware that this regression could potentially suffer from selection bias, as those better-performing firms may

[22]We focus on firms that do not start as exporters to industrialized destinations when they make first appearance in the sample, but experience entry into industrialized destinations later.

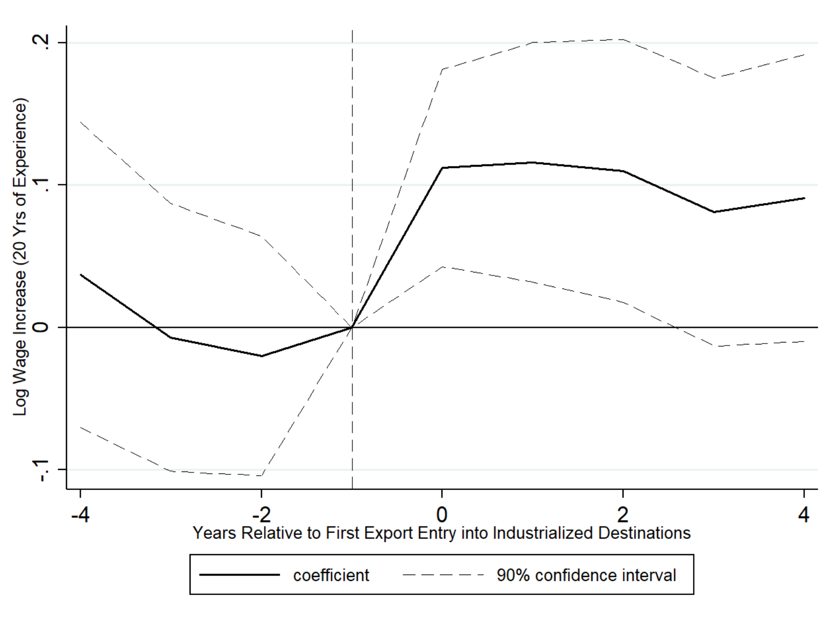
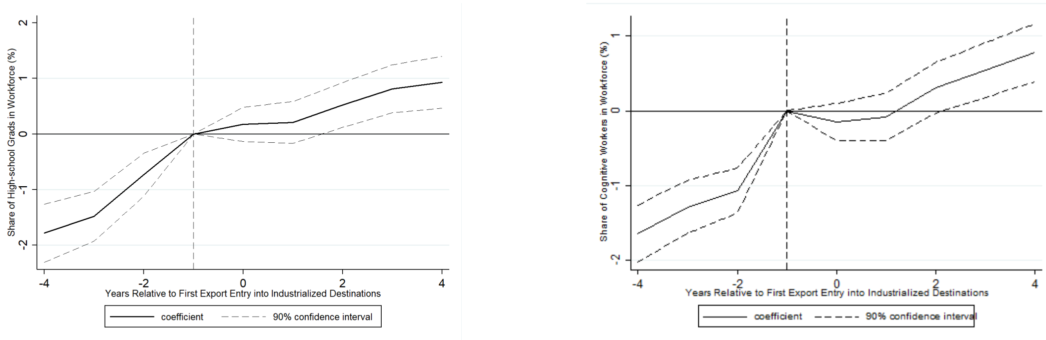


Figure 3.3: Dynamics of Firms' First Entry Into Industrialized Destinations (Survivors)

Note: The figure shows the β_τ parameters from estimating Equation (3.4). The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, the shares of high-school graduates and cognitive workers in the workforce, firm size, and a dummy variable indicating whether the firm is exporting to a non-industrialized destination. To estimate the β_τ parameters after entry, we require that firms remain exporting to industrialized destinations.

choose to start exporting (Fajgelbaum 2019). Still, it is a good exercise to understand the dynamics of experience-wage profiles before and after firms export to industrialized destinations.

Figure 3.3 presents the results from estimating Equation (3.4). After first entry into industrialized destinations, a significantly positive jump occurs in firms' experience-wage profiles, whereas experience-wage profiles do not significantly shift before firms' export entry. In addition, the increase in returns to experience stays roughly constant after entry, indicating that exporting to industrialized destinations is associated with persistent higher life-cycle wage growth. Appendix Figure C.7 shows the results from the same regression, but we do not enforce a requirement that firms remain exporting to industrialized destinations after entry to identify $\beta_\tau, \tau > 0$. We find in that case that the gains in experience-wage profiles tend to decline several years after firms' entry into industrialized destinations, as some firms gradually quit exporting to industrialized destinations. Appendix Figure C.8 estimates the β_τ parameters for the firm's first export entry into non-industrialized destinations at time $t = t^*$ ($\tau = 0$). We find no statistically significant



(a) Share of High-school Grads (%) (b) Share of Cognitive Occupations (%)

Figure 3.4: Dynamics of Firms' First Entry Into Industrialized Destinations

Note: The figure shows the β_τ parameters from estimating Equation (3.4). The dependent variable is the share of high-school graduates in the workforce in Panel (a) and the share of cognitive workers in the workforce in Panel (b). All regressions control for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a non-industrialized destination. To estimating the β_τ parameters after entry, we require that firms remain exporting to industrialized destinations.

change in returns to experience before and after firms export to non-industrialized destinations.

Finally, in Figure 3.4, we assign the shares of high-school graduates and cognitive workers as dependent variables in Equation (3.4) to analyze the dynamics of labor composition around firms entry into industrialized destinations. We find that firms gradually improve their labor composition even before exporting, and this gradual improvement continues after export entry. This suggests that export entry may be endogenous. Nevertheless, their labor composition does not significantly change immediately after export entry, whereas we observe the immediate jump in life-cycle wage growth after firms' entry into industrialized destinations. This suggests that the jump in returns to experience is more likely driven by changes in export status rather than changes in labor composition. In the following section, we rely on a quasi-experiment to address the endogeneity problem in the exporting decision.

3.3 Case Study: Brazilian Currency Crisis

From our previous analysis, it is possible that the estimated destination-specific returns to experience may still reflect firms' selection into exporting, as exporting firms may experience improvements prior to exporting. To corroborate our argument that the destination-specific effects are shaped by exporting activities, this section describes an event study using the 1999 currency devaluation, which led to a quasi-experimental surge in exporting activities.

In January and February 1999, Brazil experienced a massive devaluation of its domestic currency, with the Brazilian Real per U.S. dollar increasing from 1.20 in December 1998 to 1.93 in February 1999, a 60% devaluation within two months.[23] The abrupt currency devaluation was detrimental to the economy in many ways, but nonetheless it improved Brazilian firms' competitiveness in the global market and induced more firms to export. In Figure 3.5b, we show that the probability of firms exporting strongly increased after 1999 (relative to year 1998, after controlling for firm fixed effects and industry fixed effects), while there was no effect in the year prior to the large devaluation episode and a small increase in the previous years. Similarly, Verhoogen (2008) finds that the Mexican peso crisis in 1994 led to more firms' entry into exporting.

We exploit this large devaluation episode and apply a difference-in-difference approach to analyze how exporting affects experience-wage profiles due to exogenous shifts (from individual firms' perspective) in exporting opportunities. We perform the following regression:

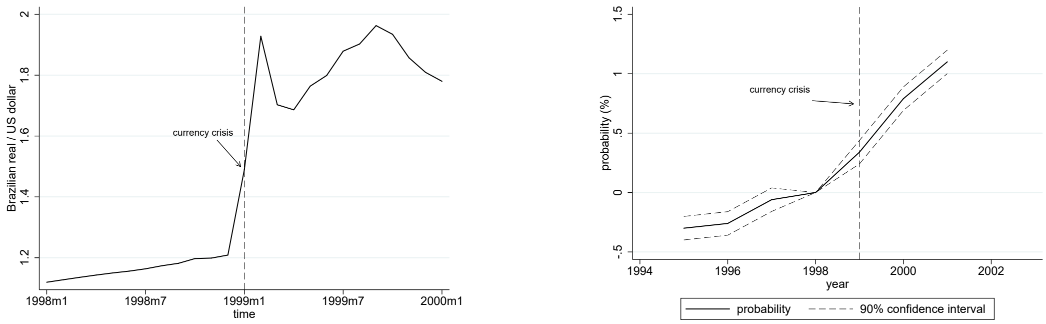
$$y_{\omega,t} = \sum_{d \in D} \beta_d \times 1\{d\}_t \times 1\{post\_1999\} + 1\{post\_1999\} + \theta_\omega + \mathbf{X}'_{\omega,t}\mathbf{b} + \psi_{j(\omega,t)} + \delta_t + \varepsilon_{\omega,t}. \quad (3.5)$$

The dependent variable is still firm-year-level returns to 20 years of experience: $y_{\omega,t} = 5 \times \sum_{x \in \{1-5,\ldots,16-20\}} \phi^x_{\omega,t}$. We control for firm fixed effects θ_ω, industry fixed effects $\psi_{j(\omega,t)}$, and year fixed effects δ_t. Firm-level controls $\mathbf{X}_{\omega,t}$ include the share of high-school graduates, the share of workers in cognitive occupations, and firm size. β_d captures changes in experience-wage profiles if firms started to export to destination d after the devaluation episode.[24] We estimate this regression on the set of non-exporters[25] before the Brazilian currency crisis.

[23]The devaluation came as a surprise, and many factors may have led to this crisis. Many economists believed that the crisis had roots in the financial turmoil following the Asian financial crisis and fundamental problems of the Brazilian economy (such as budget and current account deficits).

[24]The set of destinations is denoted as D.

[25]Specifically, we focus on firms that ran business (for at least one year), yet did not export during the 1996–1998



(a) Brazil Currency Crisis

(b) Exporting Probability

Figure 3.5: Brazil Currency Crisis and Exporting Probability

Note: Panel (a) presents the monthly Brazilian nominal exchange rates (per U.S. dollar). Panel (b) presents the probability of a firm exporting in each year. To obtain the probability, we regress the dummy variable of the export status (1, if the firm exports, and otherwise 0) on firm fixed effects, industry fixed effects, and year fixed effects. We plot the coefficients on year effects relative to 1998 (the baseline year) in Panel (b).

In this difference-in-difference design, we impose two implicit assumptions for identification: (1) most changes in firms' export status after 1999 were due to improved competitiveness with currency devaluation; (2) this currency devaluation affected returns to experience through changes in exporting activities, but was uncorrelated with other factors that shift returns to experience. These assumptions are more likely to be true within a narrow time frame of the currency crisis; therefore, we estimate Equation (3.5) using the observations within 1–3 years around the episode year, 1999.

Table 3.5 presents the results. Regardless of the chosen time frame, the results show that firms which started exporting to industrialized destinations after currency devaluation saw increases in experience-wage profiles. On the other hand, the coefficients for firms exporting to non-industrialized destinations after the devaluation are not significant.

Moreover, in Appendix Tables C.8 and C.7, we assign the shares of cognitive workers and high-school graduates in the workforce as dependent variables. We show that within a year around the shock (between 1998 and 2000), no significant change occurred in the labor composition for firms exporting to industrialized destinations, whereas an improvement occurred in the labor composition (in terms of the share of high-school graduates) for firms that started exporting

period.

Table 3.5: Firm-year-level Log Hourly Wage Increase (20 Years of Experience)

time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
$1\{$export to industrialized dests$\}$	0.422*	0.392**	0.277**
$\times 1\{$post_1999$\}$	(0.236)	(0.164)	(0.124)
$1\{$export to non-industrialized dests$\}$	-0.076	-0.048	-0.106
$\times$ $1\{$post_1999$\}$	(0.156)	(0.107)	(0.085)
$1\{$export to both types of dests$\}$	0.387	0.111	-0.047
$\times 1\{$post_1999$\}$	(0.377)	(0.220)	(0.159)
Year, industry and firm FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Obs	37,267	61,390	85,266
R-squared	0.563	0.446	0.382

Note: This table presents estimates from Equation (3.5). The dependent variable is firm-year-level log hourly wage increase after 20 years of experience. The regression includes firm, industry, and year fixed effects. Firm-level controls include the shares of high-school graduates and cognitive occupations, and firm size. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

to non-industrialized destinations. Therefore, consistent with our explanation in the previous subsection, improvement of labor composition is unlikely to explain increases in experience-wage profiles for exporters to industrialized destinations.

We are aware of two possible caveats to our approach. First, firms that started to export after currency devaluation were "marginal exporters," in the sense that they were close to export thresholds. Therefore, if our identification assumptions hold, our estimated effects actually capture "local average treatment effects." Second, although this experiment addresses the endogeneity of exporting, selection of destinations may still occur, as firms may choose different destinations after the devaluation due to time-variant factors (not captured by firm fixed effects), such as product quality (Manova & Zhang 2012). We will discuss selection of destinations in the next section and show that it is unlikely to cause destination-specific returns to experience.

3.4 Connecting Destination-Specific Results with Theory

In this section, we briefly discuss four plausible explanations for our finding on the interaction between returns to experience and different destinations: (1) selection of firms into different export destinations; (2) differential changes in labor composition; (3) job search and screening; and (4) human capital accumulation. We propose that faster human capital accumulation from exposure to advanced countries is the most likely explanation. Appendix Section C.5 provides the detailed procedure and results of robustness checks.

Selection of Firms into Different Export Destinations. Our first hypothesis states that firms exporting to industrialized destinations are better than other exporters due to factors not captured by firm fixed effects, or they enjoy more favorable linkages with destinations. We argue that this is unlikely to explain our destination-specific effects. First, as Table 3.4 shows, firms exporting to both types of destinations appear to be the most productive even after controlling for firm fixed effects, as they are the biggest and have the largest shares of high-school graduates. Nonetheless, they do not enjoy the largest increase in experience-wage profiles after exporting. Second, our results in Column (4) of Table 3.3 remain similar after controlling for unit prices of exports,[26] as a proxy for product quality (Manova & Zhang 2012). Finally, our results in Column (4) of Table 3.3 remain unchanged, after controlling for industry-year fixed effects or gravity variables (e.g., bilateral distance, sharing a language). Therefore, industry-year-level common shocks or bilateral linkages of destinations with Brazil cannot capture destination-specific returns to experience.

Differential Changes in Labor Composition. The second plausible hypothesis states that changes in labor composition after exporting favor exporters to industrialized destinations. We argue that this may not be the case for the following reasons. First, as Table 3.4 shows,

[26] The firm-level export value and quantity are available by destinations and 8-digit HS products in 1997–2000. We take an export-weighted average of unit prices across destinations and HS products to construct firm-year-level unit prices of exports. Given the heterogeneity in values of HS products, we experimented with first normalizing the unit price by the unit price of the same HS product exported from Brazil to the U.S.. The results remain very similar under this normalization.

firms exporting to both types of destinations have the best workforce among all firms, and their workforce become more educated after exporting. Changes in labor composition may favor firms exporting to both types of destinations, but nonetheless, firms exporting to industrialized destinations perceive the largest increase in returns to experience.

There could still be unobserved workers' characteristics not captured by education levels and occupations. We undertake two sets of robustness checks. First, we construct a proxy for workers' unobserved ability, using the residual wage of their first appearance in the sample, after removing year and age effects. Controlling for the average ability of the workforce does not change our results in Column (4) of Table 3.3. In addition, when we compute firm-year-level profiles in year t, we use workers employed within the same firm in both years $t-1$ and t. If current workers are unaware of whether firms would change export status in one year, we could compare profiles for firm-year-level observations in years $t-1$ and t with a switch in export status between those years. We rerun our regression in Column (4) of Table 3.3 with these observations around switches and find similar results.

Job Search and Screening. Our third hypothesis states that the observed destination-specific effects are due to job search and screening. Though we focused on workers staying in the same firm to construct firm-level wage profiles, workers' wage growth may still result from changes in job surplus and wage renegotiations in the presence of on-the-job search and firms' monopsony power.[27] Alternatively, workers' wage growth may originate from screening when information frictions occur (Jovanovic 1979).[28] Moreover, given initial uncertainty about workers' abilities, exporters may offer back-loaded wage contracts.

[27]For example, in a calibrated model with wage bargaining like Cahuc et al. (2006), Fajgelbaum (2019) shows that workers in potential exporters experience faster wage growth due to wage renegotiations and larger job surplus after exporting. Our destination-specific results may thus arise due to larger surplus from exporting to industrialized destinations. Acemoglu & Pischke (1998) argue that firms monopsony power on workers ability information affects firms wage determination. Through the lens of their model, our results may arise if firms exporting to industrialized destinations have the least monopsony power and therefore design the steepest experience-wage profiles to avoid poaching from other firms.

[28]In particular, larger job surplus after exporting may interact with screening based on workers' abilities (Helpman et al. 2017) or match-specific quality (Donovan et al. 2020), leading to different patterns of worker turnover and our observed experience-wage profiles.

We cannot entirely rule out numerous stories in the literature, but nonetheless we provide several checks to show that job search and screening are unlikely to explain destination-specific effects. First, as shown in Section 3.2.5, export value per worker does not affect returns to experience, indicating that changes in job surplus may not trigger destination-specific shifts in returns to experience.[29] Second, we find that exporting to industrialized destinations leads to higher returns to experience in more manual or less skill-intensive industries, where workers may have lower bargaining power. Third, as workers' tenure can be used as a proxy for firms' monopsony power, we control for workers' average tenure, which does not change our results in Column (4) of Table 3.3. Finally, as shown in Section 3.2.6 and 3.3, the jump in experience-wage profiles happens immediately after entry into industrialized destinations. If exporters offer back-loaded wage contracts, we must expect an initial decline in experience-wage profiles after switching to exporting.

Human Capital Accumulation and Knowledge Diffusion. There is a long tradition, starting with Becker (1964), using experience-wage profiles to implicitly measure human capital accumulation (e.g., Caselli 2005, Manuelli & Seshadri 2014). Clearly, one potential way to interpret our destination-specific results is through human capital theory. In addition, the literature argues that knowledge diffusion is central to human capital accumulation (e.g., Lucas & Moll 2014), and that trade transmits knowledge across borders (e.g., Buera & Oberfield 2020).

Our destination-specific returns to experience are consistent with faster human capital accumulation due to exposure to advanced countries. First, workers enjoy steeper experience-wage profiles if firms export to industrialized destinations, in line with larger knowledge diffusion from trading with more advanced destinations (Alvarez et al. 2013, Buera & Oberfield 2020). Moreover, increases in returns to experience from industrialized destinations are larger in industries with

[29]Even if we control for export value per worker, job surplus may still be higher if firms exporting to industrialized destinations enjoy higher markups than other firms. There is not much evidence on it. If any, Keller & Yeaple (2020) find that the markups of U.S. multinationals' affiliates decline with the GDP per capita of the host country. De Loecker & Eeckhout (2020) estimate the aggregate markup across countries, and there is no clear relationship between markups and countries' development levels.

smaller shares of high-skill and cognitive workers. This is compatible with the theory that the least productive agents typically enjoy the largest gains in human capital from knowledge diffusion (Lucas & Moll 2014). Third, increases in returns to experience due to industrialized destinations are larger in industries with more differentiated goods, which might be associated with larger benefits for knowledge adoption.

Therefore, although we cannot entirely rule out other hypotheses, we propose that human capital accumulation due to knowledge diffusion is the most likely hypothesis to explain destination-specific returns to experience.

3.5 Exporting, Training and Technology Adoption

The Inter-American Development Bank has conducted a series of case studies on leading exporters in Brazil and other Latin American countries.[30] One consistent finding is that exporting to industrialized destinations usually requires the adoption of more sophisticated production technology, which often induces these exporters to invest in the capability of the workforce by providing training.[31] This finding supports our preferred hypothesis and indicates that the adoption of advanced technology may be the driver of faster human capital accumulation in firms that export to industrialized destinations.

In this section, we go beyond the anecdotal evidence and employ the World Bank Enterprise Surveys to provide direct evidence on workers' human capital accumulation in non-exporters and exporters. The enterprise survey (ES) is a firm-level survey of a representative sample of

[30] Apart from Brazil (Rocha et al. 2008), studies for other Latin American countries also exist, including Argentina (Artopoulos et al. 2010), Chile (Agosin & Bravo-Ortega 2009) and Uruguay (Snoeck et al. 2009).

[31] A good example is Artefama, the largest exporter of wood furniture in Brazil in 2006. To export to Europe and the U.S., this company imported production machinery from Italy, invested in new equipment to dry wood, and adopted electronic control mechanisms, since the domestic markets did not require the same standards as export markets. In the meantime, the company offered a special in-house two-year training program to its workers, which inadvertently benefited other firms. As Rocha et al. (2008) describe, "Artefama, although unwillingly, supplied skilled workers to fulfill the needs of other firms in the region, and stimulated the appearance of new entrepreneurs among their own employees" (p. 59).

an economy's private manufacturing and service industries,[32] covering around 100 countries (mostly low- and middle-income). These surveys provide two standardized waves conducted in 2002–2005 and 2006–2017 and cover a variety of topics such as firms' financial information, business environment, infrastructure, technology adoption, and on-the-job training. Owners and top managers usually answer the ES. This survey includes 1200–1800 interviews in large economies, 360 in medium-sized economies, and 150 in small economies. Finally, firms with fewer than 5 employees are usually omitted, and firms with 100% government/state ownership are not eligible to participate.

The ES provides a set of standardized questions that allow for cross-country comparison. We rely on those standardized questions. Appendix Section C.6 provides the details of the questions we use. Questions on training investments, exports, and R&D investments are recorded based on firms' activities in the last fiscal year, and the question on foreign technology adoption refers to the firm's technology in the current year. In all regressions of this section, we include country, year, and industry fixed effects. We also control for firm size, labor share, managerial experience in the industry, and the share of high-school graduates in the workforce. These control variables are computed using firms' information in the last fiscal year. Appendix Table C.11 presents the summary statistics of the variables we use in the ES. Consistent with the exporter premium found in the literature (Bernard et al. 2003), exporters have larger employment size, more experienced managers, and higher shares of educated workers in the workforce than non-exporters.

The ES asks each firm if it provides formal on-the-job training to its permanent workers. Therefore, we investigate if exporters provide more on-the-job training than non-exporters, which is direct evidence of differential human capital investments between exporters and non-exporters.

[32]The ES interviews formal firms in manufacturing and service industries (ISIC codes 15–37, 45, 50–52, 55, 60–64, and 72, ISIC Rev. 3.1). This survey has two types of questionnaires, one for manufacturing firms and one for service firms, which have questions in common for some topics and specific questions for others. The ES uses a stratified random sampling, which means that firms are grouped according to firm size, industry, and region, and a random sample within those groups is representative of that strata. In some particular surveys for some countries, the ES includes informal firms and/or firms with fewer than 5 employees.

Table 3.6: Exporting and On-the-job Training

	(1)	(2)	(3)	(4)	(5)
	Panel A: Training and Exporting				
Exporter	0.16***	0.06***	0.06***	0.06***	0.07***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.019)
Obs	109,698	107,568	86,226	83,202	44,242
R-squared	0.136	0.190	0.202	0.202	0.254
	Panel B: Training, Exporting and Technology				
Non-Exporter # Foreign Tech	0.18***	0.13***	0.12***	0.12***	0.11***
	(0.017)	(0.018)	(0.020)	(0.020)	(0.032)
Exporter # No Foreign Tech	0.16***	0.07***	0.06***	0.05***	0.06***
	(0.013)	(0.013)	(0.015)	(0.015)	(0.018)
Exporter # Foreign Tech	0.29***	0.15***	0.14***	0.15***	0.14***
	(0.020)	(0.021)	(0.026)	(0.026)	(0.028)
Obs	79,184	78,394	63,631	61,881	26,731
R-squared	0.149	0.192	0.202	0.202	0.281
Log(Emp)	No	Yes	Yes	Yes	Yes
Labor share	No	No	Yes	Yes	Yes
Managerial experience in sector	No	No	No	Yes	Yes
% High school grads	No	No	No	No	Yes

Note: This table presents estimates from regressing a dummy variable that takes the value 1 if the firm offers formal on-the-job training, on export status. The baseline groups are non-exporters for Panel A and non-exporters with no foreign technology adoption for Panel B. Exporters are defined as firms with positive sales to foreign markets. We control for country, year, and industry fixed effects in all regressions. Firm-level control variables are log (employment), the ratio of labor costs to total sales, the share of high-school graduates in the workforce, and managers' years of experience in the operating sector. We use the second standardized wave of the ES with the provided weights. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

With this in mind, we regress a dummy variable representing if the firm offers on-the-job training on export status. Panel A in Table 3.6 shows the results. Exporters are 6–16 percentage points more likely to invest in on-the-job training compared to non-exporters, under different sets of control variables, suggesting that more opportunities exist for human capital accumulation in exporters than in non-exporters.[33]

We explore whether exporters with access to better technology are more willing to invest

[33]The ES also provides information on whether firms indirectly export. Indirect exporters are firms that do not export but are selling goods to another firm which then exports the same goods, and they are not counted as exporters in our regressions. We find that indirect exporters also have a larger probability of training their workers than non-exporters, but their probability of training is lower than direct exporters. This evidence suggests that both production of exported goods and direct contact with destination markets may benefit workers' human capital, though we cannot rule out selection effects.

in human capital. In Panel B of Table 3.6, we regress our dummy variable of on-the-job training on interaction terms between export status and a dummy variable that equals 1 if the firm adopts foreign technology. Being an exporter is associated with larger human capital investments. Conditional on export status, if firms adopt foreign technology, the probability of investing in on-the-job training also increases. These results are consistent with studies finding complementarities between technology and human capital (Acemoglu & Zilibotti 2001, Porzio 2017). In Appendix Table C.12, we show that exporters who invest in R&D are more likely to train workers than exporters who do not. This also supports that exporters with access to better technology are more willing to invest in human capital. In Appendix Table C.13, we use triple interactions between foreign technology adoption, R&D investments, and export status, and find that all three are associated with larger human capital investments conditional on the other two.

Finally, in Appendix Tables C.14, we replicate these results using the Enterprise Surveys for Brazil and show that all results hold. Therefore, the evidence from the ES supports our main hypothesis in Section 3.4 that higher returns to experience observed in Brazilian exporters correspond at least partially to faster human capital accumulation, and that exposure to advanced countries may induce faster human capital accumulation.

3.6 Conclusion

Using Brazilian employer-employee and customs data, this study documents that workers' life-cycle wage growth is faster in exporters than in non-exporters. Apart from selection of firms with higher returns to experience into exporting, we find that workers enjoy steeper experience-wage profiles when firms export to industrialized destinations. We discuss several plausible explanations for the destination-specific effects on experience-wage profiles. We propose that faster human capital accumulation when exposed to advanced destinations is the most likely explanation. Using the Enterprise Surveys for more than 100 countries, we further corroborate this hypothesis by showing that exporters which adopt foreign technology are more involved in training workers than exporters which do not.

Understanding the effects of trade on workers' wages is important because of its implications for aggregate welfare and inequality. We view our study as one of the first steps to empirically understanding the effects of trade on workers' life-cycle wage growth, complementing recent efforts using structural models to study trade and wage growth (Fajgelbaum 2019, Guner et al. 2019). Our results also raise the possibility that workers' human capital accumulation may interact with destination markets. A fruitful area for future study is how this interaction impacts the effects of globalization on workers' income levels and inequality in countries with different development levels.

3.7 Acknowledgements

Chapter 3 is currently being prepared for submission for publication and is couathored with Alejandro Nakab. I would like to thank Alejandro Nakab in particular for all the invaluable discussions we had over these years. The dissertation author was a primary investigator of this material.

Appendix A

Appendix for Chapter 1

A.1 Additional Graphs and Tables

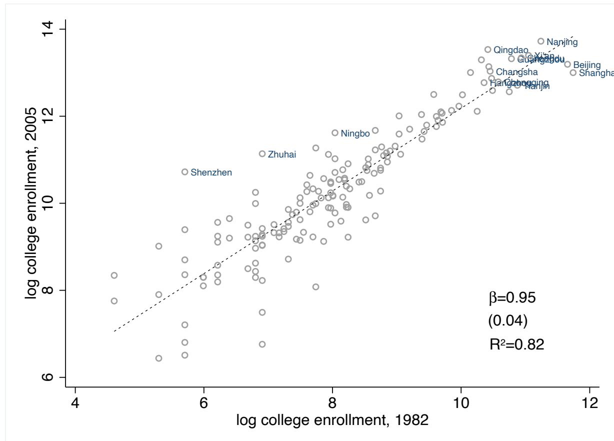
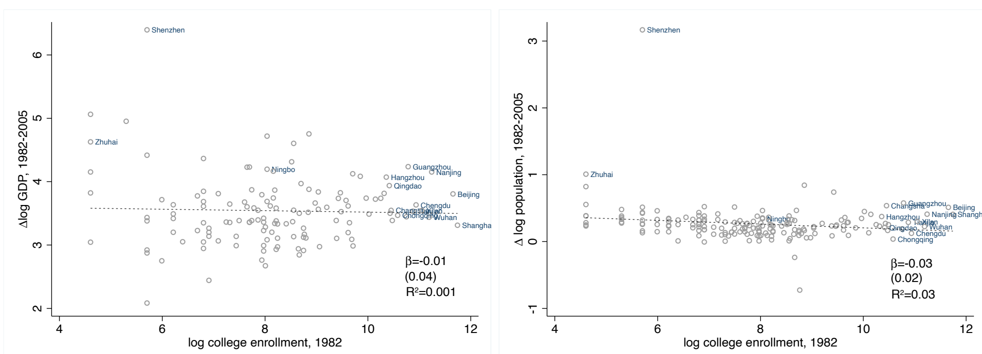


Figure A.1: College Enrollments across Cities

Note: The data come from China's City Statistical Yearbook in 2005 and Population Census 1982. I



(a) GDP (b) Population

Figure A.2: College Enrollments and Changes in GDP and Population

Note: The data come from multiple Provincial Statistical Yearbooks and Population Census 1982.

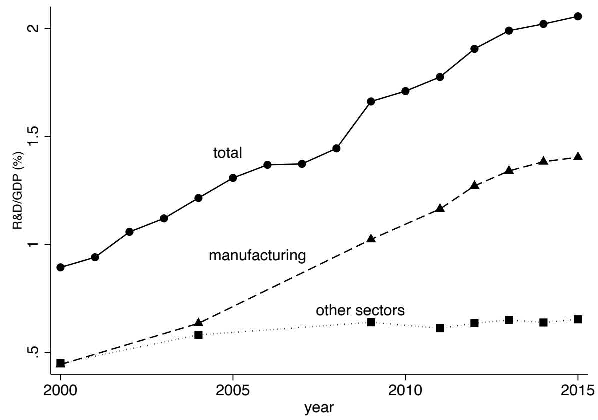


Figure A.3: China's R&D Expenses by Sectors

Note: The data come from China's Statistical Yearbook on Science and Technology and China's Statistical Yearbook 2000–2016.

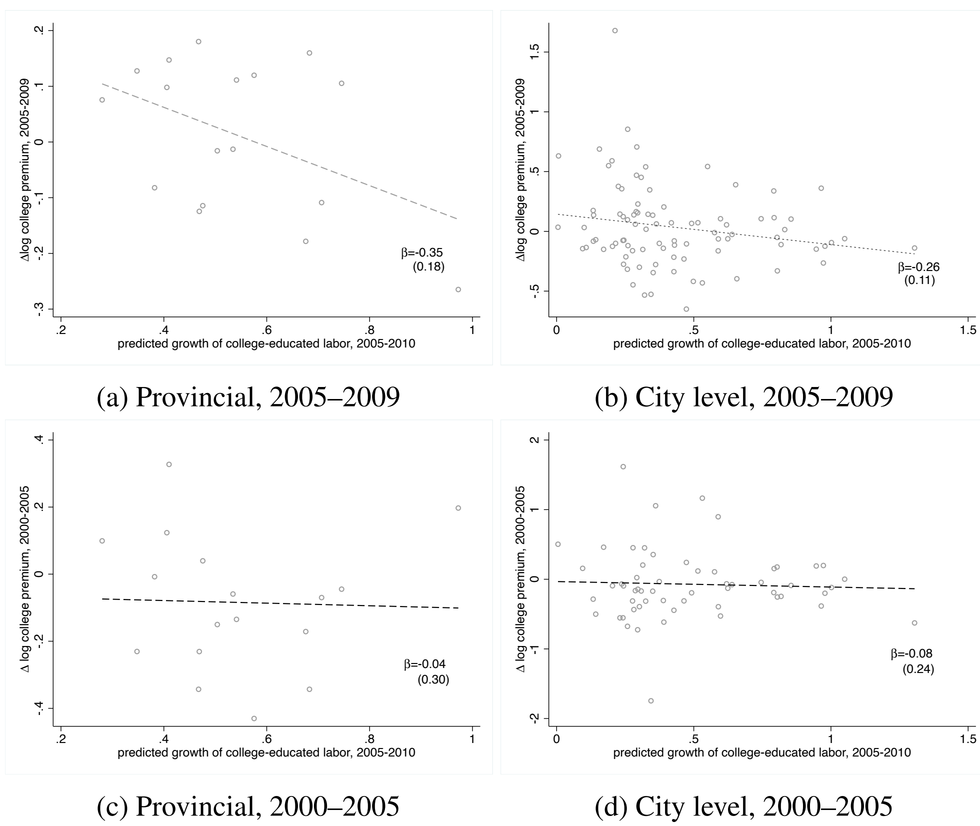


Figure A.4: IV and Changes in Young Workers' College Premium

Note: I use the Urban Household Survey and measure young workers' college premium by using the average wage of college-educated workers (aged less than 28) relative to the average wage of all workers with high-school education. For older college-educated workers, the instrumented shock was uncorrelated with changes in their college premium between 2005–2009 or 2000–2005.

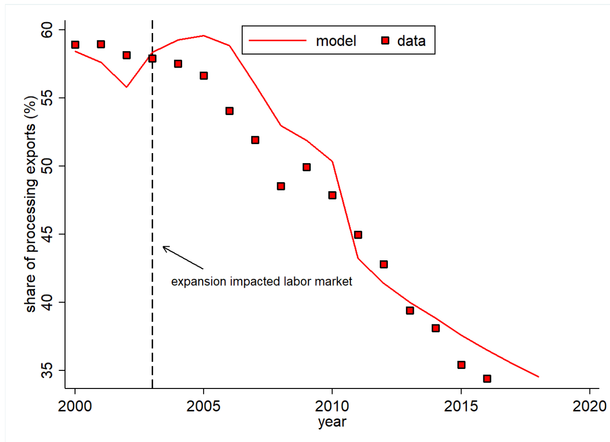
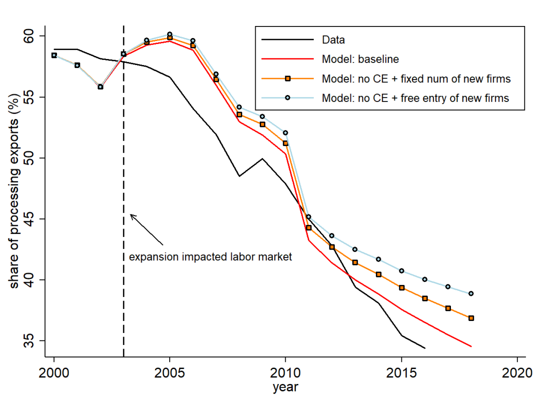
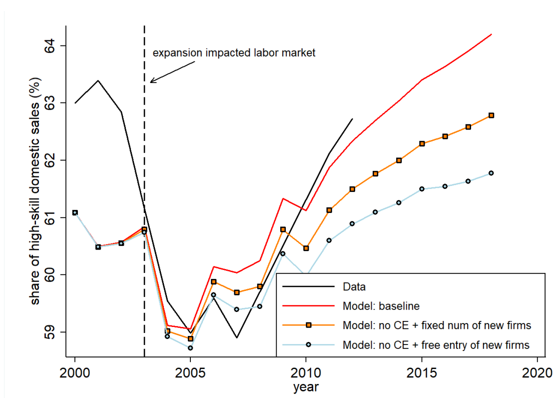


Figure A.5: Share of Processing Exports in Total Manufacturing Exports



(a) Share of Processing Exports in Exports



(b) Share of High-skill Domestic Sales

Figure A.6: Effects of the College Expansion on Manufacturing Exports and Domestic Sales

Table A.1: Dependent Variable: Province-industry-level Changes between 2005–2010

Dep var:	Δlog(dom. sales)		Δlog(ord. exports)		Δshare of R&D firms			
					non-exporter		ord. exporter	
	(1) 2SLS data	(2) 2SLS model	(3) 2SLS data	(4) 2SLS model	(5) 2SLS data	(6) 2SLS model	(7) 2SLS data	(8) 2SLS model
Exposure to CE	2.309*	2.611***	4.711***	4.974***	0.419***	0.453***	0.504**	0.525***
	(1.211)	(0.847)	(0.971)	(1.282)	(0.119)	(0.081)	(0.200)	(0.139)
Obs	745	785	587	600	783	787	586	600
R-squared	0.541	0.438	0.353	0.330	0.447	0.268	0.566	0.503
First-stage F	432.96	412.99	138.45	237.14	518.47	564.28	232.86	244.55

Note: This table provides regressions of province-industry-level changes on the exposure to the college expansion, using the same constructed shocks and instruments as in Section 1.5. In Columns (1) and (3), I use ASM 2005 and ASM 2011 to construct province-industry-level trends of domestic sales and ordinary exports, because ASM data are informative about all China's manufacturing sales. In Columns (5) and (7), I first use ASM 2005 and SAT 2010 to construct the share of R&D firms among ordinary exporters and nonexporters for each province-industry in 2005 and 2010. I then obtain province-industry-level changes between 2005–2010. Columns in even numbers replace the dependent variable with the model-generated data, respectively. I control the share of SOEs, log employment, log fixed capital, and log output in 2005 for each province-industry pair, as well as province-specific trends. I also control input and output tariff reductions. In Columns (1)–(4), regressions are weighted by the amount of domestic sales and ordinary exports within each province-industry pair in 2005. In Columns (5)–(8), regressions are weighted by the number of firms, which are separately derived for exporters and nonexporters within each province-industry pair in 2005. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

A.2 China's College System

A.2.1 College Types

The college education in Figure 1.1 refers to regular college education (universities and junior colleges) in China, which recruits students through the national college entrance examination and requires full-time attendance of students. In reality, workers could also attend part-time schools to obtain a part-time college diploma, which is of much less value than regular education in the labor market Chen & Davey (2008). Figure A.7 shows that around 1 million obtained part-time college diploma in 2000,[1] and the amount increased to around 2 million in 2018.

Many Chinese students have obtained their college degree abroad. However, as Figure A.7 shows, the number of college grads with foreign college degrees is still small relative to the number of domestic college grads. Cumulatively, 2.1 million students got foreign college degrees between 2000–2015, which was only 3% of domestic college grads from regular college education in the meantime (67.2 million).

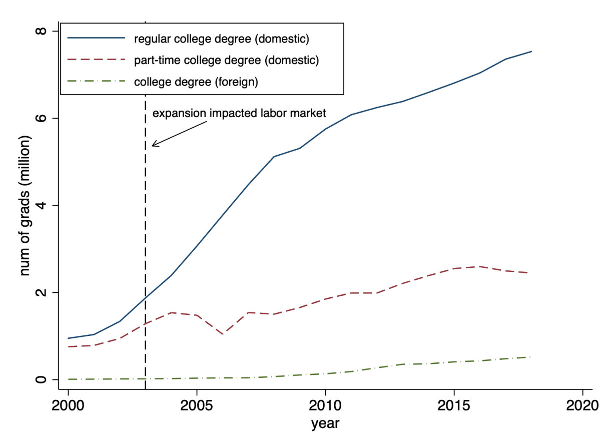


Figure A.7: Number of College Grads (Annual)

[1] I ignore those who attend part-time colleges to transform junior college diploma to university diploma.

A.2.2 Distribution of Majors

Despite China's massive college expansion, the distribution of field of study across regular college students was stable. 48% of college students studied sciences and engineering in 2000. This share slightly decreased to 42% in 2010, mainly due to declined students' percentage of studying sciences. The data after 2010 are not available because there was a break in the statistical classification of fields between 2010 and 2011. Overall, the results indicate that the skill set of college grads remained largely unchanged after 2000.

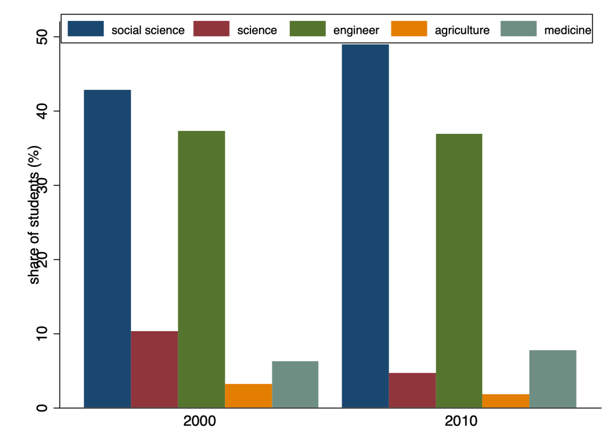


Figure A.8: Distribution of Field of Study Among Grads

Purely Processing Exporters

The subsection shows that processing exports are of lower skill intensity than ordinary exports and domestic sales. In the absence of a direct measure of skill intensity by export regimes, I follow Dai et al. (2016) to compare the firm-level ratio of workers with college degree to employment between purely processing exporters, ordinary exporters, and domestic producers. I perform this analysis using ASM 2004, in which decomposition of employment by education levels is available. For each type of firms, Table A.2 decomposes the sales into different components. A proportion of ordinary producers also performed processing exports, and henceforce I call them hybrid ordinary producers. Clearly, the primary part of purely processing firms' sales was processing exports, while hybrid ordinary exporters also exported a large amount of processing exports.

Table A.2: Decomposition of Sales for Each Type of Firms (ASM 2004)

firm types:	nonexporters	ordinary exporters pure	ordinary exporters hybrid	purely processing firms
domestic sales	100%	79%	45%	23%
ordinary exports	0%	21%	11%	0%
processing exports	0%	0%	44%	77%

Table A.3: Dependent Variable Var: Firm-level Share of Workers with College Degree

	(1)	(2)
Ordinary	0.010***	
	(0.003)	
Pure ordinary		0.033***
		(0.003)
Hybrid ordinary		-0.013***
		(0.003)
Processing	-0.051***	-0.058***
	(0.005)	(0.005)
Obs	218,599	218,599
R-squared	0.329	0.330
mean (all firms)	0.130	0.130
mean (nonexporters)	0.127	0.127

Notes: The baseline group is nonexporters. Firm-level controls are log employment, log output, and registration types (e.g., SOE). I also control city and 4-digit industry fixed effects. Standard errors are clustered by industry. Significance levels: * 10%, ** 5%, *** 1%.

In Table A.3, I regress the firm-level share of workers with college degree on dummies of firm types, city fixed effects, and industry fixed effects. I also control firm-level variables, employment size, output, and registration types. The baseline group is nonexporters. Column (1) shows that ordinary exporters were slightly more skill-intensive than nonexporters, whereas purely processing exporters were much less skill-intensive than nonexporters. The magnitude was not negligible. The average share of workers with college degree was 0.130 in 2004. Therefore, the difference between purely processing exporters and nonexporters was 40% of the skill intensity of the average firm. In Column (2), I divide ordinary exporters into purely ordinary exporters and hybrid ordinary exporters. Consistent with the fact that hybrid ordinary exporters performed a lot of processing exports, I find hybrid exporters were slightly less skill-intensive than nonexporters, whereas pure ordinary exporters were more skill-intensive than nonexporters.

A.3 Proofs

A.3.1 Proof of Migration Probabilities and Lifetime Expected Utility

Let $f_\varphi(\varphi)$ be the density function of the Type-I Extreme Value Distribution $F_\varphi(\varphi) = \exp\left(-\exp\left(-\frac{\varphi}{\nu} - \gamma\right)\right)$, with γ being the Euler constant. The migration probability from region m to n is:

$$\begin{aligned}
\Lambda^I_{m,n,a} &= \int_{-\infty}^{\infty} f_\varphi(\varphi_n) \prod_{r \neq n} F_\varphi\left(\varphi_n + \beta(U^{I'}_{n,a+1} - U^{I'}_{r,a+1}) - \tau^I_{m,n,a} + \tau^I_{m,r,a}\right) d\varphi_n \\
&= \int_{-\infty}^{\infty} \frac{\exp(-\frac{\varphi_n}{\nu} - \gamma)}{\nu} \exp\left(-\sum_r \exp\left(\frac{-\beta(U^{I'}_{n,a+1} - U^{I'}_{r,a+1}) + \tau^I_{m,n,a} - \tau^I_{m,r,a}}{\nu} - \frac{\varphi_n}{\nu} - \gamma\right)\right) d\varphi_n \\
&= \frac{1}{\sum_r \exp\left(\frac{-\beta(U^{I'}_{n,a+1} - U^{I'}_{r,a+1}) + \tau^I_{m,n,a} - \tau^I_{m,r,a}}{\nu}\right)} = \frac{\exp(\beta U^{I'}_{n,a+1} - \tau^I_{m,n,a})^{\frac{1}{\nu}}}{\sum_r \exp(\beta U^{I'}_{r,a+1} - \tau^I_{m,r,a})^{\frac{1}{\nu}}}
\end{aligned}$$

where the first equality uses that workers move to region n if and only if $\varphi_n + \beta U^{I'}_{n,a+1} - \tau^I_{m,n,a} \geq \varphi_r + \beta U^{I'}_{r,a+1} - \tau^I_{m,r,a} \; \forall \; r$. The second equality uses the definition of $f_\varphi(\varphi)$ and $F_\varphi(\varphi)$. The third equality solves the integral. Hence, I have proved equation (1.13).

Define $U^I_{m,n,a}$ as the expected utility for workers that stay in region m in this period and move to region n in the end of this period. I first derive $U^I_{m,n,a}$ and show that $U^I_{m,n,a}$ is independent of migration destination n. For skilled workers of age $0 \leq a \leq T-1$ (analogously for noncollege workers),

$$
\begin{aligned}
U^H_{m,n,a} &= \int_{-\infty}^{\infty} \left[\log \frac{S_{m,a}}{P_m} + \beta U^{H'}_{n,a+1} - \tau^H_{m,n,a} + \varphi_n\right] \\
&\quad \times \frac{\prod_{r\neq n} F_\varphi \left(\varphi_n + \beta(U^{H'}_{n,a+1} - U^{H'}_{r,a+1}) - \tau^H_{m,n,a} + \tau^H_{m,r,a}\right)}{\Lambda^H_{m,n,a}} f_\varphi(\varphi_n) d\varphi_n \\
&= \log \frac{S_{m,a}}{P_m} + \beta U^{H'}_{n,a+1} - \tau^H_{m,n,a} + \int_{-\infty}^{\infty} \frac{\varphi_n \exp(-\frac{\varphi_n}{\nu} - \gamma)}{\nu \Lambda^H_{m,n,a}} \\
&\quad \times \exp\left(-\sum_r \exp\left(\frac{-\beta(U^{H'}_{n,a+1} - U^{H'}_{r,a+1}) + \tau^H_{m,n,a} - \tau^H_{m,r,a}}{\nu} - \frac{\varphi_n}{\nu} - \gamma\right)\right) d\varphi_n \\
&= \int_{-\infty}^{\infty} y + \nu \log\left(\sum_r \exp\left(\frac{-\beta(U^{H'}_{n,a+1} - U^{H'}_{r,a+1}) + \tau^H_{m,n,a} - \tau^H_{m,r,a}}{\nu}\right)\right) f_\varphi(y) dy \\
&\quad + \log \frac{S_{m,a}}{P_m} + \beta U^{H'}_{n,a+1} - \tau^H_{m,n,a} = \log \frac{S_{m,a}}{P_m} + \nu \log\left(\sum_r \exp\left(\beta U^{H'}_{r,a+1} - \tau^H_{m,r,a}\right)^{\frac{1}{\nu}}\right).
\end{aligned}
$$

The first equality uses the definition of the expected utility. The second equality uses the definition of $f_\varphi(\varphi)$ and $F_\varphi(\varphi)$. The third equation uses integration by substitution of $y = \varphi_n - \nu \log\left(\sum_r \exp\left(\frac{-\beta(U^{H'}_{n,a+1} - U^{H'}_{r,a+1}) + \tau^H_{m,n,a} - \tau^H_{m,r,a}}{\nu}\right)\right)$. The fourth equality comes from $\int f_\varphi(y)dy = 1$ and $\int y f_\varphi(y) dy = 0$. Therefore, I obtain:

$$
U^H_{m,a} = U^H_{m,n,a} = \log \frac{S_{m,a}}{P_m} + \nu \log\left(\sum_r \exp\left(\beta U^{H'}_{r,a+1} - \tau^H_{m,r,a}\right)^{\frac{1}{\nu}}\right).
$$

The expected utility for workers of age 0 and T can be obtained analogously. ***Q.E.D.***

A.3.2 Sequential Equilibrium

I first define a static equilibrium at any time t, and I omit time t for ease of description. Let $\Pi_{m,n,j}$ be the share of expenses in region n that source from region m, which is determined as:

$$\Pi_{m,n,j} = \frac{\int \int_{\Omega_{m,n,j}} \varepsilon_{m,n,j}(\omega) \left(\frac{c_{m,j} d_{m,n,j}}{z(\omega)} \right)^{1-\sigma} d\omega}{\sum_{m'} \int \int_{\Omega_{m',n,j}} \varepsilon_{m',n,j}(\omega) \left(\frac{c_{m',j} d_{m',n,j}}{z(\omega)} \right)^{1-\sigma} d\omega} \tag{A.1}$$

where $\Omega_{m,n,j}$ is the set of goods sold from m to n, determined by export thresholds according to equation (1.7) and the distribution of state variables $N_{m,j}(\mathbf{s})$. As shown in equation (1.5), the unit cost $c_{m,j}$ is also a function of wages and price indices.

Let $Y_{m,j}$ be the total firms' production of industry j in region m. The goods market clearing requires:

$$Y_{m,j} = \sum_n \Pi_{m,n,j} \left(\frac{\sigma - 1}{\sigma} \sum_{j'} \gamma^{j}_{m,j'} Y_{n,j'} + \frac{\gamma_j^{\theta} P_{n,j}^{1-\theta}}{\sum_{j'} \gamma_{j'}^{\theta} P_{n,j'}^{1-\theta}} I_n \right) \tag{A.2}$$

where $I_m = \sum_j \left(\frac{1}{\sigma} + \frac{\sigma-1}{\sigma} (1 - \sum_{j'} \gamma^{j'}_{m,j}) \right) Y_{m,j}$ is the total expenses on final goods in region m (by workers, firm owners, and the government). The left-hand side is the total production, while the right-hand side sums up demand across different destinations.

The labor marketing clearing requires:

$$W_m L_m = \sum_j \frac{\alpha_j^{\rho_x} W_m^{1-\rho_x}}{\alpha_j^{\rho_x} W_m^{1-\rho_x} + (1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}} \frac{\sigma - 1}{\sigma} \left(1 - \sum_{j'} \gamma^{j'}_{m,j} \right) Y_{m,j} \tag{A.3}$$

$$S_m H_m = \sum_j \frac{(1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}}{\alpha_j^{\rho_x} W_m^{1-\rho_x} + (1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}} \frac{\sigma - 1}{\sigma} \left(1 - \sum_{j'} \gamma^{j'}_{m,j} \right) Y_{m,j} + \gamma_r P_{m,r} Q_{m,r} \tag{A.4}$$

where the left-hand side is the supply of labor, whereas the right-hand side is the demand for labor from production. For educated labor, there is additional demand from R&D expenditures aggregated across all firms.

Combining equations (A.1)–(A.4) and price $P_{m,j} = \left(\sum_n \int \varepsilon_{n,m,j}(\omega) p_{n,m,j}(\omega)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}$

solves $\{\Pi_{m,n,j}, X_{m,j}, W_m, S_m, P_{m,j}\}$. Then I can solve all variables in the static equilibrium.

Given sequences of wages and prices over time t and initial distributions $\{\mathcal{N}_0, \mathcal{L}_0\}$, the sequential equilibrium also requires: (1) the evolution of firm distribution $\mathcal{N}_t$ is consistent with firms' optimal choices of innovation, aggregate and idiosyncratic productivity growth, and firm entry and exits, as discussed in Section 1.3.2; and (2) the law of motion for labor distribution $\mathcal{L}_t$ is consistent with workers' migration choices as well as workers' entry and exits, as shown in Section 1.3.3.

A.3.3 Proof of Proposition 2

I now prove the response of relative wages to the relative supply of skilled workers in the autarkic economy. By firms' cost minimization, I have:

$$h_{C,j}(\omega)/l_{C,j}(\omega) = \left((1-\alpha_j)W_C/\alpha_j S_C\right)^{\rho_x}$$

for each firm ω in industry j. I define $H_{C,j} = \int h_{C,j}(\omega)d\omega$ and $L_{C,j} = \int l_{C,j}(\omega)d\omega$ as aggregate labor demand within region C and industry j, and I still obtain $H_{C,j}/L_{C,j} = \left((1-\alpha_j)W_C/\alpha_j S_C\right)^{\rho_x}$. Log differentiating this equation, I obtain:

$$\hat{H}_{C,j} - \hat{L}_{C,j} = -\rho_x(\hat{S}_C - \hat{W}_C) \tag{A.5}$$

For each industry, I notice $H_{C,j}S_C + L_{C,j}W_c = \frac{\sigma-1}{\sigma}(\gamma_j)^{\theta}\left(\frac{P_{C,j}}{P_C}\right)^{1-\theta}E_C$ from equation (1.1), where E_C is the total expenditure on the final good in region c. The ratio $\frac{\sigma-1}{\sigma}$ is the share of labor costs in the total revenue. Log differentiating this equation, I further derive:

$$\hat{E}_C + (\theta-1)(\hat{P}_C - \hat{P}_{C,j}) = (1-SI_{C,j})(\hat{W}_C + \hat{L}_{C,j}) + SI_{C,j}(\hat{S}_C + \hat{H}_{C,j}) \tag{A.6}$$

where $SI_{C,j} = \frac{H_{C,j}S_C}{H_{C,j}S_C + L_{C,j}W_C}$ is educated labor's share in the total wage bill in the initial equilibrium. Because I abstract from new firm entry and there are no fixed costs of selling in local markets, I obtain that in Chinese regions:

$$P_{C,j}^{1-\sigma} = N_{C,j}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_C^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_C^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}}\int z^{\sigma-1}dG_{C,j}(z). \tag{A.7}$$

where $N_{C,j}$ is the number of firms located in region C. $G_{C,j}(z)$ is the productivity distribution of firms in region C and industry j. Log differentiating this equation indicates:

$$\hat{P}_{C,j} = (1 - SI_{C,j})\hat{W}_C + SI_{C,j}\hat{S}_C \tag{A.8}$$

where I used the definition $SI_{C,j}$ and $H_{C,j}/L_{C,j} = \left((1-\alpha_j)W_C/\alpha_j S_C\right)^{\rho_x}$.

Combining equation (A.5), (A.6) and (A.8), I obtain:

$$\theta\hat{W}_C = (\rho_x - \theta)SI_{C,j}(\hat{S}_C - \hat{W}_C) - \hat{L}_{C,j} + \hat{E}_C + (\theta-1)\hat{P}_C \tag{A.9}$$

$$\theta\hat{S}_C = (\theta - \rho_x)(1 - SI_{C,j})(\hat{S}_C - \hat{W}_C) - \hat{H}_{C,j} + \hat{E}_C + (\theta-1)\hat{P}_C \tag{A.10}$$

Note that I do not consider innovation here, and therefore all the labor is used in production. I then have $\hat{L}_C = \sum_j \Lambda_{C,j}^L \hat{L}_{C,j}$ and $\hat{H}_C = \sum_j \Lambda_{C,j}^H \hat{H}_{C,j}$, where $\Lambda_{C,j}^H$ ($\Lambda_{C,j}^L$) is the amount of college (noncollege) labor in industry j as the share of the amount of regional college (noncollege) workers. Combining this with equation (A.9) and (A.10), I obtain:

$$\hat{S}_C - \hat{W}_C = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{C,j}(\Lambda_{C,j}^H - \Lambda_{C,j}^L))}(\hat{L}_C - \hat{H}_C). \tag{A.11}$$

I next show $1 \geq \sum_j SI_{C,j}(\Lambda_{C,j}^H - \Lambda_{C,j}^L) \geq 0$. Proving the first part $1 \geq \sum_j SI_{C,j}(\Lambda_{C,j}^H - \Lambda_{C,j}^L)$ is straightforward as $\sum_j SI_{C,j}(\Lambda_{C,j}^H - \Lambda_{C,j}^L) \leq \max_j SI_{C,j}\sum_j \Lambda_{C,j}^H = \max_j SI_{C,j} \leq 1$. For the second part, I first notice that $\Lambda^H_{C,j}/\Lambda^L_{C,j}$ is an increasing function in $SI_{C,j}$ because:

$$SI_{C,j} = \frac{H_{C,j}S_C}{H_{C,j}S_C + L_{C,j}W_C} = \frac{H_C S_C}{H_C S_C + L_C W_C \Lambda^L_{C,j}/\Lambda^H_{C,j}}$$

Therefore, $SI_{C,j}$ is larger when $\Lambda^H_{C,j}/\Lambda^L_{C,j} > 1$ than when $\Lambda^H_{C,j}/\Lambda^L_{C,j} < 1$. Then, I have

$$\begin{aligned}\sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j}) &= \sum_{j,\Lambda^H_{C,j}/\Lambda^L_{C,j}>1} \sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j}) - \sum_{j,\Lambda^H_{C,j}/\Lambda^L_{C,j}\leq 1} \sum_j SI_{C,j}(\Lambda^L_{C,j} - \Lambda^H_{C,j}) \\ &\geq 0\end{aligned}$$

Since $\sum_j \Lambda^L_{C,j} = \sum_j \Lambda^H_{C,j} = 1$, I have $\sum_{j,\Lambda^H_{C,j}/\Lambda^L_{C,j}>1} \sum_j(\Lambda^H_{C,j} - \Lambda^L_{C,j}) = \sum_{j,\Lambda^H_{C,j}/\Lambda^L_{C,j}\leq 1} \sum_j(\Lambda^L_{C,j} - \Lambda^H_{C,j})$, whereas the former is multiplied by larger weights $SI_{C,j}$ in the formula above. Hence, $\sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j}) \geq 0$.

Finally, I define Φ_C as:

$$\Phi_C = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j}))}. \tag{A.12}$$

Note the denominator is $\theta + (\rho_x - \theta)(1 - \sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j})) > 0$, because $\rho_x > 0$, $\theta > 0$ and $0 \leq \sum_j SI_{C,j}(\Lambda^H_{C,j} - \Lambda^L_{C,j}) \leq 1$. Therefore, I have proved Proposition 2. ***Q.E.D.***

A.3.4 Proof of Proposition 3

Result (i). To prove Result (i) in Proposition 3, I note that a Chinese firm's domestic sales can be written as:

$$R_{C,j} = \frac{p^{1-\sigma}_{C,C,j}}{P^{1-\sigma}_{C,C,j} + P^{1-\sigma}_{F,C,j}} \gamma^\theta_j \left(\frac{P_{C,j}}{P_C}\right)^{1-\theta} E_m, \tag{A.13}$$

where $p_{C,C,j}$ is the price charged by the Chinese firm, and $P_{F,C,j}$ is the aggregate price index for foreign firms exporting to China. Domestic firms' aggregate price index is given by

$$P_{C,C,j}^{1-\sigma} = N_{C,j}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_C^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_C^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}}\int z^{\sigma-1}dG_{C,j}(z). \tag{A.14}$$

where $N_{C,j}$ is the number of firms that are located in region C. $G_{C,j}(z)$ is the productivity distribution of firms in region C and industry j. The aggregate price indices can be obtained as:

$$P_{C,j}^{1-\sigma} = P_{C,C,j}^{1-\sigma} + P_{F,C,j}^{1-\sigma}.$$

Note that $\Pi_{C,C,j} = \frac{P_{C,C,j}^{1-\sigma}}{P_{C,C,j}^{1-\sigma}+P_{F,C,j}^{1-\sigma}}$ is the share of expenditures in region C on domestic goods.

Log differentiating equation (A.13), I would obtain

$$\hat{R}_{C,j} = (1-\sigma)(1-\Pi_{C,C,j})\hat{P}_{C,C,j} + (1-\theta)\Pi_{C,C,j}\hat{P}_{C,C,j} + (\theta-1)\hat{P}_C + \hat{E}_C \tag{A.15}$$

Log differentiating equation (A.14) gives me proportional changes in domestic price indices:

$$\hat{P}_{C,C,j} = (1-SI_{C,j})\hat{W}_C + SI_{C,j}\hat{S}_C. \tag{A.16}$$

Combining equations (A.15) and (A.16) leads to proportional changes in domestic sales.

Now consider exports for a firm that exports before and after the shock. First note that exports can be written as:

$$R_{F,j} = \left(\frac{p_{C,F,j}}{P_{F,j}}\right)^{1-\sigma}\gamma_j^{\theta}\left(\frac{P_{F,j}}{P_F}\right)^{1-\theta}E_F, \tag{A.17}$$

where $P_{F,j}$ and P_F are industry-level and final price indices in Foreign. For a Chinese firm's price

$p_{C,F,j}$, it can be written as:

$$p_{C,F,j}^{1-\sigma} = \left(\frac{\sigma}{(\sigma-1)z_j}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_C^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_C^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}}. \tag{A.18}$$

I assumed in Section 1.4 that Chinese regional economies will not affect equilibrium outcomes in foreign regions, which indicates that $P_{F,j}$ and P_F remain constant. Therefore, log differentiating equation (A.17), I can derive:

$$\hat{R}_{F,j} = (1-\sigma)\hat{p}_{C,F,j}, \tag{A.19}$$

where $\hat{p}_{C,F,j}$ can be derived by log differentiating equation (A.18),

$$\hat{p}_{C,F,j} = (1-SI_{C,j})\hat{W}_C + SI_{C,j}\hat{S}_C. \tag{A.20}$$

Combining these two equations, I derive proportional changes in exports in Result (i).

Result (ii). Note that the export threshold for industry j can be solved as:

$$\frac{R_{F,j}}{\sigma} - f_{C,F,j}P_C = 0 \Rightarrow z_j^* = \left(\frac{\sigma f_{C,F,j}P_C}{E_F P_F^{\theta-1} P_{F,j}^{\sigma-\theta}\gamma_j^{\theta}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{(\sigma-1)}\left[\frac{\alpha_j^{\rho_x}}{W_C^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_C^{\rho_x-1}}\right]^{\frac{1}{1-\rho_x}} \tag{A.21}$$

where z_j^* is the export threshold in industry j. It is easy to show:

$$\hat{z}_j^* = (1-SI_{C,j})\hat{W}_C + SI_{C,j}\hat{S}_C \tag{A.22}$$

Therefore, the threshold z_j^* declines more in the more skill-intensive industry when $\hat{W}_C - \hat{S}_C > 0$. If the density of firms around the export threshold is identical in two industries, there would be more export entry in the more skill-intensive industry.

Result (iii). Finally, consider that there is no new export entry. If $\sigma > \theta$ and self-import ratios $\Pi_{C,C,j} > 0$ are similar across industries, for two industries with skill intensities $SI_{C,j} > SI_{C,j'}$, from Result (i), I have:

$$\underbrace{(\sigma-1)(SI_{C,j}-SI_{C,j'})}_{\text{relative growth in exports}} > \underbrace{(\sigma-1)(SI_{C,j}-SI_{C,j'})+(\theta-\sigma)\left(\Pi_{C,C,j}SI_{C,j}-\Pi_{C,C,j'}SI_{C,j'}\right)}_{\text{relative growth in domestic sales}}. \tag{A.23}$$

where the left-hand side is the relative growth of exports across two industries, and the right-hand side is the relative growth of domestic sales. Therefore, the difference in growth rates between more and less skill-intensive industries is larger for exports than for domestic sales. In other words, the skill structure of exports shifts more toward high skill-intensity industries than domestic sales. I can obtain analogous results when there is new export entry and the productivity distribution is Pareto—which implies that the extensive margin of exports is identical across industries. This completes the proof. ***Q.E.D.***

A.3.5 Proof of Proposition 4

Result (i) combines proportional growth of domestic sales and exports from Result (i) of Proposition 3. Result (ii) comes from the observation that starting to export improves revenues, thus increasing returns to innovation. ***Q.E.D.***

A.4 Robustness of Empirical Analysis

A.4.1 Mapping from Reduced-form Estimate to Structural Parameters

In Proposition 3, I abstract from input-output linkages, innovation, firm entry, operation costs, and demand and productivity shocks. I discuss how these abstractions affect the mapping between the reduced-form estimates and the structural parameters.

First, incorporating input-output linkages does not affect the transmission of production costs to exports and domestic sales. Therefore, the mapping remains the same.

Second, introducing innovation makes the transmission of the college expansion to changes in production costs firm-specific, because different firms have different innovation levels. However, it does not affect the transmission of changes in production costs to changes in exports and domestic sales. As long as I use the same set of firms to estimate the responses to the college expansion, modelling innovation does not affect the mapping between the reduced-form estimates and the structural parameters. Appendix A.4.2 shows that restricting all regressions to exporters only slightly changes the implied between-industry and within-industry elasticities of substitution.

Third, modelling firm entry could bias the mapping, because more skill-intensive industries could experience more firm entry that reduces sales for incumbent firms. In Column (1) of Table A.4, I regress changes in the number of new entrants between 2005–2011 in each province-industry pair,[2] where entrants are identified by firms' birthyear, on the exposure to the college expansion. I find that larger exposure to the college expansion triggered more firm entry. In Column (2) of Table A.4, for each province-industry pair, I regress the sale share in 2011 of firms that entered between 2005–2011, on the exposure to the college expansion. The result shows that the college expansion did not significantly affect sales across industries in 2011 through firm entry between 2005–2011, as new firms tended to be small.

Finally, modelling operation costs and idiosyncratic shocks could also bias the mapping, as firms that operated in 2005 might exit in later years, and firms that remained operating in 2010 could be selective. Because more productive firms were less likely to suffer from selection effects, I experimented with restricting the sample to initially large firms (in terms of employment, output value, or export value), which leads to quantitatively similar regression results as in Table 1.1.

As another check, I look into how exiting firms affected industry sales. In Column (3)

[2] I use ASM 2005 and 2011 for regressions because ASM provides a full coverage of firms above certain sales threshold, while SAT is only a sample of firms. One concern is that ASM 2005 and 2011 have different sales truncation. I experimented with implementing the same sales truncation for two years as well as using ASM 2005 and SAT 2010 for regressions, and the results in this subsection remain qualitatively unchanged.

Table A.4: Dependent Variable: Province-industry-level Variables in 2005–2011

Dep var:	Δlog(num of entrants)	% entrants' sales	% exiters	% exiters' sales
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
Exposure to CE	2.411**	-0.152	-0.471***	0.112
	(1.180)	(0.245)	(0.110)	(0.448)
Obs	585	789	798	798
R-squared	0.474	0.388	0.483	0.465
First-stage F	425.10	481.99	402.56	414.61

Note: This table provides estimates from regressions, treating regions as provinces, using the same constructed shocks and instruments as in Section 1.5. I also exclude purely processing exporters to be consistent with Section 1.5. I control the share of SOE firms, log employment, log fixed capital, and log production value for each province-industry-pair in 2005, as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Regressions in Column (1) and (3) are weighted by the number of entrants and the total number of firms in each province-industry pair in 2005, respectively. Regressions in Column (2) and (4) are weighted by the total sales of firms in each province-industry pair in the corresponding year. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

of Table A.4, for each province-industry pair, I regress the number of firms that exited between 2005–2011,[3] normalized by the number of firms in 2005, on the exposure to the college expansion. I find that larger exposure to the college expansion led to fewer firm exits. In Column (4), for each province-industry pair, I regress the sales share in 2005 of firms that exited between 2005–2011, on the exposure to the college expansion. The result shows that exiting firms between 2005–2011 due to the college expansion were small and did not significantly affect sales across industries in 2005.

A.4.2 Robustness Checks of Empirical Results

Alternative Instruments

Using U.S. College Employment Shares. I draw total employment and college-educated workers' employment on the three-digit industry level from the U.S. 1990 Census.[4] I then take efforts to map these data to 2-digit industries based on China's Indutsrial Classification. By doing

[3]The exiting firm is defined as a firm that showed up in ASM 2005 but disappeared in ASM 2011.

[4]The data are drawn from IPUMS International.

so, I obtain an alternative measure of skill intensities of Chinese industries from the U.S. data. I replace $SI_{m,j}$ with this alternative measure in constructing exposure to the college expansion $SI_{m,j}x_m$ and the related instrument $SI_{m,j}x_m^*$. I replicate the regressions in Table 1.1 and 1.2. The results are quantitatively similar to my baseline results, as shown in Table A.5 and A.6, with the implied between-industry and within-industry elasticities of substitution being $1.7 \sim 2$ and $9.7 \sim 13.3$.

Using Instruments Based on the 1948 Distribution of Colleges. The Statistical Yearbook of Education in 1948[5] provides detailed information on locations and enrollments of each college that was in operation by 1948. I take efforts to digitize this yearbook. I then construct two new instruments x_m^*, by replacing the share of college enrollments in the national total in 1982 in equation (1.16) with either the share of college number in the national total or the share of college enrollments in the national total in 1948. I then use these two instruments to replicate the regressions in Table 1.1 and 1.2. The results can be found in Table A.5 and A.6. The implied between-industry and within-industry elasticities of substitution are $3.4 \sim 4.6$ and $6.4 \sim 7.4$, which are similar to the estimates in Table 1.1.

Using Instruments Based on China's Reallocation of University Departments. In the 1950s, Chinese government implemented massive reallocation of college departments that were largely induced by political reasons: see Glaeser & Lu (2018) for a detailed description. I obtain each city's number of transfer-in and transfer-out college departments during this process, by digitalizing each college's detailed history in Ji (1992). I compute the ratio of the net number of transfers (transfer-in minus transfer-out) to college employment for each city in 2005. I use this ratio as another alternative instrument for x_m and replicate the regressions in Table 1.1.[6] I find that this instrument lacks variation and gives quite imprecise estimates, especially when I aggregate transfers by provinces to construct the instrument for province-level shocks.[7] The

[5]The data can be found in https://www.naer.edu.tw/files/15-1000-7981,c1311-1.php?Lang=zh-tw.

[6]I do not display results for innovation because they are all insignificant.

[7]I do not report regressions based on province-level shocks because the estimates on domestic sales, exports, and

Table A.5: Robustness Checks of Table 1.1

Dep var:	Δlog(ord. exports)		Δlog(dom. sales)		Δlog(export prices)	
Geographic level:	city	province	city	province	city	province
Alternative instruments:						
(1) Use U.S. data to measure industry-level skill intensities	4.397*** (0.876)	5.477*** (0.901)	1.270*** (0.469)	1.348*** (0.488)	-0.509* (0.282)	-0.443* (0.257)
(2) Use 1948 college number to instrument for labor shocks	3.188*** (0.857)	3.633*** (0.797)	2.338*** (0.519)	2.001*** (0.503)	-0.587** (0.260)	-0.619** (0.261)
(3) Use 1948 college enroll to instrument for labor shocks	3.137*** (0.837)	3.469*** (0.812)	2.180*** (0.567)	1.749*** (0.541)	-0.562** (0.269)	-0.540** (0.264)
(4) Use 1950s univ change to instrument for labor shocks	4.734* (2.766)	–	4.571* (2.831)	–	-0.928 (1.537)	–
Different Data:						
(5) Use goods exported in two periods to construct exports	3.315*** (0.700)	3.687*** (0.665)	2.006*** (0.420)	1.820*** (0.421)	-0.628*** (0.230)	-0.645*** (0.229)
(6) Use changes btw 2005–07 for estimation	1.356*** (0.537)	1.441*** (0.506)	0.597*** (0.146)	0.455*** (0.129)	-0.212* (0.114)	-0.227** (0.104)
(7) Restrict to exporters	3.679*** (0.721)	3.796*** (0.717)	2.693*** (0.733)	2.407*** (0.733)	-0.628*** (0.230)	-0.645*** (0.229)

Note: This table replicates the corresponding regressions in Table 1.1 with alternative instruments or data construction. Standard errors are clustered on the province-industry level. Significance levels: * 10%, ** 5%, *** 1%.

coefficients on changes in ordinary exports or domestic sales are similar to the estimates in Table 1.1. I do not report the implied elasticities of substitution because the coefficients on export prices are insignificant.

Alternative Data Construction

Using Goods Exported in Both Periods to Construct Exports and Export Price Changes. I use 6-digit HS goods exported in both periods to construct changes in exports to avoid firms' switches of products. I replicate the regressions in Table 1.1, and the results are shown in Table A.5. The resulting between-industry and within-industry elasticities of substitution are $3.1 \sim 3.7$ and $6.3 \sim 6.7$.

prices are all insignificant.

Table A.6: Robustness Checks of Table 1.2

Dep var:	ΔR&D status					
	nonexporter	ord. exporter	nonexporter	ord. exporter	all firms	export share<0.4
	(1) Alternative instrument: Use U.S. data to measure industry-level skill intensities					
Exposure to CE	0.525***	0.566***	0.447***	0.639***	0.516***	0.463***
	(0.137)	(0.191)	(0.129)	(0.214)	(0.124)	(0.125)
Exposure to CE × export share					0.342	3.454***
					(0.487)	(1.328)
	(2) Alternative instrument: Use 1948 college number to instrument for labor shocks					
Exposure to CE	0.510***	0.607***	0.423***	0.652***	0.524***	0.473***
	(0.108)	(0.173)	(0.097)	(0.209)	(0.097)	(0.101)
Exposure to CE × export share					-0.015	2.844**
					(0.444)	(1.461)
	(3) Alternative instrument: Use 1948 college enrollments to instrument for labor shocks					
Exposure to CE	0.483***	0.541***	0.399***	0.586***	0.484***	0.442***
	(0.107)	(0.169)	(0.092)	(0.207)	(0.100)	(0.101)
Exposure to CE × export share					-0.016	2.469*
					(0.495)	(1.479)
	(4) Alternative data construction: Use changes between 2005–2007 for estimation					
Exposure to CE	0.283***	0.294***	0.229***	0.278***	0.295***	0.278***
	(0.059)	(0.086)	(0.060)	(0.091)	(0.056)	(0.059)
Exposure to CE × export share					-0.087	1.300**
					(0.239)	(0.628)

Note: This table replicates the corresponding regressions of Table 1.2 with alternative instruments or data construction. Standard errors are clustered on the province-industry level. Significance levels: * 10%, ** 5%, *** 1%.

Using Changes between 2005–2007. I use log changes in domestic sales, exports, and export prices between 2005–2007 as dependent variables, which are drawn from the constructed firm-level balanced panel in 2005 and 2007. I only use the ASM to construct the panel and can now show that my results are not due to the use of different datasets (ASM and SAT). I replicate the regressions in Table 1.1 and Table 1.2. The magnitude of the coefficients tends to be smaller, because I look into the shorter period. As suggested by Table A.5, the implied between-industry and within-industry elasticities of substitution are $2.0 \sim 2.9$ and $7.3 \sim 7.4$, which are slightly smaller than the estimates in Table 1.1.

Table A.7: Dependent Variable: Province-industry-level Annualized Changes

Dep var:	Δlog(dom. sales)		Δlog(ord. exports)		Δshare of R&D firms			
					nonexporter		ord. exporter	
Period	01–05	05–11	01–05	05–11	01–05	05–10	01–05	05–10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Exposure to CE	-0.913***	0.385*	0.511	0.785***	0.027	0.084***	0.042	0.101**
	(0.203)	(0.202)	(0.466)	(0.162)	(0.027)	(0.024)	(0.042)	(0.040)
Obs	786	745	600	587	785	783	600	586
R-squared	0.400	0.541	0.225	0.353	0.194	0.447	0.175	0.566
First-stage F	502.38	432.96	147.09	138.45	635.23	518.47	302.85	232.86

Note: This table provides estimates from regressions of province-industry-level changes on the exposure to the college expansion, using the same constructed shock and instrument as in Section 1.5. I use ASM 2001, ASM 2005, and ASM 2011 to construct province-industry-level trends of domestic sales and ordinary exports between 2001–2005 and 2005–2010, because ASM data are informative about all China's manufacturing sales by industry. I use ASM 2001, ASM 2005, and SAT 2010 to construct the share of R&D firms among ordinary exporters and nonexporters for each province-industry in each year. I then obtain province-industry-level changes between 2001–2005 and 2005–2010. I control the share of SOEs, log employment, log fixed capital, and log production value in the initial year for each province-industry pair, as well as province-specific trends. I also control input and output tariff reductions on the 2-digit industry level. In Columns (1)–(4), regressions are weighted by the amount of domestic sales and ordinary exports within each province-industry pair in the initial year. In Columns (5)–(8), regressions are weighted by the number of firms, which are separately derived for exporters and nonexporters within each province-industry pair in the initial year. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

Restricting the Sample to Exporting Firms. Because my regressions of changes in ordinary exports and export prices are only focused on exporting firms, a final robustness check of Table 1.1 is that I restrict the regression of changes in domestic sales to exporting firms as well. As suggested by Table A.5, the implied between-industry elasticity of substitution is $4.2 \sim 4.9$, which is slightly larger than the estimates in Table 1.1. The implied with-industry elasticity of substitution remains identical to my baseline results.

A.4.3 Pre-trend Tests

As suggested by Goldsmith-Pinkham et al. (2018), I perform pre-trend tests to support the validity of my instrument. I regress province-industry-level trends of sales and innovation before and after 2005 on the exposure to the college expansion between 2005–2010, using the same constructed shock and instrument as in Section 1.5. Table A.7 shows that the college expansion between 2005–2010 had no positive effects on industry-level changes in domestic sales, exports, and innovation between 2001–2005 (when the college expansion had small effects on labor markets). The effects on the changes after 2005 were sizable.

A.5 Calibration

A.5.1 Incorporating Processing Producers into the Model

I follow Liu & Ma (2018) to allow for each Chinese region and manufacturing industry to have a number of processing firms. Production functions in Chinese region $m \in \mathcal{C}$ are now specific to export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$. Specifically, final goods in each region and export regime are composed of regime-specific industry-level intermediate goods:

$$Q_{m(k)} = \left(\sum_j \gamma_j Q_{m(k),j}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}.$$

Industry-level intermediate goods in each China's province-regime are composed of varieties sourced from foreign firms as well as ordinary firms in China, as processing output cannot be sold domestically:

$$Q_{m(k),j} = \left(\int \varepsilon_{F,m(k),j}(\omega)^{\frac{1}{\sigma}} q_{F,m(k),j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \sum_{n \in \mathcal{C}} \int \varepsilon_{n(\mathcal{O}),m(k),j}(\omega)^{\frac{1}{\sigma}} q_{n(\mathcal{O}),m(k),j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}.$$

Research goods in each province and export regime are produced using regime-specific final goods and educated labor:

$$Q_{m(k),r} = A_{m,r} E_{m(k),r}^{\gamma_r} H_{m(k),r}^{1-\gamma_r}.$$

Firms' output in each province-regime-industry is produced using educated labor, less educated labor, and raw materials from other industries, with regime-specific input-output parameters and skill intensities,

$$q_{m(k),j} = z_{m(k),j} \left[\alpha_{j(k)} l^{\frac{\rho_x - 1}{\rho_x}} + (1 - \alpha_{j(k)}) h^{\frac{\rho_x - 1}{\rho_x}} \right]^{\frac{\rho_x \gamma^L_{m(k),j}}{\rho_x - 1}} \prod_{j'=1}^{J} b_{j'}^{\gamma^{j'}_{m(k),j}}.$$

The following parameters are regime-specific: input-output parameters $\{\gamma^L_{m(k),j}, \gamma^{j'}_{m(k),j}\}_{m \in \mathcal{C}}$, skill intensities $\{\alpha_{j(k)}\}$, inter-provincial trade costs $\{d_{n(k'),m(k),j}\}_{m,n \in \mathcal{C}}$, import/export trade costs in China $\{d_{F,m(k),j}, d_{m(k),F,j}\}_{m \in \mathcal{C}}$, marketing costs for imports and exports $\{f_{F,m(k),j}, f_{m(k),F,j}\}_{m \in \mathcal{C}}$, operation costs $\{f_{m(k),j}\}_{m \in \mathcal{C}}$, exogenous productivity growth $\{g_{m(k),j}\}_{m \in \mathcal{C}}$, and the number of entrants $\{N_{m(k),j}\}_{m \in \mathcal{C}}$ (or entry costs $\{f^e_{m(k),j}\}_{m \in \mathcal{C}}$).

Parameters of processing firms differ from ordinary firms in the following aspects.

- Processing exporters are duty-free and intensively use imports. Therefore, I let variable import trade costs $d_{F,m(k),j}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$ and be disciplined by shares of imports in total expenditures in each region-regime-industry.

- Processing exporters have lower valued added shares than ordinary exporters (Kee & Tang 2016). I thus let parameters in firm production $\{\gamma^L_{m(k),j}, \gamma^{j'}_{m(k),j}\}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$.

- Processing exporters have lower skill intensities than ordinary exporters, and thus I let skill intensities in firm production $\alpha_{j(k)}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$.

- Processing exporters cannot sell to domestic markets, and thus trade costs for processing producers in domestic markets are $d_{n(\mathcal{P}),m(k),j} \to \infty\ \forall n, m \in \mathcal{C}, k \in \{\mathcal{O}, \mathcal{P}\}$.

- Processing exporters barely innovate. Therefore, I do not consider processing exporters' innovation decisions.

I assume that workers are perfectly mobile between processing and ordinary firms in each province, and thus adding processing firms does not change workers' problem. The only change for Foreign is that foreign industry-level intermediate producers now source varieties from both China's processing and ordinary firms.

A.5.2 Provinces and Industries

I calibrate a 33-industry version of my model with 30 Chinese provinces and a constructed Rest of World. I omit Tibet Province due to the lack of data. I group industries according to China's Industry Classification System (CIC) published in 2003, as shown in Table A.10. I consider agriculture, mining, and services as nontradable, whereas all manufacturing industries are tradable. Thus, only manufacturing industries produce processing exports.

A.5.3 Description of Data Sources

Output and Exports. I obtain China's manufacturing output by industry and province between 2000–2012 from ASM. I obtain processing and ordinary exports by province and industry from the matched ASM-Customs Database.[8] For each province-industry, the difference between total output and processing exports is the output of ordinary production. I draw provincial production in agriculture, mining, and services by province between 2000–2012 from input-output tables.[9] To match the aggregate data from the statistical yearbook, for each year, I rescale manufacturing firms' output, services' output, and mining output to match the ratio of manufacturing firms' sales to GDP as well as the share of services and mining in China's GDP.

I obtain foreign output by industry between 2000–2011 from the World Input-Output Table Database. Because these data are based on the ISIC classification, I convert foreign industrial output to my 33 industries using concordances in Dean & Lovely (2010).[10]

[8]As the match between ASM and Customs Database is imperfect, for each province, I adjust the value of processing (ordinary) exports in the matched sample proportionally to match the total value of processing (ordinary) exports in customs data.

[9]I obtain provincial production in agriculture, mining and services in 2002, 2007, and 2012 from input-output tables and interpolate the values in missing years using the linear trend interpolation.

[10]Because the World Input-Output Table Database only records 2-digit industries, there are lots of multiple-

As my data on China and foreign industry-level output are not available after 2012, I will calibrate productivity growth to match GDP growth rates of China relative to Foreign after 2012. The GDP growth rates between 2012–2018 are available from Penn Table 9.1. Between 2018–2030, I assume that China's GDP grows at an annualized rate of 2% relative to Foreign, according to predictions in the World Economic Outlook Reports.

Input-Output Tables. I obtain China's input-output parameters from China's input-output tables in 2005, and rescale value added shares separately for processing and ordinary firms to match the ones computed from the ASM-Customs matched data. I allow for input-output parameters in Foreign to differ from China, using the World Input-Output Database to compute input-output parameters for Foreign.

Imports by Industry and Regime. I obtain imports by export regimes and province from China's Customs Transactions Database. The original data are based on 8-digit HS products. I aggregate these data into my 33 industries using the concordances between HS products and ISIC in WITS and between ISIC and CIC in Dean & Lovely (2010).

Export and Import Tariffs by Industry and Regime. I obtain tariff data for 4-digit HS products between 2000–2012 from UNCTAD TRAINS Database and compute weighted-average tariffs for China's exports and imports by 33 industries, using the concordances between HS products and ISIC in WITS and between ISIC and CIC in Dean & Lovely (2010). I assume that China's export and import tariffs remain unchanged after 2012.

Inter-provincial Trade by Industry and Regime. I obtain China's inter-provincial bilateral trade flows using China's regional input-output table for 42 CIC industries in 2007. I deflate these trade flows to the year 2005 using growth rates of China's industrial output between 2005–2007 and aggregate them into 33 industries.

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to-multiple correspondences between ISIC and China's CIC industries. To deal with this, I use 4-digit U.S. manufacturing industries' output to compute the percentage of each 2-digit ISIC industry's output that corresponds to each China's industry.

The raw data do not report export regimes, and I construct trade flows between province-regime-industries following Liu & Ma (2018). Because processing production is not allowed to sell domestically, inter-provincial trade flows from regional input-output tables reflect domestic sales from ordinary producers. I compute the amount of domestic sales to processing producers at each destination and industry, using input-output tables, processing exports, and processing imports.[11] The rest of domestic sales are sold to ordinary intermediate-good producers. I further assume that processing and ordinary producers at each destination and industry have identical expenditure shares on goods from each domestic origin to obtain trade flows between province-industry-regimes.[12]

Firm Distribution. I obtain the number of firms by province and industry from Firm Census 2004, 2008, and 2013, and divide the number of firms in each province-industry into two export regimes (ordinary or processing) using the relative number of two types of firms in the matched ASM-Customs Database 2000–2012. I interpolate and extrapolate the data for the missing years between 2000–2030 using the linear trend. Due to the lack of firm data in Foreign, I assume that in 2005, for each industry, the ratio of firm numbers in Foreign to China's firm numbers is equal to the relative output ratio. I then use employment growth to obtain firm numbers in Foreign for all other years.

Labor Market Data. I obtain employment by age, province, and education levels in 2000 and 2005 from Population Census. The data in 2005 also provides wage data. I adjust workers of lower education levels to the equivalents of high-school grads, using relative wages of different education groups[13] I adjust part-time college grads to the equivalents of college grads with regular

[11] I use input-output tables and processing exports to compute expenditures on raw materials for processing exporters at each destination and industry. The difference between all the raw materials needed and processing imports is the amount of goods sourced from domestic origins.

[12] This is because I do not have details on whether each trade flow (from an origin) is sold to ordinary or processing producers in the destination. The assumption of proportionality is typical in the trade literature (e.g., Johnson & Noguera 2016).

[13] I estimate a Mincer regression of log earnings on a set of dummies indicating different education levels as well as province fixed effects. I also control for a dummy variable indicating whether the worker is in agriculture

degrees, using their relative wages from Xu et al. (2008). I use inter-provincial migration flows in Population Census 2000 to inform migration costs.

I obtain the number of college grads by each province between 2000–2014 from China's City Statistical Yearbook and extrapolate these data until 2018 using the distribution of grads in 2014 and changes in the total amount of college grads. When I simulate the model until 2030, I set the number of college grads between 2019–2030 by province to be identical as in 2018. I infer the amount of new noncollege labor between 2000–2018 from changes in China's labor force and the number of college grads. I set the growth rate of the labor force between 2019–2030 to be -0.3%, according to the predicted pattern of World Population Prospects on those aged 20–65 in China. Due to the lack of data, I set the distribution of new noncollege labor across provinces to be the same as that in the 2000 Population Census. I also set the distribution of birthplace provinces for new college-educated and noncollege workers in each province according to the 2000 Population Census.

I obtain foreign college-educated and noncollege employment by age between 2000–2018 from Barro & Lee (2013) and adjust each year's employment proportionally to match the total amount of employment from the World Bank. I adjust noncollege workers to the equivalents of high-school grads (12 years of schooling) by assuming that the returns to one year of schooling are 10%. I further extrapolate these data until 2030 using the linear trend of the labor force before 2018 (1.5% annual growth rate).

I also use the Urban Household Survey 1988–2009 to understand how the college premium changes over time. This survey is implemented yearly by National Bureau of Statistics to solicit information on demographics and income from China's urban households. It covers a representative sample of urban households in 18 provinces of China for the years 1988-2009 (repetitive cross sections). The sample size is around 30 thousand in the early period (1988-2001) and increases to 100 thousand in the later period (2001–2009).

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sector, given persistent differences in wage levels between agricultural and nonagricultural workers. I then use the coefficients on education levels to adjust workers of lower education levels to the equivalents of high-school grads.

A.5.4 Calibration Procedure

I consider several sets of parameters as time-variant: the amount of new college-educated and noncollege workers over time $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{\mathcal{C},F\}}$; productivity growth $\{g_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$; aggregate productivity of research goods $\{A_{u,r,t}\}_{u\in\{\mathcal{C}\}}$; international trade costs $\{d_{u,F,j,t}, d_{F,u,j,t}\}_{u\in\tilde{\mathcal{C}}}$; the amount of exogenous firm entrants $\{N_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ (or entry costs $\{f^e_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ under free entry); and the schedule of R&D tax incentives $\zeta_t(\cdot)$.

Pre-determined Parameters

A period in the model is one year. I set $T = 45$ years for the length of the working life (aged 20–64), the discount rate $\beta = 0.95$, and migration elasticity $\nu = 2$ of annual frequency from Caliendo, Dvorkin & Parro (2015). I use input-output linkages $\{\gamma^L_{u,j}, \gamma^{j'}_{u,j}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ from China's and the World Input-Output Tables for 2005. I use the amount of new college-educated and noncollege workers $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{\mathcal{C},F\}}$ in each year from the data. The schedule of R&D tax incentives $\zeta_t(\cdot)$ is drawn from Chen et al. (2018).

I next show how I calibrate other parameters. I order the data moments in a sequence relating to the most relevant parameters, and the parameters are exactly identified.

Step 1: Calibrating Production Parameters and Trade Costs

As shown in Section 1.3.4, given labor and firm distributions, my model is a static trade model. I thus pin down production parameters and trade costs by simulating the static equilibrium for 2005, in which year distributions of workers and firms are available.

I calibrate the following parameters. (1) Parameters $\{\gamma_j\}$ in final-good production,[14] which determine the relative demand of industry-level goods. (2) Parameter γ_r in research-good production, which determines the usage of college-educated labor in research processes. (3) Parameters $\{\alpha_{j(k)}\}_{k\in\{\mathcal{O},\mathcal{P}\}}$ in firm production, which govern skill intensities by industry and

[14] I normalize $\sum_j \gamma_j = 1$ as changing $\{\gamma_j\}$ by the same proportion does not affect the relative output.

export regime. (4) Parameters $\{\beta_a^H\}$ and $\{\beta_a^L\}$ in labor supply function,[15] which pin down the relative productivity of workers across ages. (5) Variance of demand shifters $\frac{\sigma_\varepsilon^2}{1-\rho_\varepsilon^2}$, determining the dispersion of idiosyncratic demand. (6) I introduce a new parameter c_{agr}. I assume that wages in agriculture are a portion c_{agr} of nonagricultural wages in China and that workers are indifferent between agriculture and nonagriculture despite wage differences.[16] This assumption is needed to match China's large agricultural employment share. (7) I parameterize inter-provincial trade costs from ordinary firms,

$$\log d_{m(\mathcal{O}),n(k'),j} = \beta_{1,j} \log dist_{m,n} + \beta_{2,j} contig_{m,n},\ \forall m,n \in \mathcal{C}, m \neq n, k' \in \{\mathcal{O},\mathcal{P}\},$$

and costs of selling locally $d_{m(\mathcal{O}),m(k'),j} = 1$. $dist_{m,n}$ is the distance between capitals of provinces m and n. $contig_{m,n}$ is a dummy variable that equals 1 if provinces m and n are contiguous, capturing "border effects." Because processing exporters cannot sell domestically, I set $d_{n(\mathcal{P}),m(k),j} \to \infty\ \forall n,m \in \mathcal{C}, k \in \{\mathcal{O},\mathcal{P}\}$. (8) International trade costs $\{d_{u,F,j,2005}, d_{F,u,j,2005}\}_{u\in\tilde{\mathcal{C}}}$. (9) Firms' marketing costs $\{f_{u,F,j}, f_{F,u,j}\}_{u\in\tilde{\mathcal{C}}}$. I consider firms' marketing costs to be zero for domestic destinations. Note that parameters (7)–(9) are considered only for tradable industries.

I target the following moments. (1) The relative output of each industry. (2) The ratio of full-time R&D workers to manufacturing employment in China. (3) The share of college-educated workers in employment by industry and export regime (relative to services), and aggregate college premium in China.[17] (4) The relative wages of workers across age groups in China. (5) The

[15] I normalize $\sum_a \beta_a^H = 1$ and $\sum_a \beta_a^L = 1$, as changing $\{\beta_a^H\}$ or $\{\beta_a^L\}$ by the same proportion has the identical effects as changing $\alpha_{j(k)}$. To reduce the number of parameters that require calibration, I divide workers' ages into three-year groups $\{$20–22,23–25,...62–64$\}$, with same β_a^H and β_a^L in each group.

[16] To rationalize wage differences between sectors, Zilibotti et al. (2019) assume that the government taxes wages in nonagriculture. The wage differences could also be rationalized by large migration costs for workers to move from agricultural to nonagricultural work (Tombe & Zhu 2019).

[17] I use relative shares because the overall share of college-educated workers in employment is already given by the data and thus does not inform the parameters. These shares are computed from ASM 2004 for manufacturing industries and export regimes, and from Population Census 2005 for other nonmanufacturing industries. The aggregate college premium is computed as the average wage of college-educated workers relative to aged 20–22 high-school grads, from Population Census 2005.

standard deviation of export-output ratios among exporters. (6) China's agricultural employment share. (7) For each industry, the sum of trade shares to nonself and contiguous provinces.[18] (8) For each industry, the share of foreign expenses sourced from each China's province-regime, and the share of each China's province-regime expenses sourced from Foreign. (9) For each industry, the share of exporting firms in each China's province-regime, and the share of exporting firms from Foreign to each China's province-regime.[19] The data moments are computed from ASM, Customs, regional input-output tables, and Population Census for 2005.

Although I know the distribution of firm numbers across region-industry-regimes, I still require firms' productivity levels to solve the model. I assume firm-level productivity to be Pareto-distributed. The shape parameter is chosen to match the Pareto tail index of sales distribution in ASM 2005. The location parameter is specific to each province-industry-regime or foreign industry and calibrated to match the output level.

Table A.8 reports the calibrated parameter values, which are reasonable compared with the literature. For instance, after transforming marketing costs into U.S. dollars using the relative output value between the data and the model, the average marketing costs are \$54,000, close to \$50,000 used by Tintelnot (2017). The relative wage between agricultural to nonagricultural workers is 0.26, close to 0.32–0.35 empirically found in Gai et al. (2020) for annual earnings and 0.24–0.37 used by Zilibotti et al. (2019).

In Table A.9, I compare the targeted moments in the model and in the data, and my model matches the data moments pretty well. The only moment with considerable deviation is the share of imports in domestic expenses for each Chinese province-industry-regime. This is because I impose the balanced trade at the province level in the model, whereas China ran trade surplus in reality.

[18]The sum of trade shares to nonself provinces is computed as $\sum_{m\in\mathcal{C}}\sum_{n\in\mathcal{C},n\neq m}\sum_{k\in\{\mathcal{O},\mathcal{P}\}}\Pi_{m(\mathcal{O}),n(k),j}$, where $\Pi_{m(\mathcal{O}),n(k),j}$ is the share of expenses in province-regime $n(k)$ on imports from ordinary producers in province m. The sum of trade shares to contiguous provinces is similarly computed.

[19]Because all processing firms export, I set firms' marketing costs to be zero for processing exporters. For each industry, I use the share of exporting firms in the U.S. from Bernard et al. (2007) as a proxy for the share of exporters in Foreign to each Chinese province-regime.

Finally, I choose firms' operation costs $\{f_{u,j}\}_{u \in \{\tilde{\mathcal{C}}, F\}}$ to equal the lowest profits among operating firms for China's province-regime-industry or foreign industry. I obtain China's import and export trade costs in year t, by adjusting $\{d_{u,F,j,t}, d_{F,u,j,t}\}_{u \in \tilde{\mathcal{C}}}$ according to tariff changes between 2005 and year t.

Step 2: Calibrating Migration Costs and Elasticities of Substitution of Labor

In the second step, given observed distributions of firm numbers across region-industry-regime pairs, I simulate my model with only workers' migration decisions.

I assume that migration costs are zero if workers stay in the current province. If the worker moves to another province, migration costs are a function of age, distance, contiguity, and a destination-specific term (if the destination is not the worker's birthplace),

$$\tau^I_{m,n,a} = \gamma^I_{age} a + \gamma^I_{dist} \log dist_{m,n} + \gamma^I_{contig} contig_{m,n} + \mathbf{1}_{n \neq birthplace} \gamma^I_n, I \in \{H, L\},\ m, n \in \mathcal{C}. \quad \text{(A.24)}$$

$dist_{m,n}$ and $contig_{m,n}$ are defined in the same way as in trade costs. The last term captures the Hukou policy following Fan (2019), because moving to a destination that is not one's birthplace could incurs welfare losses due to limited access to the destination's Hukou. Thus, I group workers based on skill types, current location of residence, and birthplaces. Bilateral migration rates $\Lambda^I_{m,n,a}$ $I \in \{H, L\}$ in the model are now employment-weighted averages across labor groups of different birthplaces.

I choose $\{\gamma^I_{age}, \gamma^I_{dist}, \gamma^I_{contig}, \gamma^I_n\}$ and the elasticities of substitution between two types of workers and across ages (ρ_x and ρ_a) to target the following moments. (1) The correlation between migration rates and workers' age, by workers' skill type. (2) The correlation between migration rates and bilateral distance, by workers' skill type. (3) The correlation between migration rates and the contiguity between origin and destinations, by workers' skill type. (4) The share of in-migrants in total employment, by province and workers' skill type.[20] (5) Across provinces, the slope of changes in college premium on the strength of college expansion, between 2003–2009. (6) Average differences in college premium between young (aged 20–28) and old workers (aged 29+) in 2009. I compute migration rates based on workers' current province and province of residence 5 years ago, drawn from Population Census 2000 and adjusted to an annual frequency. I compute college premium in 2003 and 2009 using the average log wage of college-educated workers relative to high-school grads, from the Urban Household Survey. I use the instrument x_m^* introduced in Section 1.5.1 to proxy for the strength of college expansion.

Although I focus on the 2000–2018 period, I simulate the model until 2030 as workers are forward-looking when making migration decisions (see Appendix A.5.3 for how I extrapolate the data on firms and workers to 2030). I still require firms' productivity to solve the model. Before 2011, for each region-industry-regime pair, I choose the average productivity level of firms to match the output level (the firm-level productivity is still Pareto-distributed with the same shape parameter as in Step 1). After 2012, when detailed data on industry-level output are not available, I assume that the average productivity of Chinese firms in each province-industry-regime grows at a common yearly rate (relative to foreign firms) to match the relative growth of China's GDP in each year.

Panel C in Table A.8 reports the calibrated parameters. The calibrated elasticity of substitution between college-educated and high-school workers is 1.5, which is close to the typical number used in the macro labor literature. For instance, Katz & Murphy (1992) find the elasticity of substitution between college-educated and high-school workers to be 1.4, whereas Card & Lemieux (2001) find that to be 2.5. The calibrated elasticity of substitution across age groups is 3, which is smaller than 5 reported by Card & Lemieux (2001) but allows the model to match changes in college premium across age groups pretty well, as shown in Appendix

[20] The correlation between migration rates and age is $corr(\Lambda^I_{m,n,a}, a)$ for $m \neq n$. The correlations between migration rates and distance (contiguity) are analogously obtained. The share of in-migrants in employment for province n is $\sum_{m\neq n}\sum_a H_{m,a}\Lambda^H_{m,n,a}/(\sum_m \sum_a H_{m,a}\Lambda^H_{m,n,a})$ for college-educated labor and $\sum_{m\neq n}\sum_a L_{m,a}\Lambda^L_{m,n,a}/(\sum_m \sum_a L_{m,a}\Lambda^L_{m,n,a})$ for noncollege labor.

Section A.6. I find that destination-specific migration costs are higher for noncollege people than college-educated people, and they are also higher in Beijing, Tianjin and Shanghai than in other provinces, in line with tight Hukou restrictions on noncollege people and in big cities. Finally, Panel B in Table A.9 shows that the model matches the targeted data moments pretty well.

Step 3: Calibrating Parameters Related to Firm Dynamics and Innovation

Finally, I calibrate the remaining parameters regarding firm dynamics between 2000–2018. (1) Productivity drifts $\{g_{u,j,t}\}_{u\in\{\tilde{C},F\}}$. I normalize the productivity drift of service firms in Foreign to be 0 in all years. Firms' productivity distributions in the initial year (2000) are drawn from Step 2's calibration, which match output levels across Chinese province-industry-regimes or foreign industries in 2000. (2) The number of entrants $\{N_{u,j,t}\}_{u\in\{\tilde{C},F\}}$. (3) The standard deviation of productivity growth σ_ε. (4) The exogenous exit rate δ. (5) The imperfect imitation parameter δ_p. (6) The autocorrelation of demand shifters ρ_ε. (7) The convexity of innovation costs χ. (8) The standard deviation of research intensity σ_η.[21](9) Fixed costs $\{\phi_{1,j}\}$ and variable costs of innovation $\{\phi_{2,j}\}$. (10) The aggregate productivity of research goods $\{A_{u,r,t}\}_{u\in C}$. I set the aggregate productivity of research goods to be region-specific with a common time trend $A_{u,r,t} = \bar{A}_{u,r}a_t$.[22]

I target the following moments. (1) Before 2011, the output in each Chinese province-industry-regime or foreign industry (relative to output of foreign services). After 2012, I assume that China's firm productivity grows at a commonly yearly rate relative to foreign firms to match the relative GDP growth. (2) Changes in the number of firms in each China's province-industry-regime or foreign industry between 2000–2018. (3) The standard deviation of annual sales growth for upper 10% firms (in terms of each year's sales) in 2000–2007. (4) The annual exit rate for upper 10% firms (in terms of each year's sales) in 2000–2007. (5) The sales of new entrants

[21] I normalize the average research intensity to be -3 because it cannot be separately identified from variable costs of innovation. This implies an average step size $\exp(-3) \approx 0.05$.

[22] I normalize $\bar{A}_{u,r} = 1$ for Beijing and $a_{2005} = 1$, as changing all $A_{u,r,t}$ proportionally has the same effects as changing $\phi_{1,j}$ and $\phi_{2,j}$.

(identified by firms' birthyear) relative to incumbents in 2000–2007. (6) The autocorrelation parameter of a firm's ordinary exports in adjacent years, in 2000–2007. (7) The slope of a firm's sales growth on its R&D intensity in the previous year, in 2001–2007.[23] (8) The standard deviation of R&D intensity among R&D firms in 2005. (9) The share of R&D firms and the average R&D intensity in 2005 for each industry. (10) The share of R&D firms in each province in 2005, and aggregate manufacturing R&D intensity in 2000–2018. I use ASM 2000–2007 to compute moments (2)–(9), and other moments come from aggregate data. As I focus on Chinese manufacturing firms' innovation, moments (7)–(10) are computed based on China's manufacturing industries. I set other industries' R&D expenses as given by the data.

For computational tractability, I simplify the next-period's firm value as $V^{'}(\mathbf{s}_{c(m),j}) = C_s\left(\sum_n \pi^{+'}_{m,n,j} - f_{m,j}P^{'}_{m,j}\right)$, with the constant $C_s = \sum_{t=0}^{\infty} \frac{(1-\text{average profit tax})(1-\delta)^t}{(1+r)^t}$ reflecting profit taxes, death rates and interest rates. I set the average profit tax rate to be 30% and the interest rate r to be 0.01.

Panel D in Table A.8 presents the parameter values. The parameter values are reasonable. For instance, the convexity of innovation costs χ is 0.68, implying that the elasticity of successful innovation to R&D costs is $\frac{1}{1+\chi} = 0.59$. This is close to 0.5 typically used in the literature (see Acemoglu et al. (2018)). I find that average fixed costs of innovation are \$9,100 in 2005 in terms of U.S. dollars, which are relatively small compared with fixed costs of exporting. This indicates that additional increases in sales due to innovation are typically smaller than the revenues from selling to the foreign market. Panel C in Table A.9 shows that my model moments match the data moments pretty well.

Free Entry of New Firms

In this scenario, I face two quantitative challenges. First, China has experienced very fast growth in the number of manufacturing firms. If I directly apply equation (1.10) to compute

[23] I compute this by regressing a firm's sales growth on its ratio of R&D to sales in the previous year, controlling the previous year's firm sales (small firms tend to grow fast), and firm and year fixed effects.

entry costs, 30% of Chinese college-educated workers needs to be used in producing research goods for entry of manufacturing firms in 2018, and this percentage seems to be unrealistic. Second, as shown by Kucheryavyy et al. (2017), free entry of new firms implies large economies of scale and may lead to corner solutions. Therefore, I modify equation (1.10) for a Chinese province-industry-regime $u \in \tilde{\mathcal{C}}$ as:

$$f^e_{u,j} P_{u,r} N^{\nu_F}_{u,j} = \rho V^e_{u,j}.$$

The parameter $\nu_F > 0$ captures the inverse elasticity of the number of entrants with regard to the value of entrants, allowing me to avoid corner solutions. I use $\nu_F = 0.27$ following Serrato & Zidar (2016).[24] I also introduce the parameter $0 < \rho < 1$ to capture collateral constraints, because it is difficult to capitalize future profits in China (Song et al. 2011). I choose $\rho = 0.15$, which implies that entry costs are around one-year expected profits of an entrant, and that 4.5% of college-educated workers is used in producing research goods for entry of manufacturing firms in 2018. I can then use this modified equation to compute entry costs $\{f^e_{u,j,t}\}_{u \in \{\tilde{\mathcal{C}},F\}}$ that generate the same amount of entrants as $\{N_{u,j,t}\}_{u \in \{\tilde{\mathcal{C}},F\}}$.

A.6 The College Premium

I show how my model matches the observed changes in the college premium. To obtain the college premium in a given year, I estimate the following regression:

$$\log w_{im} = \beta_0 + \sum_{x \in X} \phi_{x,1} D^x_{it} + \sum_{x \in X} \phi_{x,2} D^x_{it} \times \mathbf{1}_{col} + \beta_1 agr_{im} + \iota_m + \varepsilon_{it}$$

[24] Although the model in Serrato & Zidar (2016) is based on firm location sorting, the parameter $\sigma^F > 0$ in their paper also captures the inverse elasticity of the number of entrants with regard to the value of entrants in a locality. They estimate $\sigma^F = 0.27$.

$\log w_{im}$ is log yearly wage for worker i in province m. $X = \{23–25, 26–28, ...\}$ is the set of three-year age bins. $\mathbf{1}_{col}$ is a dummy variable indicating college-educated workers. I interpret $\phi_{x,2}$ as the college premium for workers in age group $x \in X$, relative to average wages of noncollege workers in the same age group. Control variable agr_{im} is a dummy variable indicating whether the worker is in agriculture, because workers' wages are much lower in agriculture than in other industries. ι_m is a set of province fixed effects.

I use workers' yearly wage data in the Urban Household Survey in 2000–2009 to estimate the observed college premium.[25] I restrict the sample to workers with high-school education or above, and therefore the baseline group in the regression is workers with high-school education. In the calibrated model, I perform the same regression with noncollege labor (high-school grads) and educated labor (college-educated workers).

Figure A.9 presents the results. My model captures the observed changes in the college premium in the 2000s. Between 2000–2009, the model and the data both predicted the decline of the college premium for young workers, and the increase of college premium for old workers. The decline in the college premium was driven by a large inflow of young college grads into the labor market, thanks to China's college expansion.

The increase in the college premium in the 2000s was due to the fast growth of manufacturing firms' output. The ratio of manufacturing output to GDP increased by 73% in 2000 to around 140% in 2010s, which led to more intensive use of college-educated workers in production and an overall increase in the college premium in the 2000s.

It is worth noting that a portion of China's manufacturing output is not produced by manufacturing firms, but instead by other production units, mainly production cooperations and self-employed people in rural areas.[26] Manufacturing production in rural areas is very low-skilled.

[25] I use the college premium by ages in Population Census 2005 to calibrate the relative productivities of workers across skills and ages. I find that the college premium by ages is quantitatively similar in Population Census 2005 and Urban Household Survey 2005. The wage information is not available in other years' Population Censuses except for the 2005 version.

[26] China's Industrial Census 1995 shows that more than 20% of China's industrial employment were self-employed or working in production cooperations in rural areas.

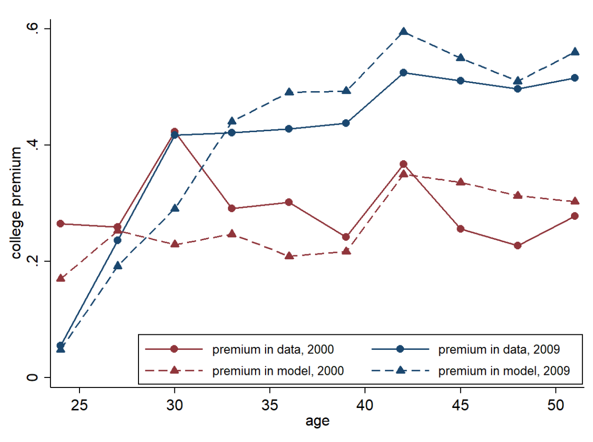


Figure A.9: College Premium in Model and Data

Population Census 2000 shows that the share of college-educated workers in manufacturing employment was 0.9% in villages, compared to 10.2% in cities. In my baseline calibration, I treat manufacturing output not produced by manufacturing firms as agricultural output to reflect its low skill intensities.[27]

[27]The share of college-educated workers in agricultural employment was 0.2% in 2000. Alternatively, I experimented with calibrating manufacturing output in the model to match China's overall manufacturing output in the data. In this scenario, my model cannot capture the same magnitude of increases in the college premium in the 2000s without additional skill-biased technological changes. However, the effects of China's college expansion are very similar in the baseline calibration and in this alternative calibration, as the effects of college expansion mainly manifested after 2010s.

Table A.8: Parameter Values

Notation	Value	Description
Panel A: Pre-determined Parameters		
(1) T	45	Workers' lifetime
(2) β	0.95	Discount rate
(3) ν	2	Migration elasticity
(4) $\{\gamma^L_{u,j}, \gamma^{j'}_{u,j}\}_{u\in\{\tilde{C},F\}}$		Input-output parameters, by region/industry/regime
(5) $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{C,F\}}$		Num of college and noncollege entrants, by province
(6) $\zeta_t(\cdot)$		R&D tax incentives
Panel B: Step 1 of Calibration		
(1) $\{\gamma_j\}$	0.03 (0.04)	Share of industry-level goods in final goods
(2) γ_r	0.41	Cost share of college-educated labor in R&D production
(3) $\{\beta^H_a, \beta^L_a\}$	0.07 (0.02)	Age-specific productivity in labor supply
(4) $\{\alpha_{j(k)}\}_{k\in\{O,\mathcal{P}\}}$	0.71 (0.09)	Skill intensities by industry and regime
(5) $\frac{\sigma^2_\varepsilon}{1-\rho^2_\varepsilon}$	0.32	Variance of demand shifters
(6) c_{agr}	0.26	Wages in agriculture relative to nonagriculture
(7.1) $\{\beta_{1,j}\}$	0.14 (0.05)	Inter-provincial trade costs w.r.t. distance by industry
(7.2) $\{\beta_{2,j}\}$	-0.06 (0.07)	Inter-provincial trade costs w.r.t. contiguity by industry
(8) $\{d_{u,F,j,2005}, d_{F,u,j,2005}\}_{u\in\tilde{C}}$	3.71 (4.11)	International trade costs by region/industry/regime
(9) $\{f_{u,F,j}, f_{F,u,j}\}_{u\in\tilde{C}}$	$5e{-}4(4e{-}3)$	Marketing costs by region/industry/regime
Panel C: Step 2 of Calibration		
(1) $\gamma^H_{age}, \gamma^L_{age}$	0.01, 0.04	Effects of age on migration costs, by skill type
(2) $\gamma^H_{dist}, \gamma^L_{dist}$	2.40, 2.68	Effects of distance on migration costs, by skill type
(3) $\gamma^H_{contig}, \gamma^L_{contig}$	0.21, 0.01	Effects of contiguity on migration costs, by skill type
(4.1) $\{\gamma^H_n\}_{n\in C}$	2.50 (2.57)	Effects of destination-specific migration costs, college
(4.2) $\{\gamma^L_n\}_{n\in C}$	2.89 (3.48)	Effects of destination-specific migration costs, noncollege
(5) ρ_x	1.5	Elast. of substitution btw college/noncollege labor
(6) ρ_a	3	Elast. of substitution across age groups
Panel D: Step 3 of Calibration		
(1) $\{g_{u,j,t}\}_{u\in\{\tilde{C},F\}}$	0.01 (0.18)	Exg. productivity growth, by region/industry/regime
(2) $\{N_{u,j,t}\}_{u\in\{\tilde{C},F\}}$	5,505 (169,682)	Num of new firm entrants, by region/industry/regime
(3) σ_ε	0.08	Standard deviation of productivity growth
(4) δ	0.1	Exogenous exit rates
(5) δ_p	0.48	Imperfect Imitation parameter
(6) ρ_ε	0.6	Autocorrelation of demand shifters
(7) σ_η	1.6	Standard deviation of research intensity
(8) χ	0.68	Convexity of innovation costs
(9.1) $\{\phi_{1,j}\}$	$1e{-}4(1e{-}4)$	Fixed costs of innovation
(9.2) $\{\phi_{2,j}\}$	0.27 (0.91)	Variable costs of innovation
(10.1) $\{\bar{A}_{m,r}\}_{m\in C}$	1.76 (0.58)	Research productivity by province
(10.2) $\{a_t\}$	2.31 (1.35)	Time trend of research productivity

Notes: For parameters with multiple values, I report the averages across all the specific and nonzero values, with standard deviations of these values in parenthesis.

Table A.9: Targeted Moments in the Model and in the Data

Description	Data	Model
Panel A: Targeted Moments in Step 1		
(1) Output of each industry relative to services	0.05 (0.17)	0.05 (0.17)
(2) Ratio of full-time R&D workers to manufacturing employment	0.48%	0.48%
(3.1) College employment shares, by industry/regime (relative to services)	0.80 (0.50)	0.80 (0.50)
(3.2) Aggregate college premium	1.85	1.88
(4) Wages of different age groups relative to youngest workers	1.17 (0.13)	1.17 (0.13)
(5) Std of export-output ratios among exporters	0.27	0.31
(6) Share of agricultural employment in total employment	0.42	0.45
(7.1) Sum of trade shares to nonself provinces, by industry	18.92 (5.65)	18.21 (6.32)
(7.2) Sum of trade shares to contiguous provinces, by industry	4.12 (1.51)	4.22 (1.57)
(8.1) Share of China's exports in foreign expenses, by region/industry/regime	$6e{-}4$ ($3e{-}3$)	$6e{-}4$ ($3e{-}3$)
(8.2) Share of imports in China's expenses, by region/industry/regime	0.26 (0.35)	0.34 (0.37)
(9.1) Share of Chinese firms that export, by region/industry/regime	0.16 (0.14)	0.16 (0.14)
(9.2) Share of foreign firms exporting to China, by region/industry/regime	0.22 (0.12)	0.22 (0.12)
Panel B: Targeted Moments in Step 2		
(1) Corr btw migration rates and age, college/noncollege labor	-0.08,-0.12	-0.08,-0.12
(2) Corr btw migration rates and distance, college/noncollege labor	-0.01,-0.02	-0.01,-0.02
(3) Corr btw migration rates and contiguity, college/noncollege labor	0.09,0.13	0.13,0.13
(4.1) Share of in-migrants in college-educated emp, by province	0.008 (0.007)	0.008 (0.007)
(4.2) Share of in-migrants in noncollege emp, by province	0.008 (0.011)	0.007 (0.010)
(5) Slope of college premium changes to strength of expansion, 03–09	0.33	0.35
(6) Avg diff in provincial college premium between young and old, 2009	-0.45	-0.45
Panel C: Targeted Moments in Step 3		
(1.1) Output rel. to foreign services, by region/industry/regime (before 2011)	$3e{-}5$ ($1e{-}4$)	$3e{-}5$ ($1e{-}4$)
(1.2) China's yearly GDP growth relative to Foreign in 2012–2018	0.08 (0.05)	0.08 (0.05)
(2) Changes in num of firms over time, by region/industry/regime	988 (42,143)	987 (42,143)
(3) Std of sales growth for upper 10% firms in 2000–2007	0.42	0.42
(4) Exit rates for upper 10% firms in 2000–2007	0.10	0.10
(5) Sales of entrants relative to incumbents in 2000–2007	0.67	0.66
(6) Autocorrelation of log ordinary exports in 2000–2007	0.75	0.80
(7) Slope of sales growth to R&D intensity in 2000–2007	1.9	1.9
(8) Std of research intensity among R&D firms in 2005	0.022	0.024
(9.1) Share of R&D firms in 2005, by industry	0.10 (0.08)	0.10 (0.08)
(9.2) R&D intensity in 2005, by industry	0.006 (0.006)	0.006 (0.006)
(10.1) Share of R&D firms in 2005, by province	0.12 (0.04)	0.12 (0.04)
(10.2) Aggregate manufacturing R&D intensity in each year (00–18)	0.008 (0.002)	0.008 (0.002)

Notes: For moments with multiple values, the results refer to averages across all the pairs with specific values, with standard deviations in parenthesis.

Table A.10: Industry Classification in the Calibrated Economy

Industry name	CIC code
Agriculture	1-5
Mining	6-11
Manufacturing industries:	
Agricultural and non-staple foodstuff	13
Foodstuff	14
Beverage	15
Tobacco	16
Textile	17
Textile costumes, shoes, and caps	18
Leather, fur, feather and their products	19
Wood processing	20
Cabinetmaking industry	21
Papermaking and paper product	22
Printing and reproduction of record media	23
Culture, education, and sports goods	24
Petroleum processing, coking and nuclear fuel	25
Chemical feedstock and chemicals	26
Medicine	27
Chemical fiber	28
Rubber production	29
Plastic industry	30
Non-metallic minerals product	31
Ferrous metal smelting and extrusion	32
Non-ferrous smelting and extrusion	33
Metalwork industry	34
General-purpose equipment	35
Special-purpose equipment	36
Transport and communication facilities	37
Electric machinery and equipment	39
Communication equipment, computers and other electronic equipment	40
Instruments and meters, and machinery for culture and office	41
Instruments and meters, and machinery for culture and office	42
Processing of discarded resources, and waste and scrap recovery	43
Services	44-98

Appendix B

Appendix for Chapter 2

B.1 Proofs

B.1.1 Proof of Lemma

To prove the lemma, we first establish the following results regarding the joint distribution of Y and Z.

$$P\Big(Y = l(m) \ \&\ Z = z\Big) = \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}} \times \left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^{1-\gamma} \theta z^{-\theta-1},$$

$$P\Big(Y = j \ \&\ Z = z\Big) = \frac{\psi_{j,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}} \times \left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^{1-\gamma} \theta z^{-\theta-1}.$$

The proof follows closely from ARRY. For ease of notations, we omit n and s in the proof and denote $\xi = cd\tilde{t}$.

$$\begin{aligned}
&P\Big(\widetilde{\phi}_{l(m)} \leq x_{l(m)}, \widetilde{\phi}_j \leq x_j, \forall l,m,j\Big) = P\Big(\phi_{l(m)} \leq \xi_{l(m)} x_{l(m)}, \phi_j \leq \xi_j x_j,\ \ \forall l,m,j\Big) \\
&= 1 - \left[\sum_l \left(\sum_m A_{l(m)} \xi_{l(m)}^{-\frac{\theta}{1-\rho}} x_{l(m)}^{-\frac{\theta}{1-\rho}}\right)^{\frac{1-\rho}{1-\gamma}} + \sum_j A_{j,s} \xi_j^{-\frac{\theta}{1-\gamma}} x_j^{-\frac{\theta}{1-\gamma}}\right]^{1-\gamma}.
\end{aligned}$$

The first equality holds since by definition, $\widetilde{\phi} = \frac{\phi}{\xi}$. The derivative of the CDF with respect to an arbitrary element $x_{k(o)}$ is

$$P\Big(\widetilde{\phi}_1 \leq x_1, ..., \widetilde{\phi}_{k(o)} = x_{k(o)}, ..., \widetilde{\phi}_N \leq x_N\Big) = \frac{\partial P\Big(\widetilde{\phi}_1 \leq x_1, ..., \widetilde{\phi}_{k(o)} = x_{k(o)}, ..., \widetilde{\phi}_N \leq x_N\Big)}{\partial x_{k(o)}}.$$

Using our multivariate Pareto CDF function, this derivative further equals

$$\theta \left[\sum_l \left(\sum_m A_{l(m)} \xi_{l(m)}^{-\frac{\theta}{1-\rho}} x_{l(m)}^{-\frac{\theta}{1-\rho}}\right)^{\frac{1-\rho}{1-\gamma}} + \sum_j A_j \xi_j^{-\frac{\theta}{1-\gamma}} x_j^{-\frac{\theta}{1-\gamma}}\right]^{-\gamma} \frac{A_{k(o)} \xi_{k(o)}^{-\frac{\theta}{1-\rho}} x_{k(o)}^{-\frac{\theta}{1-\rho}}}{\left(\sum_m A_{l(m)} \xi_{l(m)}^{-\frac{\theta}{1-\rho}} x_{l(m)}^{-\frac{\theta}{1-\rho}}\right)^{1-\frac{1-\rho}{1-\gamma}} x_{k(o)}}.$$

Evaluating the derivative of the CDF at a common productivity level z gives the joint probability for firms to choose k and n at that productivity level, which equals

$$\begin{aligned} P\Big(Y = k(o) \ \& \ Z = z\Big) &= P\Big(\widetilde{\phi}_1 \le z, ..., \widetilde{\phi}_{k(o)} = z, ..., \widetilde{\phi}_{l(m)} \le z\Big) \\ &= \frac{\psi_{k(o),n,s}}{\sum_m \psi_{k(m),n,s}} \times \Psi_{k,n,s} \times \Big[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\Big]^{-\gamma} \theta z^{-\theta-1}. \end{aligned}$$

The second equality holds by plugging z into formula (B.1).

$$\psi_{k(o),n,s} = A_{k(o),s}\Big(c_{k(o),s} d_{k(o),n,s} \tilde{t}_{i,n,s}\Big)^{-\frac{\theta}{1-\rho}}, \qquad \psi_{j,n,s} = A_{j,s}\Big(c_{j,s} d_{j,n,s} \tilde{t}_{j,n,s}\Big)^{-\frac{\theta}{1-\gamma}},$$

and $\Psi_{k,n,s} = \Big[\sum_m \psi_{k(m),n,s}\Big]^{\frac{1-\rho}{1-\gamma}}$.

Analogously, the derivative of the CDF with respect to an arbitrary element x_j is

$$\theta \left[\sum_l \left(\sum_m A_{l(m)} \xi_{l(m)}^{-\frac{\theta}{1-\rho}} x_{l(m)}^{-\frac{\theta}{1-\rho}}\right)^{\frac{1-\rho}{1-\gamma}} + \sum_j A_j \xi_j^{-\frac{\theta}{1-\gamma}} x_j^{-\frac{\theta}{1-\gamma}}\right]^{-\gamma} \frac{A_j \xi_j^{-\frac{\theta}{1-\gamma}} x_j^{-\frac{\theta}{1-\gamma}}}{x_j}.$$

Evaluating the derivative of CDF at a common productivity level z, we have

$$P\Big(Y = j \ \& \ Z = z\Big) = \psi_{j,n,s} \times \Big[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\Big]^{-\gamma} \theta z^{-\theta-1}.$$

The probability density function of the maximum productivity is

$$\begin{aligned} P\Big(Z = z\Big) &= \sum_{l,m} P\Big(Y = k(o) \ \& \ Z = z\Big) + \sum_j P\Big(Y = j \ \& \ Z = z\Big) \\ &= \Big[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\Big]^{1-\gamma} \theta z^{-\theta-1}. \end{aligned}$$

By the definition of conditional probability,

$$P\Big(Y=l(m)|Z=z\Big)=\frac{P\Big(Y=l(m)\ \&\ Z=z\Big)}{P\Big(Z=z\Big)}=\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}\times\frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}}.$$

Note that $P\Big(Y=l(m)|Z=z\Big)$ is not a function of z, implying that firms' location choices and the productivity distribution conditional on location choices are independent (Y and Z are independent). Thus

$$P\Big(Y=l(m)\Big)=\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}\times\frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}}.$$

In addition,

$$P\Big(Y=l\Big)=\sum_m P\Big(Y=l(m)\Big)=\frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}},$$

and by conditional probability again,

$$P\Big(Y=m|l\Big)=\frac{P\Big(Y=l(m)\Big)}{P\Big(Y=l\Big)}=\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}.$$

One implication is that $P\Big(Y=l(m)\Big)$ reflects not only the probability of locations among exporting firms, but also the probability of locations among all firms, since independence property implies $P\Big(Y=l(m)\mid Z>\min Z\Big)=P\Big(Y=l(m)\mid Z>\widetilde{\phi}^{*}_{l(m),n,s}\Big)$. Denote $P\Big(Z=z\mid Y=l(m)\Big)$ as the productivity distribution conditional on locating in China's province l and regime m, and $P\Big(Z=z\mid Y=j\Big)$ as the productivity distribution in foreign country j. The independence implies that these two conditional productivity distributions have the following density function (same as $P\Big(Z=z\Big)$)

$$\Big[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\Big]^{1-\gamma}\theta z^{-\theta-1}.$$

This implies a CDF function for cost-adjusted productivity in each location as

$$1-\left(\sum_{l}\Psi_{l,n,s}+\sum_{j}\psi_{j,n,s}\right)^{1-\gamma} z^{-\theta}.$$

Using this, we can obtain the conditional distribution of unadjusted productivity as in equation (2.9).

B.1.2 Decomposing the Aggregate Trade Elasticity

Recall that the derivative of trade flows with regard to trade costs has three terms as follows

$$-\frac{\partial X_{l(m),n,s}}{\partial d_{l(m),n,s}} = \underbrace{-M_s R \int_{\phi^*}^{+\infty} \frac{\partial x_{l(m),n,s}(\phi)}{\partial d_{l(m),n,s}} \, \mathrm{d}G(\phi)}_{\text{Intensive Margin}} + \underbrace{M_s R \, x_{l(m),n,s}(\phi^*) G'(\phi^*) \frac{\partial \phi^*}{\partial d_{l(m),n,s}}}_{\text{Extensive Margin}}$$
$$\underbrace{-\frac{\partial R}{\partial d_{l(m),n,s}} M_s \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi) \, \mathrm{d}G(\phi) \right]}_{\text{New-firm and Export-regime Margins}}.$$

1) The *Intensive Margin* of Trade Elasticity: recall that $x_{l(m),n,s}(\phi)$ is the sales from $l(m)$ to n in sector s for firms which have productivity ϕ, and is equal to

$$x_{l(m),n,s}(\phi) = \Big(\frac{\sigma}{\sigma - 1} \frac{\tilde{t}_{i,n,s} c_{l(m),s} d_{l(m),n,s}}{\phi_{l(m),n,s}} \Big)^{1-\sigma} E_{n,s} P_{n,s}^{\sigma-1}.$$

The first term can be rewritten as

$$M_s R \int_{\phi^*}^{+\infty} \frac{\partial x_{l(m),n,s}(\phi)}{\partial d_{l(m),n,s}} \, \mathrm{d}G(\phi) = \frac{1-\sigma}{d_{l(m),n,s}} M_s R \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi) \, \mathrm{d}G(\phi) \right].$$

Then the *intensive margin* of trade elasticity is

$$- M_s R \int_{\phi^*}^{+\infty} \frac{\partial x_{l(m),n,s}(\phi)}{\partial d_{l(m),n,s}} \, \mathrm{d}G(\phi) \Bigg/ \frac{X_{l(m),n,s}}{d_{l(m),n,s}}$$
$$= -\frac{1-\sigma}{d_{l(m),n,s}} M_s R \left[\int_{\phi^*}^{+\infty} x_{l(m),n,s}(\phi) \, \mathrm{d}G(\phi) \right] \Bigg/ \frac{X_{l(m),n,s}}{d_{l(m),n,s}} = \sigma - 1.$$

2) The *Extensive Margin* of Trade Elasticity: The second term can be rewritten as

$$M_s R\, x_{l(m),n,s}(\phi^*) G'(\phi^*) \frac{\partial \phi^*}{\partial d_{l(m),n,s}} = M_s R\, x_{l(m),n,s}(\phi^*)\ \phi^*\ G'(\phi^*)\ \frac{1}{d_{l(m),n,s}}$$
$$= \theta M_s R \Big(\frac{\sigma}{\sigma-1}\tilde{t}_{i,n,s} c_{l(m),s} d_{l(m),n,s}\Big)^{1-\sigma} E_{n,s} P_{n,s}^{\sigma-1} \Big(\phi^*\Big)^{\sigma-1-\theta}\ \frac{1}{d_{l(m),n,s}}.$$

The first equality holds since $\frac{\partial \phi^*}{\partial d_{l(m),n,s}} = \frac{\phi^*}{d_{l(m),n,s}}$. The *extensive margin* of trade elasticity is:

$$\frac{M_s R\, x_{l(m),n,s}(\phi^*) G'(\phi^*) \frac{\partial \phi^*}{\partial d_{l(m),n,s}}}{\frac{X_{l(m),n,s}}{d_{l(m),n,s}}} = \frac{M_s R \Big(\frac{\sigma}{\sigma-1}\tilde{t}_{i,n,s} c_{l(m),s} d_{l(m),n,s}\Big)^{1-\sigma} E_{n,s} P_{n,s}^{\sigma-1} \Big(\phi^*\Big)^{\sigma-1-\theta}}{M_s R \Big(\frac{\sigma}{\sigma-1}\tilde{t}_{i,n,s} c_{l(m),s} d_{l(m),n,s}\Big)^{1-\sigma} E_{n,s} P_{n,s}^{\sigma-1} \int_{\phi^*}^{+\infty} \phi^{\sigma-2-\theta} \mathrm{d}\phi}$$
$$= \frac{\Big(\phi^*\Big)^{\sigma-1-\theta}}{\Big(\phi^*\Big)^{\sigma-1-\theta} \Big/ \Big(\theta-\sigma+1\Big)}$$
$$= \theta - \sigma + 1.$$

3) The *Export-regime* and *New-firm margins* of Trade Elasticity: Recall that R can be written as

$$R = \frac{M_{l(m),s}}{M_{l,s}} \frac{M_{l,s}}{M_s} \Big[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\Big]^{1-\gamma} \Big(\tilde{t}_{i,n,s} c_{l(m),s} d_{l(m),n,s}\Big)^{\theta},$$

where $\frac{M_{l(m),s}}{M_{l,s}} = \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}$ is the share of firms that are engaged in regime m, conditional on those that export to n and are located in province l; $\frac{M_{l,s}}{M_s} = \frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}}$ is the share of firms that are located in province l, conditional on those that export to n. According to the chain rule, $\frac{\partial R}{\partial d_{l(m),n,s}}$ is the summation of four terms. We derive each term as follows.

The derivative of the first term can be derived as

$$\frac{\partial \frac{M_{l(m),s}}{M_{l,s}}}{\partial d_{l(m),n,s}} = \frac{-\frac{\theta}{1-\rho}\psi_{l(m),n,s}\frac{1}{d_{l(m),n,s}}\left[\sum_m \psi_{l(m),n,s}\right] + \frac{\theta}{1-\rho}\psi_{l(m),n,s}\psi_{l(m),n,s}\frac{1}{d_{l(m),n,s}}}{\left(\sum_m \psi_{l(m),n,s}\right)^2}$$

$$= -\frac{\theta}{1-\rho}\frac{\left[\sum_m \psi_{l(m),n,s} - \psi_{l(m),n,s}\right]\psi_{l(m),n,s}\frac{1}{d_{l(m),n,s}}}{\left(\sum_m \psi_{l(m),n,s}\right)^2}$$

$$= -\frac{\theta}{1-\rho}\frac{1}{d_{l(m),n,s}}\left[1-\frac{M_{l(m),s}}{M_{l,s}}\right]\frac{M_{l(m),s}}{M_{l,s}},$$

where $\psi_{l(m),n,s} = A_{l(m),s}\left(c_{l(m),s}d_{l(m),n,s}\right)^{-\frac{\theta}{1-\rho}}$. The implied elasticity is

$$-\frac{\partial \frac{M_{l(m),s}}{M_{l,s}}}{\partial d_{l(m),n,s}} \Bigg/ \frac{\frac{M_{l(m),s}}{M_{l,s}}}{d_{l(m),n,s}} = \frac{\theta}{1-\rho}\left(1-\frac{M_{l(m),s}}{M_{l,s}}\right). \tag{B.1}$$

The derivative of the second term can be derived as

$$\frac{\partial \frac{M_{l,s}}{M_s}}{\partial d_{l(m),n,s}} = -\frac{\theta}{1-\gamma}\frac{1}{d_{l(m),n,s}}\frac{\left[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s} - \Psi_{l,n,s}\right]\left[\sum_m \psi_{l(m),n,s}\right]^{\frac{1-\rho}{1-\gamma}-1}\psi_{l(m),n,s}}{\left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^2}$$

$$= -\frac{\theta}{1-\gamma}\frac{1}{d_{l(m),n,s}}\frac{\left[\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s} - \Psi_{l,n,s}\right]\Psi_{l,n,s}\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}}{\left(\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}\right)^2}$$

$$= -\frac{\theta}{1-\gamma}\frac{1}{d_{l(m),n,s}}\left[1-\frac{M_{l,s}}{M_s}\right]\frac{M_{l(m),s}}{M_{l,s}}\frac{M_{l,s}}{M_s},$$

where $\Psi_{l,n,s} = \left[\sum_m \psi_{l(m),n,s}\right]^{\frac{1-\rho}{1-\gamma}}$. The implied elasticity is

$$-\frac{\partial \frac{M_{l,s}}{M_s}}{\partial d_{l(m),n,s}} \Bigg/ \frac{\frac{M_{l,s}}{M_s}}{d_{l(m),n,s}} = \frac{\theta}{1-\gamma}\left(1-\frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}}. \tag{B.2}$$

The derivative of the third term can be derived as

$$
\begin{aligned}
\frac{\partial\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{1-\gamma}}{\partial d_{l(m),n,s}} &= -\theta\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{-\gamma}\left[\sum_m \psi_{l(m),n,s}\right]^{\frac{1-\rho}{1-\gamma}-1}\psi_{l(m),n,s}\frac{1}{d_{l(m),n,s}} \\
&= -\theta\frac{1}{d_{l(m),n,s}}\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{-\gamma}\Psi_{l,n,s}\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \\
&= -\theta\frac{1}{d_{l(m),n,s}}\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{1-\gamma}\frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}}\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \\
&= -\frac{\theta}{d_{l(m),n,s}}\frac{M_{l(m),s}}{M_{l,s}}\frac{M_{l,s}}{M_s}\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{1-\gamma}.
\end{aligned}
$$

The implied elasticity is

$$
-\frac{\partial\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{1-\gamma}}{\partial d_{l(m),n,s}}\Bigg/\frac{\left[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\right]^{1-\gamma}}{d_{l(m),n,s}} = \theta\frac{M_{l(m),s}}{M_{l,s}}\frac{M_{l,s}}{M_s}. \tag{B.3}
$$

The implied elasticity for the fourth term is

$$
-\frac{\partial\left(c_{l(m),s}d_{l(m),n,s}\tilde{t}_{i,n,s}\right)^{\theta}}{\partial d_{l(m),n,s}}\Bigg/\frac{\left(c_{l(m),s}d_{l(m),n,s}\tilde{t}_{i,n,s}\right)^{\theta}}{d_{l(m),n,s}} = -\theta. \tag{B.4}
$$

Finally, we add up the elasticity in (B.2), (B.3), (B.4) and (B.5) to have

$$
\begin{aligned}
&\frac{\theta}{1-\rho}\left(1-\frac{M_{l(m),s}}{M_{l,s}}\right)+\frac{\theta}{1-\gamma}\left(1-\frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}}+\theta\frac{M_{l(m),s}}{M_{l,s}}\frac{M_{l,s}}{M_s}-\theta \\
=&\frac{\theta}{1-\rho}\left(1-\frac{M_{l(m),s}}{M_{l,s}}\right)+\frac{\theta}{1-\gamma}\left(1-\frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}}-\theta\left(1-\frac{M_{l(m),s}}{M_{l,s}}\frac{M_{l,s}}{M_s}\right) \\
=&\left(\frac{\theta}{1-\rho}-\theta\right)\left(1-\frac{M_{l(m),s}}{M_{l,s}}\right)+\left(\frac{\theta}{1-\gamma}-\theta\right)\left(1-\frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}} \\
=&\frac{\theta\rho}{1-\rho}\left(1-\frac{M_{l(m),s}}{M_{l,s}}\right)+\frac{\theta\gamma}{1-\gamma}\left(1-\frac{M_{l,s}}{M_s}\right)\frac{M_{l(m),s}}{M_{l,s}}.
\end{aligned}
$$

B.1.3 The Derivation of Trade Shares and Price Index

The trade flows from $l(m)$ to n can be written as (we drop subscripts n and s for most variables to simplify the notation)

$$
\begin{aligned}
X_{l(m),n,s} &= M_s P\Big(Y=\{l,m\}\Big)\int_{\widetilde{\phi}^*}^{+\infty} x_{l(m),n,s}(\widetilde{\phi})P\Big(Z=\widetilde{\phi}\mid Y=\{l,m\}\Big)\mathrm{d}\widetilde{\phi} \\
&= \theta M_s \frac{\psi_{l(m)}}{\sum_m \psi_{l(m)}}\Psi_l\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\Big(\frac{\sigma}{\sigma-1}\Big)^{1-\sigma}\left[\int_{\widetilde{\phi}^*}^{+\infty}\Big(\widetilde{\phi}\Big)^{\sigma-\theta-2}\mathrm{d}\widetilde{\phi}\right]E_{n,s}P_{n,s}^{\sigma-1} \\
&= \frac{\theta\big(\frac{\sigma}{\sigma-1}\big)^{1-\sigma}}{\theta-\sigma+1}M_s\frac{\psi_{l(m)}}{\sum_m \psi_{l(m)}}\Psi_l\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\Big(\widetilde{\phi}^*\Big)^{\sigma-\theta-1}E_{n,s}P_{n,s}^{\sigma-1} \\
&= \Theta M_s\frac{\psi_{l(m)}}{\sum_m \psi_{l(m)}}\Psi_l\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\tilde{t}_i^{\vartheta}\Big(c_{n,s}f_{n,s}\Big)^{\vartheta}E_{n,s}^{\frac{\theta}{\sigma-1}}P_{n,s}^{\theta},
\end{aligned}
$$

where $\Theta=\sigma^{\frac{\sigma-\theta-1}{\sigma-1}}\left(\frac{\theta}{\theta-\sigma+1}\right)\left(\frac{\sigma}{\sigma-1}\right)^{-\theta}$, and $\vartheta=\frac{\sigma-1-\theta}{\sigma-1}$. The second equality holds by plugging in $P\Big(Y=\{l,m\}\Big)$ as in (2.6), $x_{l(m),n,s}(\widetilde{\phi})$ as in (22), and $P\Big(Z=\widetilde{\phi}\mid Y=\{l,m\}\Big)$ as in (2.9).

Analogously, one can derive the trade flows from country j to n as

$$
\begin{aligned}
X_{j,n,s} &= M_s P\Big(Y=\{j\}\Big)\int_{\widetilde{\phi}^*}^{+\infty} x_{j,n,s}(\widetilde{\phi})P\Big(Z=\widetilde{\phi}\mid Y=\{j\}\Big)\mathrm{d}\widetilde{\phi} \\
&= \Theta M_s\psi_j\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\tilde{t}_j^{\vartheta}\Big(c_{n,s}f_{n,s}\Big)^{\vartheta}E_{n,s}^{\frac{\theta}{\sigma-1}}P_{n,s}^{\theta}.
\end{aligned}
$$

The aggregate price index is

$$
\begin{aligned}
P_{n,s} &= \Bigg[M_s P\Big(Y=\{l,m\}\Big)\sum_{l,m}\int_{\widetilde{\phi}^*_{i,n,s}}^{+\infty} p(\widetilde{\phi})^{1-\sigma} P\Big(Z=\widetilde{\phi}\mid Y=\{l,m\}\Big)\mathrm{d}\widetilde{\phi} \\
&\quad + M_s P\Big(Y=\{j\}\Big)\sum_{j}\int_{\widetilde{\phi}^*_{j,n,s}}^{+\infty} p(\widetilde{\phi})^{1-\sigma} P\Big(Z=\widetilde{\phi}\mid Y=\{j\}\Big)\mathrm{d}\widetilde{\phi}\Bigg]^{\frac{1}{1-\sigma}} \\
&= \Bigg[M_s\theta\sum_{l,m}\frac{\psi_{l(m)}}{\sum_m \psi_{l(m)}}\Psi_l\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\Big(\frac{\sigma}{\sigma-1}\Big)^{1-\sigma}\Big[\int_{\widetilde{\phi}^*_{i,n,s}}^{+\infty}\widetilde{\phi}^{\sigma-\theta-2}\mathrm{d}\widetilde{\phi}\Big] \\
&\quad + M_s\theta\sum_j \psi_j\Big[\sum_l \Psi_l+\sum_j \psi_j\Big]^{-\gamma}\Big(\frac{\sigma}{\sigma-1}\Big)^{1-\sigma}\Big[\int_{\widetilde{\phi}^*_{j,n,s}}^{+\infty}\widetilde{\phi}^{\sigma-\theta-2}\mathrm{d}\widetilde{\phi}\Big]\Bigg]^{\frac{1}{1-\sigma}} \\
&= \Bigg[\Theta M_s\Big(\frac{c_{n,s}f_{n,s}}{E_{n,s}}\Big)^{\vartheta} P_{n,s}^{\theta-\sigma+1}\Big[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\Big]^{-\gamma}\Bigg(\sum_l \Psi_l \tilde{t}^{\vartheta}_{i,n,s}+\sum_j \psi_j \tilde{t}^{\vartheta}_{j,n,s}\Bigg)\Bigg]^{\frac{1}{1-\sigma}}
\end{aligned}
$$

$\Longleftrightarrow$

$$
P_{n,s}^{\theta} = \Bigg[\Theta M_s\Big(\frac{c_{n,s}f_{n,s}}{E_{n,s}}\Big)^{\vartheta}\Big[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\Big]^{-\gamma}\Bigg(\sum_l \Psi_l \tilde{t}^{\vartheta}_{i,n,s}+\sum_j \psi_j \tilde{t}^{\vartheta}_{j,n,s}\Bigg)\Bigg]^{-1},
$$

where the second equality holds because $p(\widetilde{\phi})^{1-\sigma}=\widetilde{\phi}^{\sigma-1}\Big(\frac{\sigma}{\sigma-1}\Big)^{1-\sigma}$. The third equality is obtained by noting that $\widetilde{\phi}^*=\frac{\sigma}{\sigma-1}\Big(\tilde{t}_{i,n,s}\Big)^{\frac{1}{\sigma-1}}\Big(\frac{\sigma c_{n,s}f_{n,s}}{E_{n,s}}\Big)^{\frac{1}{\sigma-1}}\frac{1}{P_{n,s}}$ and $\sum_m \frac{\psi_{l(m)}}{\sum_m \psi_{l(m)}}=1$.

Plugging the price index into trade flows, we have the trade share from $l(m)$ to n as

$$
\Pi_{l(m),n,s}=\frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}}\times\frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}}\times\frac{\Big[\sum_l \Psi_{l,n,s}\Big]\tilde{t}^{\vartheta}_{i,n,s}}{\Big[\sum_l \Psi_{l,n,s}\Big]\tilde{t}^{\vartheta}_{i,n,s}+\sum_j \psi_{j,n,s}\tau^{\vartheta}_{j,n,s}}.
$$

The price index is

$$
P_{n,s}=\Bigg[\Theta M_s\Big(\frac{c_{n,s}f_{n,s}}{E_{n,s}}\Big)^{\vartheta}\Big[\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}\Big]^{-\gamma}\Bigg(\sum_l \Psi_l \tilde{t}^{\vartheta}_{i,n,s}+\sum_j \psi_j \tilde{t}^{\vartheta}_{j,n,s}\Bigg)\Bigg]^{-\frac{1}{\theta}}.
$$

where $\Theta=\sigma^{\frac{\sigma-\theta-1}{\sigma-1}}\Big(\frac{\theta}{\theta-\sigma+1}\Big)\Big(\frac{\sigma}{\sigma-1}\Big)^{-\theta}$, and $\vartheta=\frac{\sigma-1-\theta}{\sigma-1}$. As a simple representation, we can express trade shares as

$$
\begin{aligned}
\Pi_{l(m),n,s} &= \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{\Psi_{l,n,s}\tilde{t}^{\vartheta}_{i,n,s}}{\left[\sum_l \Psi_{l,n,s}\right]\tilde{t}^{\vartheta}_{i,n,s} + \sum_j \psi_{j,n,s}\tilde{t}^{\vartheta}_{j,n,s}} \\
&= \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{\Psi_{l,n,s}}{\sum_l \Psi_{l,n,s} + \sum_j \psi_{j,n,s}} \times \frac{\tilde{t}^{\vartheta}_{i,n,s}}{\frac{\sum_l \Psi_{l,n,s}}{\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}}\tilde{t}^{\vartheta}_{i,n,s} + \frac{\sum_j \psi_{j,n,s}}{\sum_l \Psi_{l,n,s}+\sum_j \psi_{j,n,s}}\tilde{t}^{\vartheta}_{j,n,s}} \\
&= \frac{P\big(Y=\{l,m\}\big)\tilde{t}^{\vartheta}_{i,n,s}}{\sum_{l,m} P\big(Y=\{l,m\}\big)\tilde{t}^{\vartheta}_{i,n,s} + \sum_j P\big(Y=\{j\}\big)\tilde{t}^{\vartheta}_{j,n,s}} \\
&= \frac{M_{l(m)}\tilde{t}_{i,n,s}^{\frac{\sigma-1-\theta}{\sigma-1}}}{\sum_{l,m} M_{l(m)}\tilde{t}_{i,n,s}^{\frac{\sigma-1-\theta}{\sigma-1}} + \sum_j M_j\tilde{t}_{j,n,s}^{\frac{\sigma-1-\theta}{\sigma-1}}},
\end{aligned}
$$

and

$$
\Pi_{j,n,s} = \frac{M_j\tilde{t}^{\vartheta}_{j,n,s}}{\sum_{l,m} M_{l(m)}\tilde{t}^{\vartheta}_{i,n,s} + \sum_j M_j\tilde{t}^{\vartheta}_{j,n,s}}.
$$

B.1.4 The Derivation of Labor Market Variables

Migration Share: Workers choose to work in the region-sector pair that brings them the highest utility. If a worker from labor group g chooses to work in province l and sector s, it implies $x_{g,l,s} \geq \frac{\tau_{g,l',s'}x_{g,l',s'}V_{l',s'}}{\tau_{g,l,s}V_{l,s}}$. Note that $x_{g,l,s}$ is drawn from $G_{g,l,s}(x) = \exp(-x^{-\kappa})$ independently across all regions and sectors. Denote $g_{g,l,s}$ as the probability density function of the location preference distribution. Then we have:

$$
\begin{aligned}
\Lambda_{g,l,s} &= \int_0^{\infty} \prod_{l' \neq l \text{ or } s' \neq s} G_{g,l',s'}\left(\frac{\tau_{g,l,s}V_{l,s}x}{\tau_{g,l',s'}V_{l',s'}}\right) g_{g,l,s}(x)dx \\
&= \int_0^{\infty} \kappa x^{-\kappa-1}\exp\left(-\sum_{l',s'}(\tau_{g,l',s'}V_{l',s'}/\tau_{g,l,s}V_{l,s})^{\kappa}x^{-\kappa}\right)dx \\
&= \frac{(\tau_{g,l,s}V_{l,s})^{\kappa}}{\sum_{l',s'}(\tau_{g,l',s'}V_{l',s'})^{\kappa}}.
\end{aligned}
$$

The second equality is obtained by using the functional form of $G_{g,l,s}(x)$. The third equality is derived by taking the integral.

B.1.5 Model Extension

We relax the distribution in equation (2.2) to allow for the correlation of productivity draws across Chinese provinces to differ from the correlation of productivity draws across countries. Assume that the productivity vector is drawn from

$$F\left(\vec{\phi}_{l(m),s},\vec{\phi}_{j,s}\right)=1-\left\{\left[\sum_{l}\left(\sum_{m}A_{l(m),s}\phi_{l(m),s}^{-\frac{\theta}{1-\rho}}\right)^{\frac{1-\rho}{1-\gamma}}\right]^{\frac{1-\gamma}{1-\delta}}+\sum_{j}A_{j,s}\phi_{j,s}^{-\frac{\theta}{1-\delta}}\right\}^{1-\delta},$$

with the support being defined on $\phi_{l(m),s}>\left\{\left[\sum_{l}\left(\sum_{m}A_{l(m),s}\right)^{\frac{1-\rho}{1-\gamma}}\right]^{\frac{1-\gamma}{1-\delta}}+\sum_{j}A_{j,s}\right\}^{\frac{1-\delta}{\theta}}$, for all l, m, and j. This multivariate Pareto distribution has an additional correlation parameter δ, which captures firms' correlation of productivity draws across countries. It is worth mentioning that δ not only captures the correlation of productivity draws between any two foreign countries, but also captures the correlation between any China's province and a foreign country. To see this, the joint distribution between an arbitrary province-regime $l(m)$ in China, and a foreign country j is

$$F\Big(+\infty,...,\phi_{l(m),s},...+\infty,...\phi_{j,s}...+\infty\Big)=1-\left[A_{l(m),s}^{\frac{1-\rho}{1-\delta}}\phi_{l(m),s}^{-\frac{\theta}{1-\delta}}+A_{j,s}\phi_{j,s}^{-\frac{\theta}{1-\delta}}\right]^{1-\delta}.$$

Following similar steps as in the previous proof, one can obtain the share of country n's expenditure in sector s that is spent on goods produced by province l and regime m as

$$\Pi_{l(m),n,s}=\frac{\Psi_{l(m),n,s}}{\sum_{m}\Psi_{l(m),n,s}}\times\frac{\Psi_{l,n,s}}{\sum_{l}\Psi_{l,n,s}}\times\frac{\left[\sum_{l}\Psi_{l,n,s}\right]^{\frac{1-\gamma}{1-\delta}}\tilde{t}_{i,n,s}^{\vartheta}}{\left[\sum_{l}\Psi_{l,n,s}\right]^{\frac{1-\gamma}{1-\delta}}\tilde{t}_{i,n,s}^{\vartheta}+\sum_{j}\Psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}}.$$

where $\psi_{l(m),n,s} = A_{l(m),s}\left(c_{l(m),s}d_{l(m),n,s}\tilde{t}_{l(m),n,s}\right)^{-\frac{\theta}{1-\rho}}$, $\Psi_{l,n,s} = \left[\sum_m \psi_{l(m),n,s}\right]^{\frac{1-\rho}{1-\gamma}}$, and $\psi_{j,n,s} = A_{j,s}\left(c_{j,s}d_{j,n,s}\tilde{t}_{j,n,s}\right)^{-\frac{\theta}{1-\delta}}$.

B.1.6 Variables in Proportional Changes

Denote the proportional change for variable x as $\widehat{x} = \frac{x'}{x}$, where x' represents variables in the counterfactual equilibrium, and x refers to variables in the observed equilibrium. The proportional changes of the equilibrium system can be expressed as

$$\widehat{\Pi}_{r,n,s} = \frac{\widehat{M}_{r,n,s}\widehat{\tilde{t}}^{\vartheta}_{r,n,s}}{\sum_{r'} \widehat{M}_{r',n,s}\widehat{\tilde{t}}^{\vartheta}_{r',n,s}\Pi_{r',n,s}}, \tag{B.5}$$

where $\widehat{M}_{r,n,s} = \widehat{P}\left(Y = r\right)$. When r refers to a province-regime combination in China, then

$$\widehat{P}\left(Y = \{l,m\} \mid Y = \{l\}\right) = \frac{\widehat{\psi}_{l(m),n,s}}{\sum_m \widehat{\psi}_{l(m),n,s}\frac{M_{l(m),n,s}}{M_{l,n,s}}}, \qquad \widehat{P}\left(Y = \{l\}\right) = \frac{\widehat{\Psi}_{l,n,s}}{\sum_l \widehat{\Psi}_{l,n,s}\frac{M_{l,n,s}}{M_s} + \sum_j \widehat{\psi}_{j,n,s}\frac{M_{j,n,s}}{M_s}}.$$

Analogously, when r refers to a foreign country j, then

$$\widehat{M}_{r,n,s} = \widehat{P}\left(Y = \{j\}\right) = \frac{\widehat{\psi}_{j,n,s}}{\sum_l \widehat{\Psi}_{l,n,s}\frac{M_{l,n,s}}{M_s} + \sum_j \widehat{\psi}_{j,n,s}\frac{M_{j,n,s}}{M_s}},$$

where $\widehat{\psi}_{l(m),n,s} = \widehat{A}_{l(m),s}\left(\widehat{c}_{l(m),s}\widehat{d}_{l(m),n,s}\widehat{\tilde{t}}_{i,n,s}\right)^{-\frac{\theta}{1-\rho}}$, $\widehat{\psi}_{j,n,s} = \widehat{A}_{j,s}\left(\widehat{c}_{j,s}\widehat{d}_{j,n,s}\widehat{\tilde{t}}_{j,n,s}\right)^{-\frac{\theta}{1-\gamma}}$, and $\widehat{\Psi}_{l,n,s} = \left[\sum_m \widehat{\psi}_{l(m),n,s}\frac{M_{l(m),n,s}}{M_{l,n,s}}\right]^{\frac{1-\rho}{1-\gamma}}$.[1]

[1]The proportional change of unit costs is given by $\widehat{c}_{l(m),s} = \widehat{w}_{l(m),s}^{\lambda^L_{l(m),s}}\prod_k \widehat{P}_{l(m),k}^{\lambda^k_{l(m),s}}$. $\widehat{A}_{l(m),s} = \widehat{\bar{A}}_{l(m),s}\widehat{L}^{\alpha}_{l(m),s}$ contains both changes in fundamental productivity $\bar{A}_{l(m),s}$ and agglomeration effects that are induced through $L_{l(m),s}$.

We also have the proportional change of the aggregate price index as

$$\widehat{P}_{n,s} = \left[\left(\frac{\widehat{c}_{n,s} \widehat{f}_{n,s}}{\widehat{E}_{n,s}} \right)^{\vartheta} \frac{\left[\sum_l \widehat{\Psi}_{l,n,s} \frac{M_{l,n,s}}{\sum_l M_{l,n,s}} \right] \widehat{\tilde{t}}^{\vartheta}_{i,n,s} \Pi_{i,n,s} + \sum_j \widehat{\Psi}_{j,n,s} \widehat{\tilde{t}}^{\vartheta}_{j,n,s} \Pi_{j,n,s}}{\left(\sum_l \widehat{\Psi}_{l,n,s} \frac{M_{l,n,s}}{M_s} + \sum_j \widehat{\Psi}_{j,n,s} \frac{M_{j,n,s}}{M_s} \right)^{\gamma}} \right]^{-\frac{1}{\theta}}. \tag{B.6}$$

The proportional changes of migration flows are

$$\widehat{\Lambda}_{g,l,s} = \frac{\widehat{\tau}^{\kappa}_{g,l,s} \widehat{V}^{\kappa}_{l,s}}{\sum_{l',s'} \widehat{\tau}^{\kappa}_{g,l',s'} \widehat{V}^{\kappa}_{l',s'} \Lambda_{g,l',s'}}. \tag{B.7}$$

The final-good market clearing conditions can be written in proportional changes as

$$E_{r,s} \widehat{E}_{r,s} = \beta_s I_r \widehat{I}_r + \sum_k \lambda^s_{r,k} \left((1-\eta) \sum_u \frac{\Pi_{r,u,k} E_{u,k} \widehat{\Pi}_{r,u,k} \widehat{E}_{u,k}}{\tilde{t}_{r,u,k} \widehat{\tilde{t}}_{r,u,k}} + \eta \sum_u \frac{\Pi_{u,r,k} E_{r,k} \widehat{\Pi}_{u,r,k} \widehat{E}_{r,k}}{\tilde{t}_{u,r,k} \widehat{\tilde{t}}_{u,r,k}} \right), \tag{B.8}$$

where $\widehat{\tilde{t}}_{r,u,s} = \frac{1+t'_{r,u,s}}{1+t_{r,u,s}}$.

The labor market equilibrium for China can be written in proportional changes as:

$$\begin{aligned} &\sum_m \lambda^L_{l(m),s} \left((1-\eta) \sum_u \frac{\Pi_{l(m),u,s} E_{u,s} \widehat{\Pi}_{l(m),u,s} \widehat{E}_{u,s}}{\tilde{t}_{l(m),u,s} \widehat{\tilde{t}}_{l(m),u,s}} + \eta \sum_u \frac{\Pi_{u,l(m),s} E_{l(m),s} \widehat{\Pi}_{u,l(m),s} \widehat{E}_{l(m),s}}{\tilde{t}_{u,l(m),s} \widehat{\tilde{t}}_{u,l(m),s}} \right) \\ &= \sum_g w_{l,s} \widehat{w}_{l,s} L_{g,l,s} \widehat{L}_{g,l,s} \end{aligned} \tag{B.9}$$

And the labor market equilibrium for foreign countries is written similarly as:

$$\sum_s \lambda^L_{n,s} \left((1-\eta) \sum_u \frac{\Pi_{n,u,s} E_{u,s} \widehat{\Pi}_{n,u,s} \widehat{E}_{u,s}}{\tilde{t}_{n,u,s} \widehat{\tilde{t}}_{n,u,s}} + \eta \sum_u \frac{\Pi_{u,n,s} E_{n,s} \widehat{\Pi}_{u,n,s} \widehat{E}_{n,s}}{\tilde{t}_{u,n,s} \widehat{\tilde{t}}_{u,n,s}} \right) = w_n \widehat{w}_n L_n \widehat{L}_n. \tag{B.10}$$

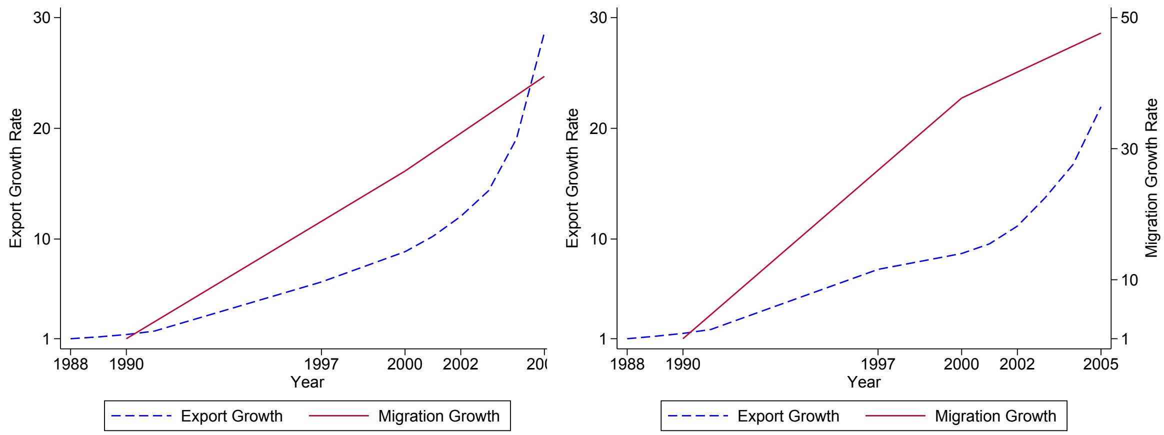
B.2 Additional Evidence on Internal Migrants

B.2.1 The Timing of Migration and Trade

We explore the time trend of provincial manufacturing exports and manufacturing migrant employment stock for coastal provinces. Panel (a) of Figure B.1 is for all five provinces, and Panel (b) is for Guangdong Province only. We normalize both variables by their initial year values. Exports are plotted in blue dashed lines and migration in red solid lines. The left-hand panel shows that Chinas exports grew steadily from the late 1980s to 2000, and accelerated after China's accession into WTO in 2001. The red solid line suggests that the massive rise in migrant workers appeared before 2000, prior to the turning point of China's export surge. Among the coastal provinces considered in Panel (a), manufacturing migrant employment grew steadily in both the period of 1990–2000 and the period of 2000–2005. Panel (b) shows that in Guangdong Province, the epic rise in migrant employment of manufacturing took place prior to 2000, and migrant employment grew relatively slowly after 2000. The time-series evidence of migration and export growth shows that massive relocation of workers to coastal provinces started, if not prior to, no later than the surge in Chinese exports to the global market. The timing is consistent with the agglomeration at coastal provinces resulting from internal migrants.

B.2.2 Sector's Processing-export Specialization and Migrant Employment

We show that the fact—that sectors which had higher migrants' employment shares were more specialized in processing exports—holds in other coastal provinces including Shanghai, Jiangsu, and Zhejiang Provinces. Figure B.2 plots migrant employment shares against the share of processing exports across manufacturing sectors for China's coastal provinces. We find a strong positive association between sector's migrant employment shares and specialization in processing exports. The size of the circle reflects provincial processing export volume in a given sector, and the blue dashed line is the linear regression fit (observations are weighted by processing export



(a) Five Coastal Provinces (b) Guangdong

Figure B.1: Growth in Exports and Manufacturing Migrant Employment for Coastal Provinces, 1990–2005

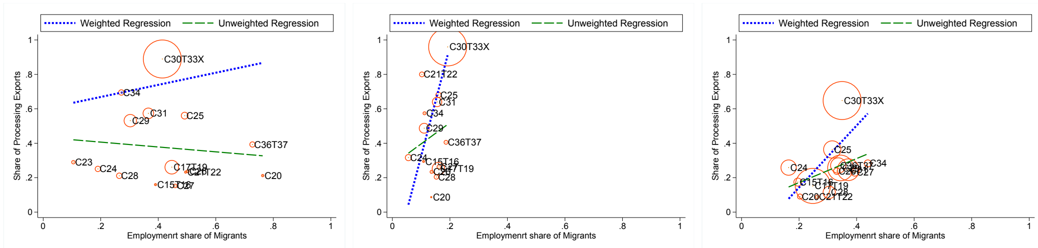
Notes: The migration data have three time points drawn from China's Population Survey (1990, 2000, and 2005). The export data are based on China's Customs Transactions Database in the years 1988-1991, 1997, 2000, and 2005. The five coastal provinces include Guangdong, Shanghai, Fujian, Zhejiang, and Jiangsu. We deflate the export volume using inflation rates.

volume).

B.3 Data Description

Dimensions of the Model: We calibrate our model to 29 sectors, 30 Chinese provinces, 35 foreign countries and a constructed rest of the world. We exclude Tibet from our analysis due to the lack of data on Tibet's inter-provincial migration and trade. Our choice of the 35 countries is fully driven by the availability of both bilateral trade flow data and labor market data. The 35 foreign countries and regions are: Argentina, Australia, Austria, Brazil, Cambodia, Canada, Chile, Denmark, France, Finland, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Norway, Philippines, Portugal, Singapore, South Africa, Spain, Sweden, Taiwan, Thailand, Turkey, UK, US, and Viet Nam.

China's Provincial Imports and Exports by Regimes: China's Customs Transactions



(a) Shanghai (b) Jiangsu (c) Zhejiang

Figure B.2: Provincial and Sectoral Migrant Employment Share vs. Share of Processing Exports

Notes: The blue dashed line is the linear fit weighted by province-sector processing export volume. The circle size reflects provincial processing export volume in each sector.

Database is collected by Chinas General Administration of Customs. It covers very dis-aggregated information on imports and exports at the transaction level. For each transaction, it records the trading price, quantity, firms' name, identification number, zip code, and whether a transaction was processing or ordinary. We aggregate firm-level transactions into the provincial level to obtain provincial imports and exports by processing and ordinary regimes with each foreign country. The product type is reported using 8-digit Harmonized System (HS) classification.

China's Inter-provincial Trade: We measure China's inter-provincial bilateral trade flows and provincial sectoral output using China's regional input-output table. Chinas National Bureau of Statistics collected its first regional input-output survey in the year 1987. After 1987, the survey has been collected for every five years. We use China's input-output table of the year 2007, which is the closest available year to the year 2005. We deflate these trade flows and output to the year 2005 by the growth rate of China's sectoral output between 2005 to 2007. China's input-output table reports industries using 2-digit China's Standard Industrial Classification Code (CSIC), and contains 42 industries.

China Labor Market: We use Chinas Population Survey 2005 and restrict the sample to individuals who were between 20 and 60 years old and not attending schools to measure Chinas internal migration flows, wages, and sectoral employment. Chinas Population Survey 2005 is a mini version of the population census. Our sample covers about 0.2% of overall population, with roughly 2.6 million observations. The data provide detailed information on individuals provinces of *Hukou* registration, the current province of residence, sectors and occupations of employment, and earnings. For the year 2005, we define China's internal migrants as those who work in a province other than the place of their *Hukou* registration. The set of migrant population we measure reflects the effect of Chinas *Hukou* reform on the "floating population". Our measure slightly differs from the previous literature. Tombe & Zhu (2019) consider both inter-provincial migrants and rural-urban migrants during 2000–2005; they define rural-urban migrants as those whose *Hukou* is in rural agriculture sector but work in industrial sectors. Fan (2019) examines pre-2000 internal migrants who are defined as the mismatch between workers place of residence and birthplace.

We use the survey data to construct the labor stock by each group $\{L_g\}$ and origin-destination-sector-level migration rates $\{\Lambda_{g,l,s}\}$ for each of our 30 labor groups based on provinces of *Hukou* registration, g, at each destination province, l, and at each sector, s. We also measure the average income earned by each labor group at each destination and sector, which is denoted as $\{w_{g,m,s}\}$. For groups which have insufficient observations at a given origin-destination-sector cell, we assign the average destination-sector wage to that group.

Industrial Aggregation and Crosswalks: China's Customs Transactions Database reports product types using 8-digit Harmonized System (HS) classification, China's input-output table reports industries using 2-digit Chinas Standard Industrial Classification Code (CSIC) for 42 industries, and China's Population Census uses Chinas Standard Industrial Classification Code (CSIC) for 96 industries. In addition, we extract bilateral trade flows between foreign countries using STAN Bilateral Trade Database and draw tariff data from the TRAINS data. The former one uses ISIC industry codes, whereas the latter one uses 6-digit HS product codes. The OECD database provides input-output tables for 48 countries for the years 1995, 2000, and 2005, and contains information for 37 ISIC Rev 3 industries.

Our strategy is to map HS codes or CSIC industry codes to the 2-digit ISIC code, and after that we group the 2-digit ISIC code to our 29 industry aggregations as shown by Table B.1. Specifically, we map 8-digit and 6-digit HS codes to the 4-digit ISIC Rev 3 code based on the concordance which is provided by the World Integrated Trade Solution (WITS). The concordance is available on the WITS website.[2] The 4-digit ISIC code has 145 unique industries. We aggregate the 4-digit ISIC code to the 2-digit ISIC code where the cluster can be simply done based on the first two digits of the 4-digits ISIC code. We also map China's CSIC code to the 2-digit ISIC code using the concordance in Dean & Lovely (2010).

Foreign Labor Markets: We only consider one aggregate labor group for each of the foreign countries that we included. Therefore, the information required for each of the foreign labor markets is a vector of shares of sectoral employment, $\{\Lambda_{g,i,s}\}$, and a vector of sectoral average wages, $\{w_{g,i,s}\}$. We extract data from IPUMSInternational and Luxembourg income study (LIS) to construct these variables. The ISIC code is available in both datasets, however manufacturing industries are reported as a single aggregation. For each country, we thus divide the share of manufacturing employment into 16 detailed (tradable) manufacturing sectors by using proportions of countries' sectoral output. When wage variables are missing in IPUM-International or LIS, we supplement sectoral wages with the Occupational Wages around the World (OWW) Database. We assume that within each country, the average wage is the same across all 16 detailed manufacturing sectors. Then we assign the average sectoral wage at the broad manufacturing sector into detailed categories. Details of the data sources used for foreign countries are provided by the table below.

Measuring the Location Choice Probability of Firms: We first use equilibrium conditions (2.6) – (2.11) to pin down the relative probability between any two locations (including any foreign country and China's provinces). Second, we divide provincial firms into processing and

[2] See https://wits.worldbank.org/product_concordance.html.

ordinary regimes using equilibrium conditions which imply the provincial share of firms in each regime equals the share of exports. Combining equations (2.6) – (2.11), one can have

$$\frac{P\Big(Y = l\Big)}{P\Big(Y = j\Big)} = \frac{\Big[\sum_m \Pi_{l(m),n,s}\Big]\tilde{t}_{i,n,s}^{-\vartheta}}{\Pi_{j,n,s}\tilde{t}_{j,n,s}^{-\vartheta}}, \tag{B.11}$$

where $\tilde{t}_{i,n,s}$ denotes China's export tariff. $\Pi_{l(m),n,s}$ and $\Pi_{j,n,s}$ are n's expenditure share in sector s on goods produced by $l(m)$ and j respectively. We also know that

$$\sum_l P\Big(Y = l\Big) + \sum_j P\Big(Y = j\Big) = 1. \tag{B.12}$$

We solve $P\Big(Y = l\Big)$ and $P\Big(Y = j\Big)$ for all l and j from the system of equations (B.12) and (B.13). Next, the share of provincial firms in each regime m equals the share of exports, such that

$$P\Big(Y = l(m) \mid Y = l\Big) = \frac{\Pi_{l(m),u,s}}{\sum_m \Pi_{l(m),u,s}}.$$

B.4 Indirect Inference of Structural Parameters

Below we describe the procedure we used to jointly search for the value of $\{\gamma, \rho\}$:

1. We start with an initial guess of $\{\gamma_0, \rho_0\}$.

2. Given ρ_0, we choose γ to target the extent to which the number of firms responded to migration shocks, targeting the estimate of Columns (3) in Table 2.1. We introduce changes in migration costs between 1990 and 2005 to our quantitative model which is calibrated to the year 2005. We search for a value of γ such that the model-generated data can produce the same estimate of β_1 as in Column (3) of Table 2.1. We compute the model-generated changes in the number of firms in a province-sector as the weighted average of changes in firms' location probability (in that province-sector) across destination markets. The weights

are the output sold to each destination market. We use the same instrument and controls as in Table 2.1.

3. Given γ_0, we choose ρ to target the extent to which the number of ordinary exporters responded to import tariff reductions, targeting the estimate of Columns (3) in Table 2.2. We introduce China's import tariff reductions between 2000 and 2005 to our model. Again, we calibrate our model to the year 2005 and search for a value of ρ such that the model-generated data can produce the same estimate of b_2 as in Column (3) in Table 2.2. Again, we compute the model-generated changes in the number of firms for a province-sector-regime as the weighted average of changes in firms' location probability (in that province-sector-regime) across destination markets. The weights are the output sold to each destination market. We use the same instrument and controls as in Table 2.2.

4. We update $\{\gamma_0, \rho_0\}$ with $\{\gamma_1, \rho_1\}$ and iterate Steps 1–3 until the convergence of $\{\gamma, \rho\}$.

B.5 Quantitative Results of Alternative Model with Firm Entry

We provide quantitative results using an alternative model with firm entry. The model assumes that to establish a firm in region r and sector s, entrepreneurs need to hire $f^e_{r,s}$ units of labor. In the equilibrium, the number of firms in a region-sector is determined by the free-entry condition, which requires firms' average profits to equal entry costs. We suppress firm's location choices and we maintain other settings of productivity distributions to be consistent with the baseline model. For a Chinese firm in province l and sector s, its productivity is Pareto-distributed with substitution between two export regimes:

$$F\left(\vec{\phi}_{l(m),s}\right) = 1 - \left(\sum_m A_{l(m),s} \phi_{l(m),s}^{-\frac{\theta}{1-\rho}}\right)^{1-\rho}. \tag{B.13}$$

The foreign firm's productivity is Pareto-distributed as $F\left(\phi_{j,s}\right) = 1 - A_{j,s}\phi_{j,s}^{-\theta}$. We calibrate the model with firm entry to the observed economy in 2005 and still apply the Exact Hat Algebra to perform counterfactual exercises without needing the estimates of entry costs. For ease of comparison, we use the same parameter values in the model with firm entry as in our baseline model, except for the absence of relocation parameter γ.

Table B.3 presents the effects of three policy changes on export growth, for the model with firm entry and our baseline model with and without firm relocation. We highlight two findings. First, the export effects of migration shocks were much stronger in the model with firm entry than in our baseline model with relocation. In the model with firm entry, the large export effect of migration is because the free-entry condition implies the number of firms is proportional to employment size. In contrast, in our model, local employment growth indirectly affects firms' location choices through lowering the labor costs. Second, the effects of tariff reductions were smaller in the model with firm entry than in our model with relocation. In the model with firm entry, the total measure of firms in a region-sector is determined by firms' total revenues. Because exports only accounted for a small fraction of firms' revenues, the changes in firm entry tended to be small. In contrast, in our model, firms choose production locations by minimizing the unit cost of exports, which is directly affected by the tariff changes.

The rest of this section presents the equilibrium conditions for the alternative model with firm entry. First, the trade share becomes:

$$\Pi_{l(m),n,s} = \frac{\psi_{l(m),n,s}}{\sum_m \psi_{l(m),n,s}} \times \frac{M_{l,s}\Psi_{l,n,s}\tilde{t}_{i,n,s}^{\vartheta}}{\left[\sum_l M_{l,s}\Psi_{l,n,s}\right]\tilde{t}_{i,n,s}^{\vartheta} + \sum_j M_{j,s}\psi_{j,n,s}\tilde{t}_{j,n,s}^{\vartheta}}, \tag{B.14}$$

where $M_{l,s}$ is the number of firms in province l and sector s, and $M_{j,s}$ is the number of firms in country j and sector s. Analogously, the share of country n's expenditure in sector s that is spent on goods produced by foreign country j is

$$\Pi_{j,n,s} = \frac{M_{j,s}\psi_{j,n,s}\tilde{t}^{\vartheta}_{j,n,s}}{\left[\sum_l M_{l,s}\Psi_{l,n,s}\right]\tilde{t}^{\vartheta}_{i,n,s} + \sum_j M_{j,s}\psi_{j,n,s}\tilde{t}^{\vartheta}_{j,n,s}}, \tag{B.15}$$

where $\psi_{l(m),n,s}$, $\Psi_{l,n,s}$, and $\Psi_{j,s}$ are still identically defined as in the main text except for $\gamma = 0$. The aggregate price index in country n and sector s is now as

$$P_{n,s} = \left[\Theta M_s\Big(\frac{c_{n,s}f_{n,s}}{E_{n,s}}\Big)^{\vartheta}\bigg(\Big[\sum_l M_{l,s}\Psi_{l,n,s}\Big]\tilde{t}^{\vartheta}_{i,n,s} + \sum_j M_{j,s}\psi_{j,n,s}\tilde{t}^{\vartheta}_{j,n,s}\bigg)\right]^{-\frac{1}{\theta}}. \tag{B.16}$$

Second, in the equilibrium, free-entry conditions in province l and sector s require:

$$M_{l,s}f^{e}_{l,s}w_{l,s} = \frac{\sigma-1}{\sigma\theta}\sum_m\sum_r \frac{\Pi_{l(m),r,s}E_{r,s}}{\tilde{t}_{l(m),r,s}}. \tag{B.17}$$

The left-hand side is the total costs of entry, whereas the right-hand side represents the total profits, where $\frac{\sigma-1}{\sigma\theta} = \frac{1}{\sigma} - \eta$ is the profit ratio after taking into account marketing costs. The free-entry condition for foreign countries can be obtained analogously.

Third, because entrepreneurs' profits now accrue to workers that they hire for entry, the market clearing condition for final goods in Chinese provinces is

$$E_{l(m),s} = \beta_s I_{l(m)} + \sum_k \lambda^{s}_{l(m),k}\left(\frac{\sigma-1}{\sigma}\sum_r \frac{\Pi_{l(m),r,k}E_{r,k}}{\tilde{t}_{l(m),r,k}} + \eta\sum_r \frac{\Pi_{r,l(m),k}E_{l(m),k}}{\tilde{t}_{r,l(m),k}}\right). \tag{B.18}$$

Workers' income is $I_{l(O)} = \sum_g\sum_s w_{l,s}L_{g,l,s} + \sum_s\sum_r \frac{t_{r,l(O),s}}{\tilde{t}_{r,l(O),s}}\Pi_{r,l(O),s}E_{l(O),s}$ and $I_{l(\mathcal{P})} = 0$.

Finally, because a portion of labor is used for entry, the labor-market clearing condition for each China's province l and sector s can be obtained as:

$$w_{l,s}M_{l,s}f^{e}_{l,s} + \sum_m \lambda^{L}_{l(m),s}\left(\frac{\sigma-1}{\sigma}\sum_r \frac{\Pi_{l(m),r,s}E_{r,s}}{\tilde{t}_{l(m),r,s}} + \eta\sum_r \frac{\Pi_{r,l(m),s}E_{l(m),s}}{\tilde{t}_{r,l(m),s}}\right) = \sum_g w_{l,s}L_{g,l,s}. \tag{B.19}$$

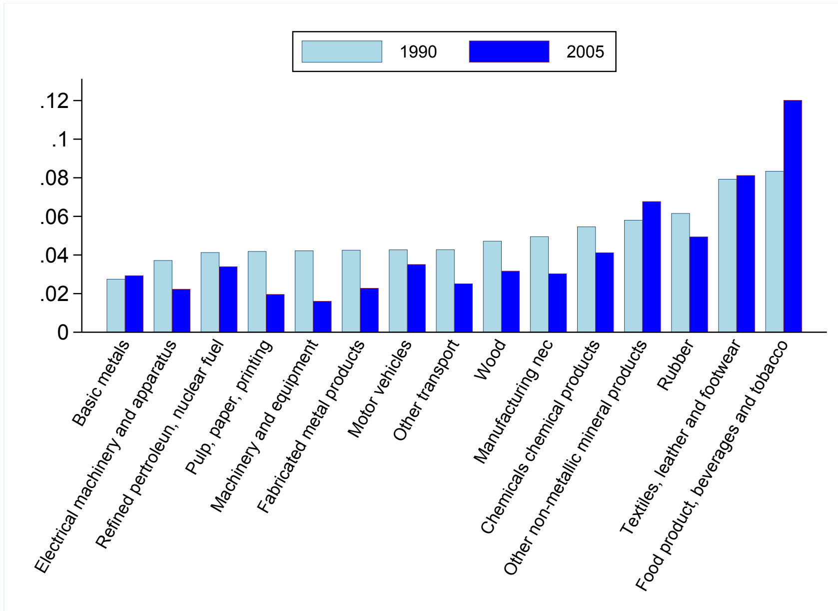


Figure B.3: China's Average Export Tariffs across Foreign Countries by Sectors, in 1990 and 2005

The left-hand side now includes entry costs.

B.6 Additional Tables and Figures

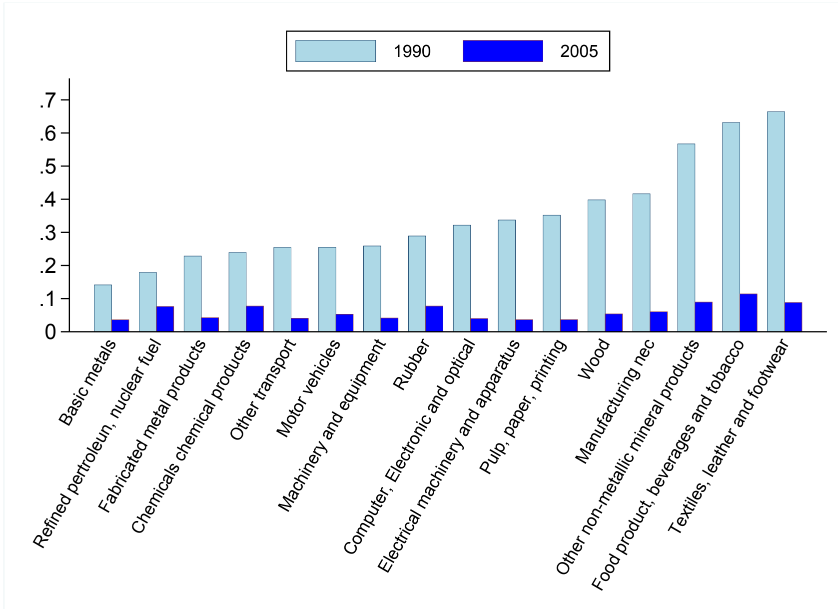


Figure B.4: China's Import Tariff by Sectors, in 1990 and 2005

Figure B.5: Provincial Annual Export Growth Rate Between 1990 and 2005

Notes: the black dots are four Special Economic Zones (SEZs) in 1980; the red dots are 14 national Economic and Technological Development Zones (ETDZs) in 1984; and the pink dots are 18 national ETDZs added in the year 1992.

Table B.1: Tradable and Non-tradable Industries by International Standard Industrial Classification (ISIC) Revision 3

Industry	ISIC, Rev 3
Panel A: 16 Tradable Industries	
Food products, beverages and tobacco	C15T16
Textiles, textile products, leather and footwear	C17T19
Wood and products of wood and cork	C20
Pulp, paper, paper products, printing and publishing	C21T22
Coke, refined petroleum products and nuclear fuel	C23
Chemicals and chemical products	C24
Rubber and plastics products	C25
Other non-metallic mineral products	C26
Basic metals	C27
Fabricated metal products	C28
Machinery and equipment, nec	C29
Computer, Electronic and optical equipment	C30T33X
Electrical machinery and apparatus, nec	C31
Motor vehicles, trailers and semi-trailers	C34
Other transport equipment	C35
Manufacturing nec; recycling	C36T37
Panel B: 13 Non-tradable Industries	
Agriculture	C01T05
Mining	C10T14
Utility supply	C40T41
Construction	C45
Retail	C50T52
Hotels and restaurants	C55
Transportation and communications	C60T64
Financial intermediation	C65T67
Real estate and business services	C70T74
Public administration and defence; compulsory social security	C75
Education	C80
Health and social work	C85
Other services	C90T95

Table B.2: Data Sources to Measure Foreign Labor Markets

Data Source	$w_{g,i,s}$	$\Lambda_{g,i,s}$
IPUMS-International	Brazil, Canada, India, Mexico, South Africa, Spain, United States	Argentina, Austria, Brazil, Canada, Chile, Denmark, Greece, Hungary, India, Indonesia, Ireland, Malaysia, Mexico, Philippines, Portugal, South Africa, Spain, Thailand, Turkey, United Kingdom, United States, Vietnam
Luxembourg Income Study	Austria, Chile, Denmark, Finland, Greece, Germany, Hong Kong, Italy, Ireland, Japan, Korea, Malaysia, Norway, Philippines, Portugal, United Kingdom	Finland, Germany, Hong Kong, Italy, Japan, Korea, Norway, Singapore
Occupational Wages around the World	Thailand, Turkey, Vietnam	N/A

Table B.3: Comparison of Baseline Model and Model with Firm Entry

Policy shock	baseline model (no relocation, $\gamma = 0$)	baseline model (with relocation, $\gamma = 0.63$)	alternative model (with firm entry)
Migration shock	0.91	1.29	1.58
Import tariff	1.08	2.30	1.31
Export tariff	0.88	1.48	0.98
Combined policies	2.87	5.07	3.87

Notes: We calculate percentage points as $\left(\widehat{\text{export}}^{\frac{1}{15}} - 1\right) \times 100$, where $\widehat{\text{export}}$ is the proportional changes of export volume between the observed equilibrium and the counterfactual.

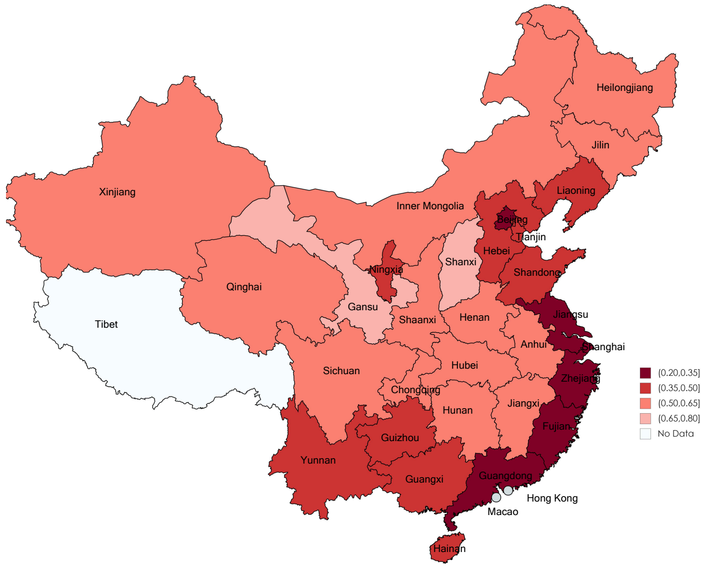


Figure B.6: Provincial Changes in Migration Frictions $\frac{\tau_{l,s,1990}}{\tau_{l,s,2005}}$ (Manufacturing Sector)

Notes: Here we show the changes in migration costs by destination provinces for manufacturing sector, which are the migrant-population weighted average across origin provinces and sectors.

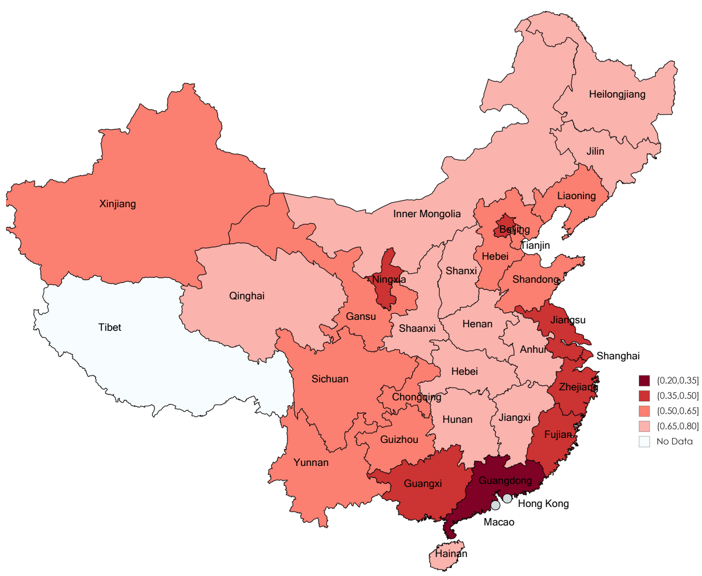
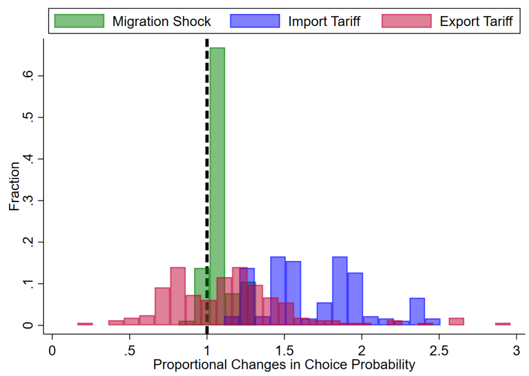
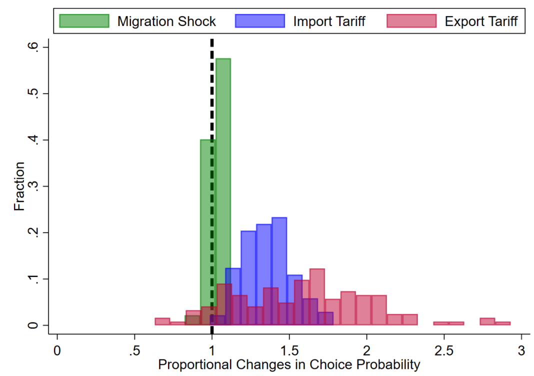


Figure B.7: Provincial Changes in Migration Frictions $\frac{\sum_s \tau_{l,s,1990}}{\sum_s \tau_{l,s,2005}}$ (All Sectors)

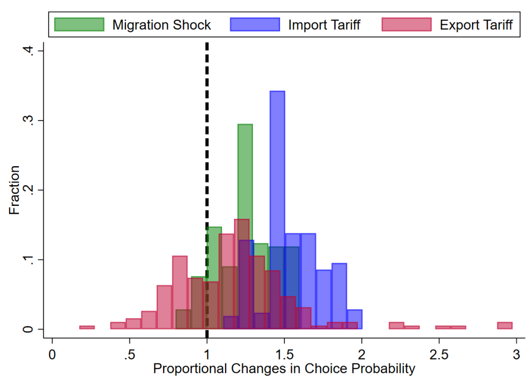
Notes: Here we show the changes in migration costs by destination provinces for all sectors, which are the migrant-population weighted average across origin provinces and sectors.



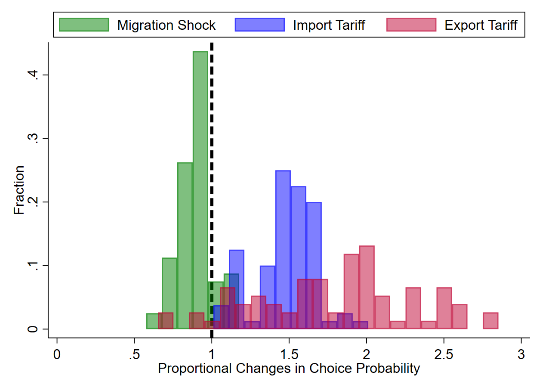
(a) Jiangsu Ordinary Exporters



(b) Jiangsu Processing Exporters



(c) Zhejiang Ordinary Exporters



(d) Zhejiang Processing Exporters

Figure B.8: The Histogram of Changes in Firms' Probability to Choose China's Province and Export-regime, $\widehat{P}\Big(Y = l(m)\Big)$

Notes: The histogram is plotted across all foreign destinations and sectors, where China's export volume was greater than 30 million US dollars in 2005. For the case of export tariffs, there is a probability mass of around 0.05 for which $\widehat{P}\Big(Y = l(m)\Big)$ takes values greater than 3. We truncate the distribution such that $\widehat{P}\Big(Y = l(m)\Big)$ takes values smaller than 3.

Table B.4: The Provincial Export Impact by Different Margins of Trade, in Percentage Points

Policy Shock	**Intensive Margin** $\theta = 3$, $\gamma = 0$, $\rho = 0$ (1)	**Intensive & Extensive Margin** $\theta = 4$, $\gamma = 0$, $\rho = 0$ (2)	**Intensive, Extensive & Regime Margin** $\theta = 4$, $\rho = 0.81$, $\gamma = 0$ (3)	**All Margins** $\theta = 4$, $\rho = 0.81$, $\gamma = 0.63$ (4)
		Guangdong Province		
Migration Shock	1.97	2.54	2.45	4.00
Import Tariff	0.80	1.12	1.01	2.34
Export Tariff	0.73	0.96	1.01	1.90
		Shanghai		
Migration Shock	1.48	1.86	1.81	2.36
Import Tariff	0.84	1.11	0.95	1.75
Export Tariff	0.60	0.75	0.79	1.26
		Jiangsu		
Migration Shock	0.18	0.23	0.21	0.38
Import Tariff	0.73	0.99	0.90	1.83
Export Tariff	0.67	0.88	0.92	1.63

Notes: the values are in units of percentage points. They are calculated in the same way as described in Table 2.5.

Table B.5: Statistics of Manufacturing Foreign-invested Firms Registered between 1990–2005

By sector			By place of origin		
ISIC code	#entrants, 90–05	share	region	#entrants, 90–05	share
C17T19	20,526	20.1%	Hong Kong	37,767	37.0%
C15T16	11,329	11.1%	Taiwan	14,054	13.8%
C29	9,949	9.7%	Korea	10,802	10.6%
C24	8,854	8.7%	United States	10,186	10.0%
C36T37	8,184	8.0%	Japan	9,171	9.0%
C30T33X	7,965	7.8%	Singapore	2,827	2.8%
C31	7,728	7.6%	British Virgin Isds	2,540	2.5%
C25	6,254	6.1%	Canada	1,638	1.6%
C28	5,196	5.1%	Australia	1,523	1.5%
C26	5,152	5.0%	Germany	1,184	1.2%
C35	3,307	3.2%	Macau	1,072	1.1%
C21T22	2,410	2.4%	United Kingdom	858	0.8%
C20	2,366	2.3%	France	682	0.7%
C27	1,475	1.4%	Malaysia	667	0.7%
C23	1,377	1.3%	Italy	644	0.6%

Appendix C

Appendix for Chapter 3

C.1 Brazilian Economic Background

Up to the 1990s, Brazil was a relatively closed economy to international trade. In the 1990s, with the economic liberalization, reductions in import tariffs, and the Mercosur Agreements, Brazil began opening to international trade. After 1999, exports started to increase substantially due to changes in the exchange rate regime and the large devaluation episode. This process sped up after 2002, with a new depreciation episode and an improvement of international agricultural prices. Table C.1 shows the trends of exports for manufacturing goods, agricultural goods, and fuel over our sample period. It is clear that there was a sharp increase in exports after 2000, and that manufacturing goods represent a large share of Brazil's exports.

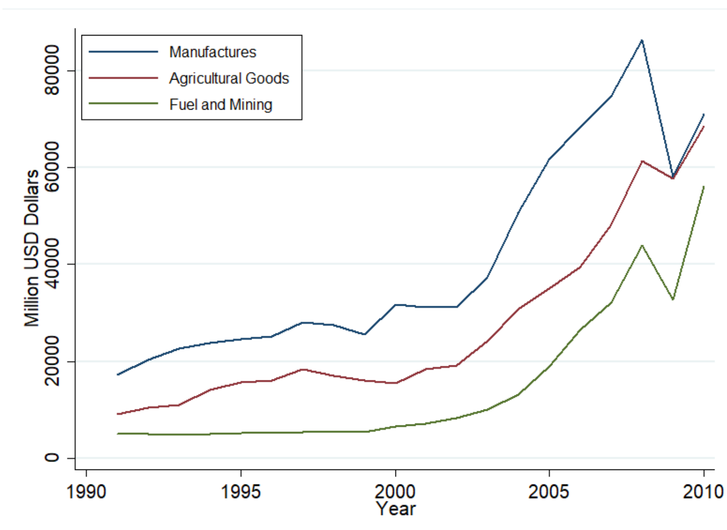


Figure C.1: Brazil's Exports in 1990–2010

Note: The data come from the WTO. This graph shows the value of exports in millions of dollars for manufacturing goods, agricultural goods, and fuels and mining products in the period 1990–2010.

Moreover, Rocha et al. (2008) explain how Brazil's exports are highly diversified across a variety of products. Apart from agricultural goods, Brazil intensively exports chemical products, pharmaceutical products, aircrafts, automobiles, and home appliances. In 2004, there were more than 10,000 different 8-digit HS products exported by more than 15,000 firms.

Table C.1 presents the share of Brazil's exports to each destination. In the 1990s, thanks to

Table C.1: Share of Exports (%) by Trading Partners

	2010	2000	1990
By Region			
Europe & Central Asia	25.63	30.78	31.93
East Asia & Pacific	25.11	10.93	15.34
Latin America & Caribbean	23.26	24.99	11.67
United States	9.64	24.29	24.62
Middle East & North Africa	7.33	3.35	0
Sub-Saharan Africa	2.49	1.52	1.91
By Country (Top 15)			
China	15.25	1.97	1.22
United States	9.64	24.29	24.62
Argentina	9.17	11.32	2.05
Netherlands	5.07	5.07	7.94
Germany	4.03	4.58	5.69
Japan	3.54	4.49	7.48
United Kingdom	2.3	2.72	3.01
Chile	2.11	2.26	1.54
Italy	2.1	3.89	5.14
Russian Federation	2.06	0.77	0
Spain	1.93	1.83	2.24
Venezuela	1.91	1.37	0.85
Korea, Rep.	1.86	1.05	1.73
Mexico	1.84	3.11	1.61
France	1.79	3.25	2.87

Note: This table presents the share of exports to each destination market. The data are collected from the WITS (the World Integrated Trade Solution). The countries and Regions are ranked by the share of exports in 2010.

the Mercosur agreement, there was an increase in the share of exports destined to Latin American countries, in particular Argentina to which its share increased from 2% in 1990 to 11% in 2000. While the U.S. was one of the biggest markets for Brazilian exporters in 1990 with 25% of total exports, this share decreased to 10% in 2010. Moreover, between 1990 and 2010, there was an increase in the share of exports going to East Asia and the Pacific, mostly explained by the increase in exports going to China (1% in 1990 to 15% in 2010). The most important takeaway from these shares is that Brazil exports to a wide variety of destinations with around half of total exports going to richer economies and half going to other developing economies.

Table C.2 presents the share of total exports, the value, and the revealed comparative

Table C.2: Exports by Products

	Product Share (%)		Value (U.S.$ Mill)		RCAI	
	2010	1990	2010	1990	2010	1990
By Type						
Raw materials	41.93	21.37	84671	6713	2.93	1.84
Intermediate goods	27.29	39.01	55109	12252	1.28	1.75
Consumer goods	14.62	20.81	29517	6537	0.44	0.56
Capital goods	14.27	15.45	28822	4854	0.42	0.35
By Product						
Minerals	15.63	8.93	31557	2804	10.79	10.26
Food Products	13.4	16.83	27056	5287	4.21	4.46
Vegetable	10.88	9.02	21961	2831	3.81	2.61
Fuels	9.83	2.17	19843	682	0.61	0.03
Transportation	8.55	7.32	17272	2299	0.88	0.35
Mach and Elec	8.03	11.17	16216	3509	0.28	0.32
Metals	7.14	17.17	14412	5393	0.9	2.89
Animal	6.7	2.07	13526	650	3.46	0.8
Chemicals	5.06	4.89	10221	1535	0.57	0.62
Wood	4.33	5.28	8740	1659	2.11	0.95
Miscellaneous	2.98	2.43	6023	762	0.33	0.17
Plastic or Rubber	2.65	2.56	5341	804	0.57	0.5
Stone and Glass	1.96	1.37	3954	431	0.36	0.56
Textiles and Clothing	1.12	3.97	2265	1248	0.28	0.67
Hides and Skins	0.92	1.03	1865	323	1.5	1.62
Footwear	0.82	3.78	1653	1188	1.07	1.95

Note: This table presents the share of exports in Columns 1–2, the value of exports in Columns 3–4, and the revealed comparative advantage indices in Columns 5–6 for the years 2010 and 1990. The data are collected from WITS (World Integrated Trade Solution). The products and products types are ranked by the share of exports in 2010.

advantage index for main products Brazil exported in the years 2010 and 1990. 22% of Brazil's exports in 1990 and 42% in 2010 were raw materials. This means that around 80% (60%) of its exports were manufactured goods in 1990 (2010). Moreover, although the share of raw materials in total exports increased in this period, it is worth noting that the export value of manufactured products also substantially increased.

C.2 Brazilian Economic Background and Informality

One possible drawback of the analysis is that we focus on the formal sector. Therefore, it is important to discuss the economic and political background of the Brazilian informal labor market in recent decades. The 90s was a period of instability for the Brazilian economy. Brazil opened up to international trade, with the Mercosur Agreements signed in 1991 and 1994. However, the 90s started with another major recession that led to high unemployment. Under these circumstances, the share of unregistered employees in total employees grew by 2 percentage points from 1990 to 2003. The 2000s were, in some sense, the opposite of what the 90s were. In the 2000's, the inflation was finally tamed, and the economy was considerably more open due to those policies adopted in the 90s. After 2002, an economic expansion took place with a rapid increase in GDP, improvements in social-economic indicators, and a considerable decrease in the amount of unemployment and unregistered workers. For an extensive review of policies and the background about the informal sector in Brazil, see Dix-Carneiro et al. (2019).

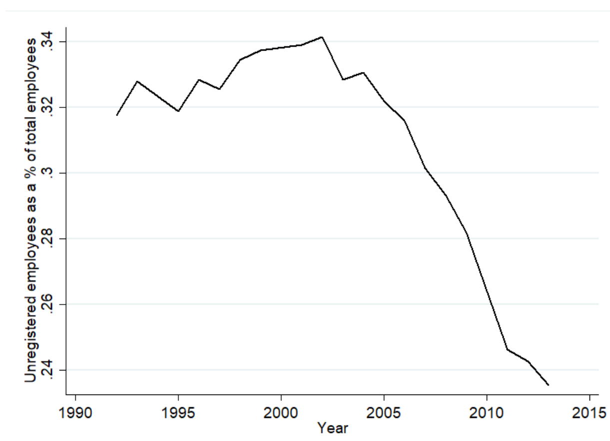


Figure C.2: Share of Unregistered Employees in Total Employees

Note: The figure shows the share of unregistered employees in total employees. The data come from the PNAD censuses.

Figure C.2 shows unregistered workers as a share of total employees. The informality rate sharply declined in recent decades, from around 33% in the 1990s to 23% in the 2010's. Besides employees, Brazilian employment also includes self-employed workers, employers, and

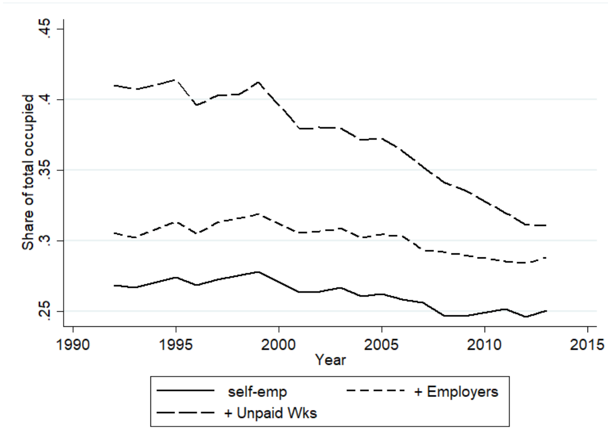


Figure C.3: Share of Non-employees Occupied Population

Note: The data come from the PNAD censuses. The share of self-employed people represents the ratio of the amount of self-employed workers to total occupied population. The share "+ employers" is the share of self-employed and employers in total occupied population. The share "+ Unpaid" is the share of self-employed, employers, and unpaid workers in total occupied population.

unpaid workers, and these three types of employment may not appear in the RAIS (except for employers who receive a wage). Figure C.3 shows the share of self-employed workers, employers and unpaid workers in Brazilian total employment. These three types of employment represented 30–40% of Brazilian employment in the 90's and 2000's.

We obtain Brazilian Population Census from IPUMS International to compare experience-wage profiles for Brazilian wage workers and self-employed workers. We estimate experience-wage profiles by applying the HLT method. Differing from the Mincer regressions estimated in Section 3.2.3, because we cannot identify individuals in Brazilian Population Census, we regress log hourly wage on a set of experience dummies, schooling, cohort effects, and year effects. We do not enforce a first difference of log wage across years, as we are not able to identify individuals. Our regression is identical as in Lagakos et al. (2018), with 10 years of no experience effects at the end of the working life and 0% depreciation rate. As shown in Figure C.5, we find that wage workers have steeper profiles than self-employed workers.

Moreover, for two years (2000 and 2010), we have information on the contract status of wage workers. We split the sample into wage workers with formal contracts and with no formal contracts. Because the data are only available for two years, we are not able to apply the HLT method. As some reference, we draw the experience-wage profiles in the cross section, following the process in Section 3.2.2. Figure C.5 plots both profiles and shows that formal workers have stepper experience-wage profiles. Dix-Carneiro et al. (2019) show that Brazilian informal workers tend to be mostly allocated in non-tradable sectors and within tradable sectors, most of workers are formally employed. Moreover, they show that the transition between formality and informality is relatively low. Therefore, given our focus on tradable industries, informality should not be a big issue. Nevertheless, even considering informal workers, because exporters are mostly formal firms, it is likely that non-exporters hire informal workers more intensively than exporters. By missing informal workers, we may underestimate the difference in experience-wage profiles between exporters and non-exporters in our main results.

Figure C.4: Experience-wage Profiles for Wage Workers and Self-Employed

Note: The figure shows experience-wage profiles separately for male wage workers and male self-employed workers, derived from the HLT method (identical regression as in Lagakos et al. (2018)). In applying the HLT method, we assume 10 years of no experience effects at the end of the working life (31–40 years of potential experience) and a 0% depreciation rate. We rely on Brazilian Census data available in IPUMS for the years 1991, 2000, and 2010.

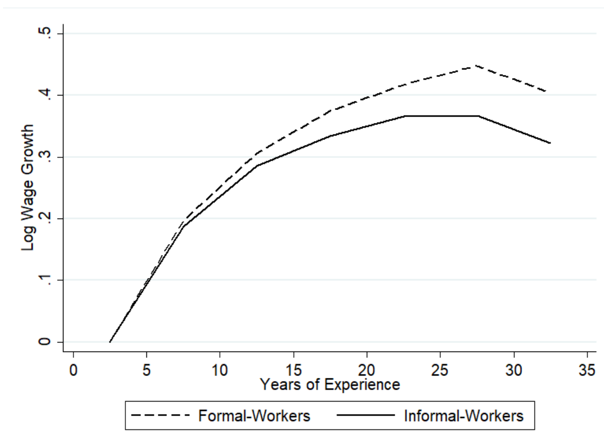


Figure C.5: Experience-wage Profiles: Workers With and Without Formal Contracts

Note: The figure shows experience-wage profiles separately for male wage workers with and without formal contracts. In each year, we obtain experience-wage profiles by computing the average of log hourly wage for workers in each 5–year experience bin, separately for workers with and without formal contracts. We normalize the value of the first experience bin (1–5 years of experience) to be 0 for each experience-wage profile. Finally, we average profiles across years to obtain experience-wage profiles for workers with and without formal contracts, respectively. We rely on Brazilian Census data available in IPUMS for the years 2000 and 2010.

C.3 Description of the RAIS and Customs Data

We use Brazilian employer-employee data named RAIS (Relacao Anual de Informacoes Sociais). Establishments receive 14-digit unique permanent tax codes (CNPJ), from which we can identify firms by the first 8 digits of the code (Muendler et al. 2012). For this study, we focus on firms and aggregate establishments into the affiliated firms. Firms are mandated by law to annually provide workers' information to RAIS, and therefore the data contain annual information on all workers employed in the Brazilian formal sector. The data are available from 1986. Nonetheless, the detailed data on age and hours worked are only available after 1994, and these two variables are important for us to accurately measure experience-wage profiles.

The occupation classification in RAIS is based on the CBO (Classificao Brasileira de Ocupaes), which has more than 350 categories and can be aggregated to 5 broad occupations (professionals, technical workers, other white-collar workers, skilled blue-collar workers, and unskilled blue-collar workers). The industry classification is based on the CNAE (Classificao Nacional de Atividade Econmica), which has 564 5-digit industries. Although there are available data on agriculture and services, we only focus on manufacturing industries, as manufacturing firms are tradable and extensively studied in the literature. The data contain monthly average wage and wages of December, which are measured by multiples of the contemporaneous minimum wage. We follow Menezes-Filho et al. (2008) to transform these earnings into the Brazilian Real and deflate them to the August 1994 price level. For the cases with more than one observations per worker-year, we keep the observation with the highest hourly wage (Dix-Carneiro 2014). Most workers are employed only at one firm in a year, and the average number of observations per worker-year is roughly 1.1.

We use firm IDs to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX (Secretaria de Comrcio Exterior) for the years 19942010, following Aguayo-Tellez et al. (2010). Thus, we use RAIS merged with customs data for the

1994–2010 period. From Brazilian customs declaration, we have data on destination markets for all firms. We split destination markets into industrialized and non-industrialized destinations. We classify the following countries into each group:

- Industrialized destinations: US, EU Countries, Canada, Hong Kong, South Korea, Australia, Israel, Japan, New Zealand.

- Non-industrialized destinations: All the rest of the countries that are not included in the industrialized group; mainly include South American, Central American and African Countries, Russia, and China.

For customs records, we have data on export value and quantity by 8-digit HS products and destinations for the years 1997–2000. We use these additional data to provide some robustness checks as discussed in the main text.

C.4 Empirical Analysis: Additional Results

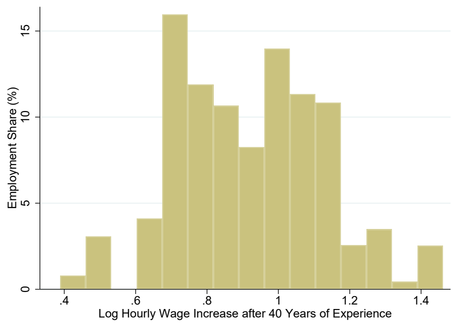
C.4.1 Between-industry Heterogeneity in Returns to Experience

The difference in the aggregate experience-wage profiles between exporters and non-exporters could be explained by different reasons. One important driver of the result could be industry composition. This is motivated by two well-established results in the literature: (1) different industries have different returns to experience (e.g., Dix-Carneiro 2014, Islam et al. 2019); (2) trade induces industry specialization and labor reallocation, possibly driven by comparative advantage (e.g., Costinot et al. 2012) or home market effects (e.g., Head & Ries 2001). Therefore, if exporters are more concentrated in industries with higher returns to experience than non-exporters, on average they will also have steeper experience-wage profiles.

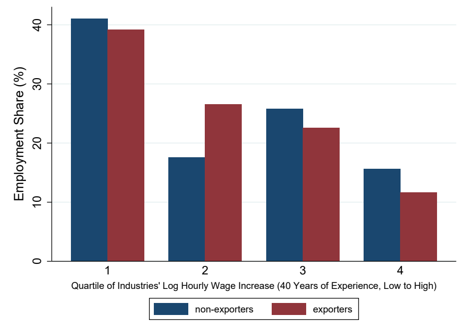
We first examine the role of industry composition in driving the difference of experience-wage profiles between exporters and non-exporters. We perform regression Equation (3.1) separately for workers in each 3-digit manufacturing industry between 1994–2010. For precision, we focus on industries with more than 0.1% of total employment and at least 10 workers in each year-experience-bin. We obtain estimation results for 91 industries (99% of manufacturing employment in the sample).[1] Figure C.6a illustrates the cross-industry distribution of wage growth for a hypothetical worker with 40 years of experience in the same industry, which is computed as $5 \times (\phi_s^{1-5} + \ldots + \phi_s^{36-40})$. It is clear that there is a large degree of heterogeneity in returns to experience across industries.

Figure C.6b presents industry-level employment distributions in 1994–2010, for exporters and non-exporters respectively. We rank industries by returns to 40 years of experience, and for ease of description, we further split industries into 4 quartiles based on returns to experience. We find that more than 65% of workers in exporters are employed in industries with lower returns to experience than the median, compared to around 57% for non-exporters.

[1] The estimation does not work for some industries with few observations.



(a) Distribution of Log Hourly Wage Increase Across Industries



(b) Distribution of Employment by Exporters and Non-exporters

Figure C.6: Returns to Experience and Industry Heterogeneity

Note: This graph presents the results from estimating Equation (3.1), separately for workers in each 3-digit manufacturing industry between 1994–2010. Panel (a) is the cross-industry distribution of returns to 40 years of experience. Panel (b) presents the employment distribution of workers in exporters and non-exporters across industries ordered by different quartiles of returns to 40 years of experience.

These findings have two main implications. First, trade changes workers' allocation across industries with heterogeneous returns to experience, as similarly found by Dix-Carneiro (2014). This force could generate gains or losses in workers' earnings growth, depending on each country's specialization pattern. For countries with comparative advantage in industries with higher returns to experience, trade openness can lead to higher earnings growth. On the other hand, for other countries such as Brazil, trade openness can generate lower earnings growth by allocating workers toward industries with lower returns to experience.

Second, in Brazil, industry composition cannot explain the aggregate difference in returns to experience between exporters and non-exporters. On the contrary, using industry-specific returns to experience and different employment distributions across industries for exporters and non-exporters, we find that after 40 years of experience, workers' wage increase would be 2 percentage points lower in exporters than in non-exporters due to industry composition.

In Table C.3, we explore what causes cross-industry heterogeneity in experience-wage profiles by regressing profiles on industry characteristics. We find that industries enjoy steeper experience-wage profiles, if they hire larger shares of high-school and cognitive workers. However, even controlling for education levels and occupations, there is still a large degree of cross-industry heterogeneity in experience-wage profiles unexplained.

Table C.3: Log Hourly Wage Increase (40 Years of Experience)

	(1)	(2)	(3)	(4)	(5)	(6)
log(industry employment)	-0.064**					-0.015
	(0.028)					(0.026)
Share of high-school grads		0.960***				0.696*
		(0.181)				(0.417)
Share of cognitive occupations			1.292***			0.588
			(0.278)			(0.391)
Share of employment in exporters				-0.086		-0.267*
				(0.161)		(0.139)
Differentiated industry					0.127**	-0.003
					(0.051)	(0.071)
Obs	91	91	91	91	91	91
R-squared	0.071	0.298	0.328	0.006	0.066	0.395
Mean (dep var)	0.914	0.914	0.914	0.914	0.914	0.914
S.D. (ind var)	0.888	0.135	0.106	0.212	0.480	–

Note: This table presents estimates from regressions of industry-level log hourly wage increase after 40 years of experience on industry characteristics, weighted by the number of each industry's observations in the restricted sample used to estimate profiles. An industry is defined as differentiated if its share of differentiated goods (based on 4-digit SITC goods exported by this industry) lies above the median of the share of differentiated goods across industries, according to the classification provided by Rauch (1999). The shares of high-school graduates, cognitive occupations, and exporters' employment in the workforce are computed based on our restricted sample, from which we obtained our estimates of industry-level experience-wage profiles. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Industry-level employment is the average of the number of all types of workers in the raw sample (including female and part-time workers) between 1994 and 2010—which reflects actual industry size and is consistent with our treatment of firm employment. It is worth noting that our results are quantitatively very similar if we instead use full-time male workers in our restricted sample to compute industry-level employment size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

C.4.2 Robustness checks on Destination-specific Effects

Table C.4: Firm-year-level Log Hourly Wage Increase (20 Yrs of Experience)

	(1)	(2)	(3)	(4)
Exporter	0.204***	0.112*	0.004	-0.003
	(0.026)	(0.059)	(0.066)	(0.066)
Exporter × Share of exports	0.087**	0.082*	0.186*	0.184*
to industrialized destinations	(0.044)	(0.045)	(0.099)	(0.099)
Exporter ×		-0.009		0.006
Log (export value per worker)		(0.008)		(0.019)
Log(firm employment)		0.094***		0.063
		(0.010)		(0.014)
Share of high-school grads		0.285***		0.307*
		(0.061)		(0.042)
Share of cognitive occupations		0.285***		-0.065
		(0.072)		(0.276)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Obs	77,071	77,071	77,071	77,071
R-squared	0.011	0.014	0.487	0.487

Note: This table presents estimates from regressions of firm-year-level log hourly wage increase after 20 years of experience on firm characteristics (Firms 1997–2000). The baseline group is non-exporters. The shares of high-school graduates and cognitive occupations in the workforce are computed based on our restricted sample, from which we obtained our estimates of firm-year-level experience-wage profiles. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table C.5: Firm-year-level Log Hourly Wage Increase (20 Years of Experience)

	(1)	(2)	(3)	(4)
Exporter	0.210***	0.131**	0.032	-0.007
	(0.023)	(0.060)	(0.061)	(0.116)
Exporter ×	0.073***	0.065**	0.111*	0.107*
Log(GDP per capita) in destination	(0.027)	(0.028)	(0.059)	(0.059)
Exporter ×		-0.010		0.006
Log (export value per worker)		(0.008)		(0.019)
Log(firm employment)		0.094***		0.063
		(0.010)		(0.053)
Share of high-school grads		0.284***		0.306*
		(0.061)		(0.186)
Share of cognitive occupations		0.285***		-0.065
		(0.072)		(0.276)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Obs	77,071	77,071	77,071	77,071
R-squared	0.011	0.014	0.487	0.487

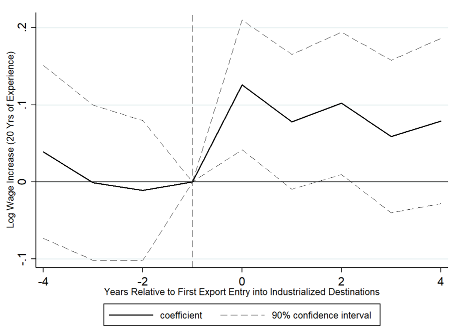
Note: This table presents estimates from regressions of firm-year-level log hourly wage increase after 20 years of experience on firm characteristics (Firms 1997–2000). The baseline group is non-exporters. We draw log real GDP per capita (2011 U.S.$) for each country in 2000 from Penn World Table 9.0 (Feenstra et al. 2015) and compute a firm-year-level export-weighted log GDP per capita across destinations, normalized by log GDP per capita in Brazil. The shares of high-school graduates and cognitive occupations in the workforce are computed based on our restricted sample, from which we obtained our estimates of firm-year-level experience-wage profiles. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table C.6: Robustness of Column (4) Table 3.3 (Baseline: Exporter, Non-Ind Dests)

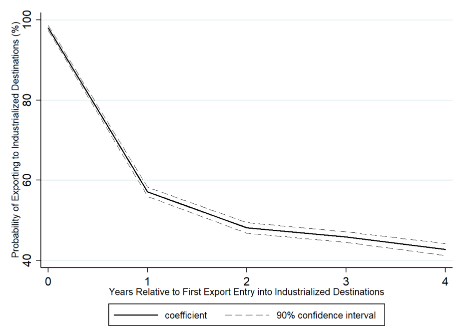
	Non-exporters		Exporter, industrial dests		Exporter, both dests	
baseline results	0.020 (0.023)		0.091** (0.039)		0.066*** (0.026)	
(1) add unit price of exports (1997–2000)	0.023 (0.066)		0.214** (0.104)		0.203*** (0.076)	
(2) add industry-year fixed effects	0.013 (0.023)		0.088** (0.039)		0.063** (0.026)	
(3) add gravity controls	-0.128 (0.177)		0.094** (0.047)		0.068*** (0.030)	
(4) add labor ability	0.024 (0.023)		0.091** (0.039)		0.068*** (0.026)	
(5) only switching periods	-0.018 (0.035)		0.151** (0.062)		0.070 (0.069)	
(6) add average tenure	0.016 (0.023)		0.089** (0.039)		0.068*** (0.026)	
(7) add differences in tenure between young and old	0.020 (0.023)		0.087** (0.039)		0.064** (0.026)	
By industry characteristics:	more	less	more	less	more	less
(8) more/less manual	0.049* (0.028)	-0.046 (0.043)	0.137*** (0.047)	-0.017 (0.070)	0.084*** (0.031)	0.016 (0.047)
(9) more/less skill-intensive	0.016 (0.039)	0.025 (0.029)	0.053 (0.070)	0.107** (0.047)	0.004 (0.043)	0.096*** (0.033)
(10) more/less differentiated	0.059* (0.035)	-0.017 (0.031)	0.157** (0.065)	0.050 (0.049)	0.088** (0.040)	0.048 (0.035)

Note: This table presents robustness checks of Column (4) of Table 3.3. All regressions control for the shares of high-school graduates and cognitive occupations in the workforce and firm size, as well as year and industry fixed effects. We use exporters to non-industrialized destinations as the baseline group, because they have the lowest returns to experience in the baseline results. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. For each firm, unit prices of exports are observed for each 8-digit HS and destination, and we take an average across destinations and HS products to obtain firm-year-level unit price of exports. Gravity controls refer to the average of log distance and bilateral cultural characteristics (with Brazil) across all of a firm's destinations, which are drawn from GeoDist database in CEPII (Mayer & Zignago 2011). Old workers refer to workers in experience bins of 31–40 years, whereas young workers refer to workers in experience bins of 1–20 years. An industry is defined as more differentiated if its share of differentiated goods (based on 4-digit SITC goods exported by this industry) lies above the median of the industry-level share of differentiated goods across all manufacturing industries, according to the classification provided by Rauch (1999). An industry is defined as more skill-intensive (manual) if its share of high-school (manual) workers averaged across firms lies above the median of industry-level averages across all manufacturing industries. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

C.4.3 Dynamics of Experience-Wage Profiles



(a) Changes in Experience-wage Profiles



(b) Survival Rate in Industrial Markets

Figure C.7: Dynamics of Firms' First Entry Into Industrialized Destinations

Note: The figure shows the β_τ parameters from estimating Equation (3.4). The dependent variable is firm-year-level returns to 20 years of experience in Panel (a) and a dummy variable that equals 1 if the firm exports to industrialized destinations in Panel (b). All regressions control for firm fixed effects, industry fixed effects, year fixed effects, the shares of high-school graduates and cognitive workers, firm size, and a dummy variable indicating whether the firm is exporting to a non-industrialized destination. To estimate the β_τ parameters, we do not enforce a requirement that firms remain exporting to industrialized destinations.

C.4.4 Case Study: 1999 Devaluation Episode

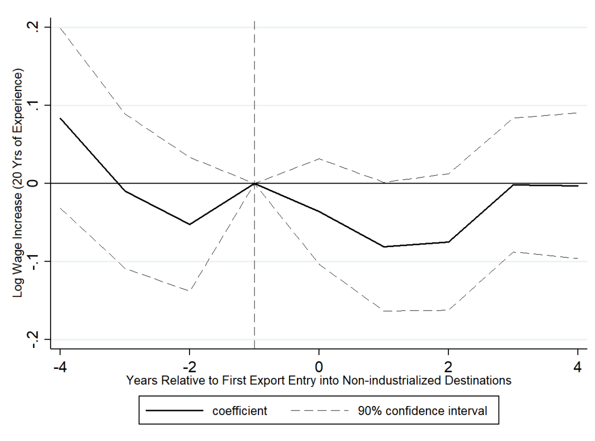


Figure C.8: Dynamics of Firms' First Entry Into Non-industrialized Destinations (Survivors)

Note: The figure shows the β_τ parameters from estimating Equation (3.4), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry into non-industrialized destinations. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, the shares of high-school graduates and cognitive workers in the workforce, firm size, and a dummy variable indicating whether the firm is exporting to an industrialized destination. To estimate the β_τ parameters after entry, we require that firms remain exporting to non-industrialized destinations.

Table C.7: Dependent Variable: Share of Cognitive Workers (Percentage Points)

time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
$1\{$export to industrialized dests$\}$	0.481	1.492***	1.651***
$\times 1\{$post_1999$\}$	(0.630)	(0.549)	(0.479)
$1\{$export to non-industrialized dests$\}$	1.793***	1.604***	1.848***
$\times$ $1\{$post_1999$\}$	(0.470)	(0.340)	(0.296)
$1\{$export to both types of dests$\}$	0.751	1.649***	2.429***
$\times 1\{$post_1999$\}$	(1.035)	(0.613)	(0.515)
Year, industry and firm FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Obs	37,267	61,390	85,266
R-squared	0.940	0.905	0.873
Average	21.12	21.44	21.74

Note: This table presents estimates from Equation (3.5). The dependent variable is the share of high-school graduates in the workforce, in terms of percentage points (%). The regression includes firm, industry, and year fixed effects. The last row shows the average share of high-school grads in the workforce (%) during the period. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table C.8: Share of High-school Grads, (Percentage Points)

time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
1{export to industrialized dests}	0.181	0.254	0.410
×1{post_1999}	(0.387)	(0.388)	(0.320)
1{export to non-industrialized dests}	0.364	0.106	0.154
× 1{post_1999}	(0.301)	(0.215)	(0.196)
1{export to both types of dests}	-0.245	0.226	0.221
×1{post_1999}	(0.804)	(0.481)	(0.366)
Year, industry and firm FE	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Obs	37,267	61,390	85,266
R-squared	0.966	0.943	0.925
Average	17.24	17.39	17.63

Note: This table presents estimates from Equation (3.5). The dependent variable is the share of cognitive occupations in the workforce, in terms of percentage points (%). The regression includes firm, industry, and year fixed effects. Cognitive occupations refer to professionals, technicians, and other white-collar workers. The last row shows the average share of cognitive workers in the workforce (%) during the period. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

C.5 Detailed Discussions on Mechanisms

In this section, we discuss four plausible explanations for our finding on the interaction between returns to experience and different destinations: (1) selection of firms into different export destinations; (2) differential changes in labor composition; (3) job search and screening; and (4) human capital accumulation. We present detailed evidence and discussions for each hypothesis.

C.5.1 Selection of Firms into Different Export Destinations

Our first hypothesis is that firms exporting to industrialized destinations are better than other exporters due to factors not captured by firm fixed effects, or they enjoy more favorable linkages with destinations, which leads to higher returns to experience. We argue that this is unlikely to explain our findings.

First, as Table 3.4 shows, firms exporting to both types of destinations appear to be the most productive even after controlling for firm fixed effects, as they are the biggest and have the largest shares of high-school workers. Nevertheless, it is the firms exporting to industrialized destinations that enjoy the largest increase in experience-wage profiles after switching to exporting. This suggests that the destination-specific results we find may not be simply explained by better firms' selection into exporting to industrialized destinations.

Second, we exploit available data on export value and quantity in 1997–2000 to construct firm-year-level unit prices of exports as a proxy for product quality (Manova & Zhang 2012).[2] We replicate the regression in Column (4) of Table 3.3 for the years 1997–2000 and control for unit prices of exports. We still find that exporting to industrialized destinations increases returns to

[2]The firm-level export value and quantity are available by destinations and 8-digit HS products in 1997–2000. We take an export-weighted average of unit prices across destinations and HS products to construct firm-year-level unit prices of exports. Given the heterogeneity in values of HS products, we experimented with first normalizing the unit price by the unit price of the same HS product exported from Brazil to the U.S.. The results remain very similar under this normalization.

experience, as shown in Row (1) of Appendix Table C.6. In Rows (2)–(3) of Appendix Table C.6, we also show that our results in Column (4) of Table 3.3 are robust to controlling for industry-year fixed effects or gravity variables (bilateral distance and sharing cultural characteristics). Therefore, industry-year-level common shocks or bilateral linkages of destinations with Brazil cannot capture destination-specific returns to experience.

C.5.2 Differential Changes in Labor Composition

The second plausible hypothesis is changes in labor composition after exporting. As shown in Table 3.4, firms exporting to both types of destinations have the largest shares of high-school graduates and cognitive workers in the workforce among all firms. Their workforce tends to become even more educated after switching to exporting, as shown by the coefficients in Table 3.4 after controlling for firm fixed effects. Therefore, it seems that changes in labor composition favor firms exporting to both types of destinations, but nonetheless firms exporting to industrialized destinations perceive the largest increase in returns to experience.

Although we control for education and occupations of the workforce in our regressions, it is possible that there are unobserved workers' characteristics, leading to higher returns to experience in firms exporting to industrialized destinations. We undertake two sets of robustness checks regarding this possibility. First, for each worker, we construct a proxy for their unobserved ability by using the residual of their log wage when she makes first appearance in the sample, after removing year and age effects. We can then obtain a measure of average ability of the workforce for each firm-year observation. We rerun the regression of Column (4) in Table 3.3 and control for this ability measure. Our destination-specific effects remain unchanged, as shown in Row (4) of Table C.6.[3]

In addition, when we compute firm-year-level experience-wage profiles in year t, we use workers employed within the same firm in both years $t-1$ and t. If current workers are unaware

[3]As expected, we find that firm-year-level experience-wage profiles increase with this ability measure.

of whether firms would change export status in one year, we could compare experience-wage profiles for firm-year-level observations in years $t-1$ and t with a switch in export status between years $t-1$ and t. We rerun the regression of Column (4) in Table 3.3 with these observations around switches and still find similar results, as shown in Row (5) in Table C.6.

C.5.3 Job Search and Screening

Our third hypothesis is that the observed destination-specific effects are due to job search and screening. Although we focus on workers staying in the same firm in the empirical analysis, workers' wage growth may still result from wage renegotiations due to job search. For example, in a calibrated model with wage bargaining like Cahuc et al. (2006), Fajgelbaum (2019) shows that workers in potential exporters experience faster wage growth due to wage renegotiations and larger job surplus after exporting. Our destination-specific results may thus arise due to larger surplus from exporting to industrialized destinations. Acemoglu & Pischke (1998) argue that firms monopsony power on workers ability information affects firms wage determination. Through the lens of their model, our results may arise if firms exporting to industrialized destinations have the least monopsony power and therefore design the steepest experience-wage profiles to avoid poaching from other firms.

Alternatively, workers' wage growth may originate from screening in the presence of information frictions (Jovanovic 1979). In particular, larger job surplus after exporting could interact with screening based on workers' abilities (Helpman et al. 2017) or match-specific quality (Donovan et al. 2020), leading to different patterns of worker turnover and our observed experience-wage profiles. Moreover, given initial uncertainty about workers' abilities, exporters may offer back-loaded wage contracts that lead to steeper wage profiles.

We cannot entirely rule out all these plausible stories, but nonetheless we provide several robustness checks to show that job search and screening are unlikely to explain destination-specific effects. First, as we discussed in Section 3.2.5, we do not find that export value per worker affects returns to experience (Appendix Tables C.4–C.5). Therefore, changes in job surplus after exporting are unlikely to trigger destination-specific shifts in returns to experience.[4] Second, we divide the sample into sub-samples based on the industry-level shares of manual workers and high-school graduates in the workforce. We perform our regression in Column (4) of Table 3.3 on the sub-samples. The results show that exporting to industrialized destinations leads to higher returns to experience in more manual or less skill-intensive industries (Rows (8)–(9) of Table C.6), where workers may have lower bargaining power. Third, as firms' monopsony power can be measured by the length of workers' tenure, we add the average tenure (current firm) as well as differences in the average tenure (current firm) between old and young workers into our regression in Column (4) of Table 3.3. Our results remain quantitatively similar, as shown in Rows (6)–(7) of Table C.6. Finally, as shown in Section 3.2.6 and 3.3, the jump in experience-wage profiles happens immediately after entry into industrialized destinations. If exporters offer back-loaded wage contracts, we should expect an initial decline in experience-wage profiles after switching to exporting.

C.5.4 Human Capital Accumulation and Knowledge Diffusion

There is a long tradition, starting with Becker (1964), using experience-wage profiles to implicitly measure human capital accumulation (e.g., Caselli 2005, Manuelli & Seshadri 2014). Clearly, one potential way to interpret our destination-specific results is through human capital theory. In addition, the literature argues that knowledge diffusion is central to human capital accumulation (e.g., Lucas & Moll 2014), and trade transmits knowledge across borders (e.g., Buera & Oberfield 2020).

Our findings on destination-specific returns to experience are consistent with faster human

[4]Even if we control for export value per worker, job surplus could still be higher if firms exporting to industrialized destinations enjoy higher markups than other firms. There is not much evidence on it. If any, Keller & Yeaple (2020) find that the markups of U.S. multinationals' affiliates decline with the GDP per capita of the host country. De Loecker & Eeckhout (2020) estimate the aggregate markup across countries, and there is no clear relationship between markups and countries' development levels.

capital accumulation due to exposure to advanced countries. First, we find that firms enjoy steeper experience-wage profiles if they export to industrialized destinations. This is consistent with advanced knowledge from trading with industrialized destinations (Alvarez et al. 2013, Buera & Oberfield 2020). Moreover, in Rows (8)–(9) of Table C.6, we find that increases in experience-wage profiles due to industrialized destinations are larger in industries with smaller shares of high-skill and cognitive workers. This evidence is compatible with the knowledge diffusion literature, which typically predicts that the least productive agents experience the largest gains in human capital from knowledge diffusion (Lucas & Moll 2014). Third, in Row (10) of Table C.6, we also find that increases in experience-wage profiles due to industrialized destinations are larger in industries that produce more differentiated goods, which might be associated with larger benefits for knowledge adoption.

Therefore, we propose that human capital accumulation due to knowledge diffusion is likely to explain destination-specific returns to experience, although we cannot entirely rule out other hypotheses. In the main text, we show that this hypothesis is also backed up by anecdotal evidence on exporters' experience and direct evidence on human capital investments, foreign technology adoption, and exporting.

C.6 Exporting, Training and Technology adoption

The ES is conducted by private contractors on behalf of the World Bank, and confidentiality is never compromised according to the ES unit. The ES is usually answered by owners and top managers with the assistance of accountants or human resources managers. Typically, the ES conducts 1200–1800 interviews in large economies, 360 in medium-sized economies, and 150 in small ones for manufacturing and service sectors. The ES interviews formal firms with more than 5 employees, although in some cases, it may include informal firms and/or firms with fewer than 5 employees. Firms with 100% government/state ownership are not eligible to participate in this survey. According to the WB-ES unit, there is a stratified random sampling. The strata for the ES are firm size, business sector and geographic region within a country, and random samples are selected within each strata. It over-samples large firms, but we rely on firm-level specifications and control for firm size in every regression, and regressions are also weighted by sample weights.

The ES has two types of questionnaires, one for manufacturing firms and one for service firms, which have identical questions for some topics and also specific questions. We rely mostly on the second standardized wave covering countries between 2006–2017. Although the first wave has similar questions, the available data do not provide weights which are needed to obtain more reliable estimates. Nevertheless, for the case of Brazil, we perform the regression about R&D investments using data in 2003, because 2003 is the only year for which there are available data on this variable for this country. In Tables C.9 and C.10, we provide the list of countries and years with available data in the first and second standardized waves.

To define exporter and indirect exporters, we use question D.3: ”In the last fiscal year, what percent of this establishments sales were: a. National sales, b. Indirect exports [sold domestically to third party that exports products], c. Direct exports?”. We rely on the following three questions to construct our dummy variables of on-the-job training, R&D investments and foreign Technology adoption. For training, the question L.10 is: “Over fiscal year [insert last complete fiscal year], did this establishment have formal training programs for its permanent, full-time employees?” For R&D investments, the question H.8 is ”In the last fiscal year, did the establishment invest in R&D?”. For foreign technology adoption, the question E.6 is ”Does this establishment at present use technology licensed from a foreign-owned company?”. Table C.11 presents the summary statistics of the variables in our sample.

Table C.9: Countries in the Enterprise Survey

Country	Year(s)	Country	Year(s)
Afghanistan	2008, 2014	Dem.Rep.Congo	2006, 2010, 2013
Albania	2007, 2013	Ecuador	2006, 2010, 2017
Algeria	2003	Egypt	2013, 2016
Angola	2006, 2010	El Salvador	2006, 2010, 2016
A.and Barbuda	2010	Eritrea	2009
Argentina	2006, 2010, 2017	Estonia	2005, 2009, 2013
Armenia	2005, 2009, 2013	Eswatini	2006, 2016
Azerbaijan	2005, 2009, 2013	Ethiopia	2011, 2015
Bahamas	2010	Fiji	2009
Bangladesh	2007, 2013	FYR Macedonia	2005, 2009, 2013
Barbados	2010	Gabon	2009
Belarus	2005, 2008, 2013	Gambia	2006, 2018
Belize	2010	Georgia	2005, 2008, 2013
Benin	2009, 2016	Germany	2005
Bhutan	2009, 2015	Ghana	2007, 2013
Bolivia	2006, 2010, 2017	Greece	2005
Bos. and Her.	2005, 2009, 2013	Grenada	2010
Botswana	2006, 2010	Guatemala	2006, 2010, 2017
Brazil	2003, 2009	Guinea	2006, 2016
Bulgaria	2005, 2007, 2009, 2013	Guinea-Bissau	2006
Burkina Faso	2006, 2009	Guyana	2010
Burundi	2006, 2014	Honduras	2006, 2010, 2016
Cambodia	2013, 2016	Hungary	2005, 2009, 2013
Cameroon	2006, 2009, 2016	India	2006, 2014
Cape Verde	2006, 2009	Indonesia	2009, 2015
Cen. Af. Rep.	2011	Iraq	2011
Chad	2009, 2018	Ireland	2005
Chile	2006, 2010	Israel	2013
China	2012	Ivory Coast	2009, 2106
Colombia	2006, 2010, 2017	Jamaica	2005, 2010
Congo	2009	Jordan	2006, 2013
Costa Rica	2005, 2010	Kazakhstan	2005, 2009, 2013
Croatia	2005, 2007, 2013	Kenya	2003, 2007, 2013
Czech Republic	2005, 2009, 2013	Kosovo	2009, 2013
Djibuti	2013	Kyrgystan	2005, 2009, 2013
Dominica	2010	Laos	2006, 2009, 2009, 2012
Dom. Republic	2005, 2010, 2016	Latvia	2005, 2009, 2013

Table C.10: Countries in the Enterprise Survey

Country	Year(s)	Country	Year(s)
Lebanon	2006, 2013	Serbia	2009, 2013
Lesotho	2009, 2016	Ser. and Mon.	2005
Liberia	2009, 2017	Sierra Leone	2009, 2017
Lithuania	2005, 2009, 2013	Slovakia	2005, 2009, 2013
Madagascar	2005, 2009, 2013	Slovenia	2005, 2009, 2013
Malawi	2005, 2009, 2014	Solomon Islands	2015
Malaysia	2015	South Africa	2007
Mali	2007, 2010, 2016	South Korea	2005
Mauritania	2006, 2014	South Sudan	2014
Mauritius	2005, 2009	Spain	2005
Mexico	2006, 2010	Sri Lanka	2004, 2011
Micronesia	2009	St. K. and Nevis	2010
Moldova	2005,'09,'13	Sudan	2014
Mongolia	2004, 2009, 2013	Suriname	2010
Montenegro	2009, 2013	Swaziland	2006
Morocco	2004, 2013	Sweden	2014
Mozambique	2007	Syria	2003
Myanmar	2014, 2016	Tajikistan	2005, 2008, 2013
Namibia	2006, 2014	Tanzania	2006, 2013
Nepal	2009, 2013	Thailand	2004, 2016
Nicaragua	2006, 2010, 2016	Timor-Leste	2009, 2015
Niger	2009, 2017	Togo	2009, 2016
Nigeria	2007, 2014	Tonga	2009
Oman	2003	Tri. and Tob.	2010
Pakistan	2007, 2013	Tunisia	2013
Panama	2006, 2010	Turkey	2005, 2008, 2013
P. New Guinea	2015	Uganda	2006, 2013
Paraguay	2006, 2010, 2017	Ukraine	2005, 2008, 2013
Peru	2006, 2010, 2017	Uruguay	2006, 2010, 2017
Philippines	2003, 2009, 2015	Uzbekistan	2005, 2008, 2013
Poland	2005, 2009, 2013	Vanuatu	2009
Portugal	2005	Venezuela	2006, 2010
Romania	2005, 2009, 2013	Vietnam	2005,
Russia	2005, 2009, 2012	W.B. and Gaza	2006, 2013
Rwanda	2006, 2011	Yemen	2010, 2013
Samoa	2009	Zambia	2007, 2013
Senegal	2007, 2014	Zimbabwe	2011, 2016

Table C.11: Sample Statistics

	Non-exporter Mean	Non-exporter S.D.	Exporter Mean	Exporter S.D.
Main variables				
On-the-job training	0.34	0.47	0.56	0.49
Foreign technology	0.11	0.32	0.25	0.43
R&D investments	0.19	0.39	0.41	0.49
Controls				
Log(employment)	3.08	1.22	4.33	1.43
Labor share (%)	21.89	19.77	19.59	18.47
Managerial years of experience in sector	16.43	10.22	19.25	10.53
Share of high-school grads (%)	61.47	35.90	66.91	33.22

Note: This table presents the summary statistics from the second standardized wave of the World Bank Enterprise Surveys, covering the period 2006–2017. This table shows the mean and the standard deviation of variables we use in the paper, computed across all firms from all countries and years. On-the-job Training, foreign technology, and R&D investments are dummy variables that equal 1 if firms perform the corresponding activity and 0 otherwise. We restrict the sample to firms with labor shares lower than 200% to avoid extreme values.

Table C.12: Exporting, On-the-Job Training and R&D Investments

	(1)	(2)	(3)	(4)	(5)
Non-Exporter # R&D Investment	0.29***	0.24***	0.25***	0.25***	0.22***
	(0.012)	(0.013)	(0.014)	(0.014)	(0.016)
Exporter # No R&D Investment	0.12***	0.06***	0.06***	0.06***	0.07***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.025)
Exporter # R&D Investment	0.36***	0.25***	0.24***	0.24***	0.25***
	(0.023)	(0.022)	(0.024)	(0.024)	(0.029)
Obs	81,094	79,906	63,258	60,951	38,588
R-squared	0.191	0.231	0.248	0.249	0.269
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes
Log(Emp)	No	Yes	Yes	Yes	Yes
Labor share	No	No	Yes	Yes	Yes
Managerial experience in sector	No	No	No	Yes	Yes
% High school grads	No	No	No	No	Yes

Note: This table presents estimates from regressing a dummy variable that takes the value 1 if the firm offers formal on-the-job training, on export status interacted with a dummy variable reflecting if the firm invests in R&D. The baseline group is non-exporters with no R&D investments. We control for country, year, and industry fixed effects in all regressions. Firm-level control variables are log (employment), the ratio of labor costs to total sales, the share of high-school graduates in the workforce, and managers' years of experience in the operating sector. We use the second standardized wave of the ES with the provided weights. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table C.13: On-the-job Training, Technology Adoption, R&D Investments and Exporting

VARIABLES	(1)	(2)	(3)	(4)	(5)
0b.exporter#0b.use_tech_foreign#1.rd_investment	0.29***	0.25***	0.26***	0.26***	0.21***
	(0.017)	(0.019)	(0.024)	(0.023)	(0.028)
0b.exporter#1.use_tech_foreign#0b.rd_investment	0.17***	0.13***	0.12***	0.12***	0.06
	(0.022)	(0.021)	(0.026)	(0.027)	(0.052)
0b.exporter#1.use_tech_foreign#1.rd_investment	0.42***	0.35***	0.33***	0.33***	0.32***
	(0.028)	(0.031)	(0.034)	(0.034)	(0.035)
1.exporter#0b.use_tech_foreign#0b.rd_investment	0.12***	0.06***	0.04***	0.05***	0.04*
	(0.017)	(0.015)	(0.017)	(0.017)	(0.023)
1.exporter#0b.use_tech_foreign#1.rd_investment	0.36***	0.25***	0.24***	0.23***	0.26***
	(0.030)	(0.027)	(0.031)	(0.031)	(0.029)
1.exporter#1.use_tech_foreign#0b.rd_investment	0.27***	0.17***	0.17***	0.18***	0.13***
	(0.031)	(0.029)	(0.030)	(0.031)	(0.037)
1.exporter#1.use_tech_foreign#1.rd_investment	0.46***	0.33***	0.32***	0.34***	0.26***
	(0.026)	(0.025)	(0.028)	(0.028)	(0.035)
Obs	61,220	60,586	48,249	46,840	25,549
R-squared	0.205	0.236	0.254	0.257	0.309
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes
Log(Emp)	No	Yes	Yes	Yes	Yes
Labor Share	No	No	Yes	Yes	Yes
Managerial experience in Sector	No	No	No	Yes	Yes
% High School Grads	No	No	No	No	Yes

Note: This table presents estimates from regressing a dummy variable that takes the value 1 if the firm offers training on interaction terms between dummies of export status, foreign technology adoption, and R&D investments. Exporters are defined as firms with positive sales to foreign markets. The baseline group is non-exporters with no R&D investments and foreign technology. We control for country, year, and industry fixed effects in all regressions. Firm-level control variables are log (employment), the ratio of labor costs to total sales, the share of high-school graduates in the workforce, and managers' years of experience in the operating sector. We use the second standardized wave of the ES with the provided weights. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table C.14: On-the-job Training , Export Status, and Technology (Brazil)

	(1)	(2)	(3)	(4)
	Panel A: Training, Exporting, and R&D			
0b.exporter#1.rd_investment	0.17***	0.13***	0.12***	0.11***
	(0.026)	(0.026)	(0.026)	(0.026)
1.exporter#0b.rd_investment	0.26***	0.13***	0.12***	0.10**
	(0.042)	(0.043)	(0.044)	(0.044)
1.exporter#1.rd_investment	0.32***	0.15***	0.15***	0.13***
	(0.033)	(0.036)	(0.037)	(0.037)
Obs	1,574	1,560	1,518	1,517
R-squared	0.099	0.156	0.165	0.176
	Panel B: Training, Exporting, and Technology			
0b.exporter#1.use_tech_foreign	0.24***	0.19**	0.13	0.13
	(0.074)	(0.075)	(0.087)	(0.088)
1.exporter#0b.use_tech_foreign	0.37***	0.15**	0.16**	0.15**
	(0.060)	(0.073)	(0.077)	(0.078)
1.exporter#1.use_tech_foreign	0.60***	0.33***	0.36***	0.35***
	(0.053)	(0.064)	(0.067)	(0.068)
Obs	1,304	1,282	1,087	1,056
R-squared	0.244	0.289	0.313	0.311
Log(Emp)	No	Yes	Yes	Yes
Labor share	No	No	Yes	Yes
Managerial experience †	No	No	No	Yes

Note: This table presents estimates from regressing a dummy variable that takes the value 1 if the firm offers formal on-the-job training and 0 otherwise, on export status interacted with a dummy variable reflecting if the firm invests in R&D (Panel A) or adopts foreign technology (Panel B). Exporters are defined as firms with positive sales to foreign markets. The baseline groups are non-exporters with no R&D investments (Panel A) or no foreign technology adoption (Panel B). We control for industry fixed effects in all regressions. Firm-level control variables are log (employment), the ratio of labor costs to total sales, and managers' years of experience in the operating sector. We use data in 2009 for Panel B to be able to use the provided weights and data in 2003 for Panel A due to the lack of data on R&D investments for Brazil in 2009. †: For the regressions about R&D investments, we use the highest education level of top manager due to the lack of data on managerial experience. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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