College Expansion, Trade and Innovation: Evidence from China

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Abstract

This paper examines how China's expansion of college education since 1999 affects innovation and exports' skill content. I develop a two-country spatial equilibrium model, featuring skill intensity differences across industries and heterogeneous firms' innovation and exporting choices. 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. I apply the resulting reduced-form estimates in the calibration to discipline key elasticities that determine the magnitude of export expansion. Under different assumptions about firm entry, 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.

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1 Introduction

"Made in China" is often viewed as low-skilled. Largely neglected is the recent skill upgrading of China's exports, as indicated by the decline in the share of (low-skill) processing exports in total exports from 55% in 2000 to 35% in 2015.[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 between 2000–2015.[2] The literature has proposed several causes for China's innovation, such as R&D tax incentives (Chen, Liu, Serrato and Xu 2018) and misallocation (König, Storesletten, Song and Zilibotti 2018).

This paper examines how China's unprecedented expansion of college education contributes to these two trends. With 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). As a result, the number of college-educated workers more than tripled between 2000–2015, while the total employment only increased by 7%.

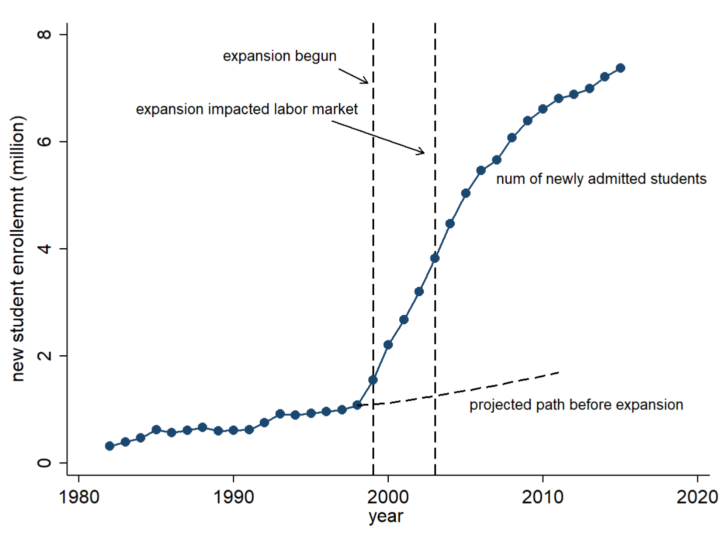
I employ theoretical, empirical, and quantitative analysis to highlight three channels through which China's college expansion affects trade and innovation. First, with an increasing number of college-educated workers, trade openness allows China to shift production to more skill-intensive industries 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.

I begin my analysis by documenting several facts on innovation and trade. I find that after China's college expansion impacted the labor market: (1) Manufacturing firms' inno-

[1]China's exports can be decomposed into processing and ordinary exports. Processing exports typically embed foreign technology and process or assemble imported materials for foreign clients. For ordinary trade, the Chinese party is responsible for the design, marketing, and distribution of products (Dai, Maitra and Yu 2016). Processing exports are much lower skilled than ordinary exports (Appendix Table D.6).

[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, Xie and Zhang 2017).

Figure 1: China's College Expansion



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

vative 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 (e.g., Acemoglu, Akcigit, Bloom and Kerr 2018).[3] In my baseline 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'

[3]See also Aghion, Meghir and Vandenbussche (2006), Aghion, Boustan, Hoxby and Vandenbussche (2009), Akcigit, Caicedo, Miguelez, Stantcheva and Sterzi (2018), and Zacchia (2019), among others.

entry. I thus consider an alternative assumption to allow endogenous firm entry: the creation of a new firm requires R&D inputs (Atkeson and 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 and Arkolakis 2014, Mian and 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, Chaudhuri and McLaren (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 and 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 (e.g., Khandelwal, Schott and Wei 2013, Brandt, Biesebroeck, Wang and Zhang 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 (e.g., Lileeva and Trefler 2010, Aghion, Bergeaud, Lequien and Melitz 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 (e.g., Eaton and Kortum 2001, Grossman and Helpman 2014, Somale 2017, Arkolakis, Ramondo, Rodríguez-Clare

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

and Yeaple 2018). My model builds on Atkeson and 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 skill intensity differences across industries, 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 and 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 education.

Finally, I relate to research about colleges' effects on innovation (e.g., Jaffe 1989, Aghion et al. 2009, Kantor and Whalley 2014, Andrews 2017, Valero and Van Reenen 2019), especially those focusing on China's college expansion (e.g., Che and Zhang 2018, Feng and Xia 2018, Li, Liu and Wu 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]

The paper is structured as follows. Section 2 describes the background of China's college expansion. Section 3 documents descriptive facts which inform the specification of the model in Section 4. Section 5 explores the model mechanisms on innovation

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

[6]Similar to Andrews (2017) and Feng and 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 8.5 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.

and exports. In Section 6, I empirically validate the model mechanisms and apply the reduced-form estimates to calibrate key structural elasticities. I calibrate other parameters in Section 7 and quantify the impact of China's college expansion in Section 8. Section 9 concludes.

2 Context

China's radical 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 sudden slowdown of the Chinese economy, due to 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 among government officers, the suggestion was surprisingly soon adopted by China's top leadership (Wang 2014).

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.[9] Second, the college admissions process is strictly controlled by the Ministry of Education (Jia and 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 exhibits 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.[10] If college enrollments grew at 3.8% that was set before 1999 (black dashed line in Figure 1), the number of college-educated workers would be 46 million lower in

[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).

[9]7% of college students were enrolled in private colleges in 2002 (the earliest year with available data).

[10]The data are from the Population Census. In absolute numbers, the amount of college-educated workers increased from 33 million in 2000 to 113 million in 2015, while total employment increased from 720 million in 2000 to 774 million in 2015. One caveat with the Population Census and the firm-level data used in Section 3.2 is that college-educated workers include not only college grads in regular schools (shown in Figure 1), but also those with a part-time college degree. As shown in Appendix C, between 2000–2015, the total amount of part-time college grads (24 million) and regular college grads (66 million) was 90 million.

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.

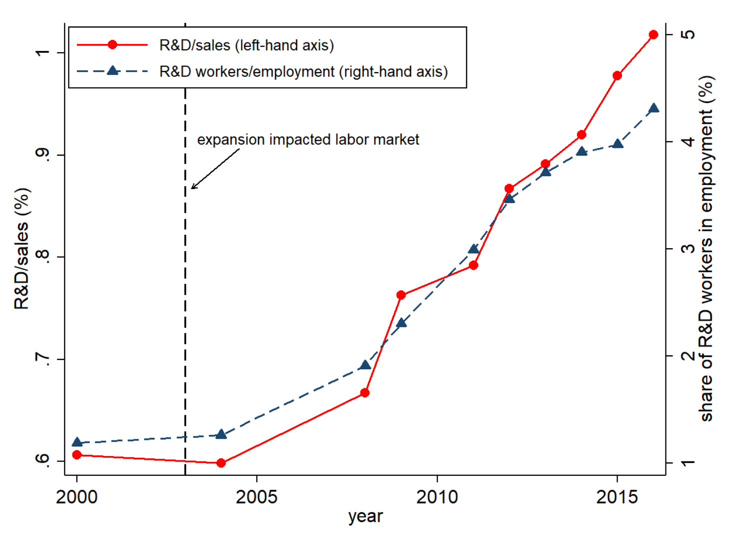
In Appendix C, I review the division of majors and college types in China. The distribution of the field of study remained roughly constant after the expansion, with 40–50% of students majoring in science and engineering. It is also worth noting that college enrollments in Figure 1 correspond to regular education. Instead of taking college entrance exams and spending 3–4 years fully on campus, workers may acquire a part-time college degree through on-the-job 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 robustness of including changes in part-time education. In this paper, 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. First, China's college expansion was attained mainly by the scale-up of enrollments in previously existing colleges (Feng and Xia 2018), which benefited regions with more college resources historically. Appendix Figure B.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 college endowments and recent regional development. Coastal areas 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 B.2 shows that the cities with more college resources in 1982 did not enjoy higher GDP and population growth afterward.

3 Descriptive Facts

I present several facts to inform the specification of the model developed in Section 4. Due to data availability and that China's innovation surge mainly happened in manufacturing after 2000 (Appendix Figure B.3), I focus on manufacturing industries/firms. Section 3.1 shows the aggregate pattern of manufacturing innovation. Section 3.2 shows a massive skill upgrading of manufacturing exports after the college expansion impacted the labor market. Section 3.3 provides evidence on the interaction between exports and innovation.

Figure 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 values aggregated over 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.

3.1 China's Innovation Surge

Figure 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.[11] 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 et al. 2018). I will capture these policy changes in my quantitative model to isolate the effects of the college expansion.

[11] 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.

3.2 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.[12] 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.[13]

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 D.6, 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 observed changes in the skill content of exports.[14]

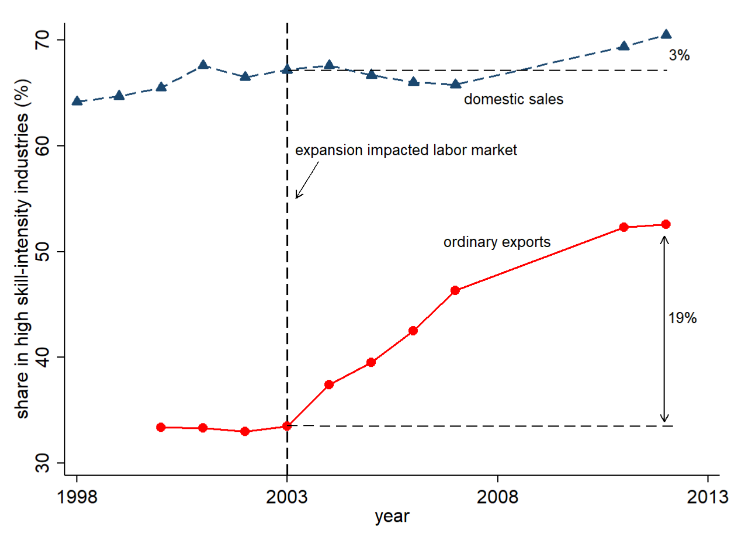
Domestic Sales and Ordinary Exports. Figure 3 plots the share of sales in high skill-intensity industries separately for domestic sales and ordinary exports, for years with available data. Ordinary exports shifted strongly to high skill-intensity industries after China's college expansion impacted the labor market. In contrast, China's domestic sales only moved slightly to high skill-intensity industries during the same period.

[12] 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.

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

[14] 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.

Figure 3: Skill Upgrading of Domestic Sales and Exports



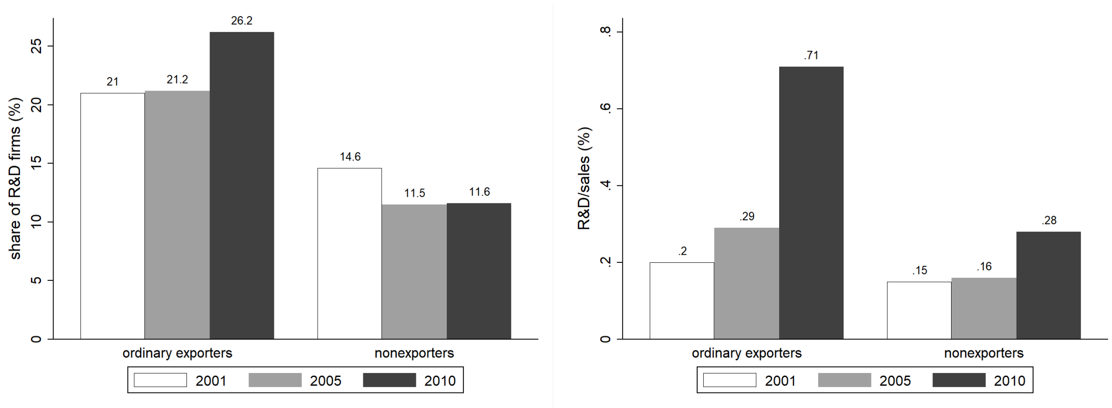
Note: The pattern is computed using ASM 1998–2007 and 2011–2012, as well as Chinese Customs Transactions Database 2000–2016.

Processing Exports. Appendix Figure B.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.

Robustness Checks. In Appendix D.1.1 and D.1.2, I show that the results of Figure 3 are not driven by regional convergence and robust to using an alternative measure of industry-level skill intensity—-the ratio of nonproduction workers to employment—computed for the U.S. economy from the NBER-CES Database.

Appendix D.1.3 performs a formal statistical analysis using continuous skill intensities and confirms that my results hold. Appendix D.1.4 reveals that the skill upgrading of China's ordinary exports did not seem to arise from demand by testing the skill upgrading of exports for other countries. I decompose changes in exports' skill content into the intensive margin (continuing exporters) and the extensive margin (firm entry/exits of exporting) in Appendix D.1.5. Both margins were essential for the skill upgrading of exports after 2003. Finally, Appendix D.1.6 shows that China's imports experienced skill degrading after 2003, in line with the direction of China's shift in comparative advantage.

Figure 4: Innovative Activities by Different Firms



(a) Share of R&D Firms

(b) R&D/sales

3.3 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 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, see Appendix D.2 for details). Consistent with the previous subsection, I omit purely processing exporters, as they barely innovate,[15] and pooling them with ordinary exporters may mask their different responses to the college expansion.

Figure 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.[16] 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

[15] 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 D.6. 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%.

[16] 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.

more considerable in terms of increases in average R&D intensities.

Robustness Checks. Appendix D.2 shows that the results in Figure 4 are robust to: (1) controlling industry composition; (2) ignoring firms that changed export status; (3) using all firms in the full sample; (4) only using the ASM data to study changes after 2007; and (5) excluding high-tech industries. I also examine patents and find large increases in the share of firms with patent applications after 2005, especially among exporters.

4 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 $\mathcal{C}$.

4.1 Aggregate-level Good Production

4.1.1 Final-good Producers

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

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

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 5.

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.

4.1.2 Industry-level Good Producers

The industry-level intermediate good is produced competitively by:

$$Q_{m,j} = \left(\sum_n \int_{\Omega_{n,m,j}} \epsilon_{n,m,j}(\omega)^{\frac{1}{\sigma}} q_{n,m,j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

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 $\epsilon_{n,m,j}(\omega)$ across varieties such that some firms may export due to a favorable draw of $\epsilon_{n,m,j}(\omega)$. This allows me to capture that many export-intensive firms in China are unproductive small firms.[17] 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 5.

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 $q = \epsilon_{n,m,j}(\omega) p^{-\sigma} P_{m,j}^{\sigma} Q_{m,j}$, where the price index $P_{m,j} = \left(\sum_n \int \epsilon_{n,m,j}(\omega) p_{n,m,j}(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$.

4.1.3 Research Good

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

$$Q_{m,r} = A_{m,r} E_{m,r}^{1-\gamma_r} H_{m,r}^{\gamma_r}, \tag{3}$$

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

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

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 and 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).[18] This allows for China's college expansion to directly affect R&D through changes in research costs.

4.2 Firms' Production, Innovation and Entry/exit

4.2.1 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 $\mathrm{s}_{m,j} = \{z_{m,j}, \epsilon_{m,n,j}, \eta_{m,j}\}$. Productivity $z_{m,j}$ and demand shifters $\epsilon_{m,n,j}$ 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 materials from other industries to produce output,

$$q = z_{m,j} \left[\alpha_j l^{\frac{\rho_x - 1}{\rho_x}} + (1-\alpha_j) h^{\frac{\rho_x - 1}{\rho_x}}\right]^{\frac{\rho_x \gamma^L_{m,j}}{\rho_x - 1}} \prod_{j'=1}^{J} b_{j'}^{\gamma^{j'}_{m,j}}. \tag{4}$$

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:

$$c_{m,j} = \Phi_{m,j} \left[\frac{\alpha_j^{\rho_x}}{W_m^{\rho_x - 1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_m^{\rho_x - 1}}\right]^{\frac{\gamma^L_{m,j}}{1-\rho_x}} \prod_{j'} P_{m,j'}^{\gamma^{j'}_{m,j}} \tag{5}$$

[18] 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 $\gamma_r < 1$.

where $\Phi_{m,j}$ is a constant.[19] 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.[20]

Productivity Evolution and Innovation. The productivity of each firm evolves in the end of the period as:

$$\Delta \log z_{m,j} = \underbrace{g_{m,j}}_{\text{aggregate growth}} + \underbrace{\xi_{m,j}}_{\text{idiosyncratic shock}} + \underbrace{i}_{\text{research intensity}} \times \underbrace{\exp(\eta_{m,j})}_{\text{step size of improvement}} . \tag{6}$$

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.[21] 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 and 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 $\epsilon_{m,n,j}$ evolve

[19] The constant can be written as: $\Phi_{m,j} = \left(\gamma_{m,j}^L\right)^{-\gamma_{m,j}^L} \prod_{j'} \left(\gamma_{m,j}^{j'}\right)^{-\gamma_{m,j}^{j'}}$.

[20] 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 and Taylor (2015) and Liu and Ma (2018).

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

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 $N^e_{m,j}$ 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, 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 $\eta \sim \mathcal{N}(\mu_\eta, \sigma^2_\eta)$.

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.

4.2.2 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:

$$\begin{aligned} \pi_{m,n,j}(\mathbf{s}_{m,j}) = \max_p pq - \frac{d_{m,n,j}c_{m,j}}{z_{m,j}} q - P_m f_{m,n,j} \\ s.t.\ q = \epsilon_{m,n,j} p^{-\sigma} P^\sigma_{n,j} Q_{n,j} \end{aligned} \tag{7}$$

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

$$p^*_{m,n,j}(\mathbf{s}_{m,j}) = \frac{\sigma}{\sigma - 1} \frac{c_{m,j} d_{m,n,j}}{z_{m,j}}. \tag{8}$$

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,

$$V(\mathbf{s}_{m,j};\mathbf{X}) = \max_{i\geq 0}\Bigg[\underbrace{(1-\zeta(\mathbf{s}_{m,j}))\left(\sum_n \pi^+_{m,n,j}(\mathbf{s}_{m,j}) - f_{m,j}P_m\right)}_{\text{after-tax profits}}$$
$$\underbrace{-z^{\sigma-1}_{m,j}\phi_{1,j}\mathbf{1}_{\{i>0\}}P_{m,r} - z^{\sigma-1}_{m,j}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}P_{m,r}}_{\text{research costs}} + \underbrace{\frac{1-\delta}{1+r}\mathbb{E}\max\{V^{'}(\mathbf{s}^{'}_{m,j};\mathbf{X}^{'}),0\}}_{\text{next-period value}}\Bigg]$$
$$\text{s.t. } \Delta\log z_{m,j} = g_{m,j} + \xi_{m,j} + i\times\exp(\eta_{m,j}),\ \ \log\epsilon_{m,n,j}\sim \text{AR(1)}, \tag{9}$$

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.

4.2.3 Endogenous Number of New Firms

Evidence in Appendix Table F.1 shows that larger exposure of a region-industry pair to the college expansion induces more entry of new firms. I thus 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 (e.g., Atkeson and Burstein 2010, Grossman and 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.[22] Thus, in the equilibrium, the number of potential entrants is thus *endogenously* decided by the free-entry condition:

$$f^e_{m,j}P_{m,r} = V^e_{m,j}. \tag{10}$$

[22] 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 $V^e_{m,j} = \frac{1-\delta}{1+r}\int \max\{V^{'}(\mathbf{s}_{m,j}),0\}dG^e_{m,j}(\mathbf{s}_{m,j})$.

4.3 Workers

I explicitly model workers' age structure following Card and Lemieux (2001), as Appendix H reveals that China's college expansion had much stronger effects on the college premium of young workers relative to older ones.[23] 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.[24]

4.3.1 Labor Supply and Age-specific Wage Rates

As in Card and 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,

$$H_m = \left(\sum_{a=1}^{T} \beta_a^H H_{m,a}^{\frac{\rho_a-1}{\rho_a}}\right)^{\frac{\rho_a}{\rho_a-1}}, \quad L_m = \left(\sum_{a=1}^{T} \beta_a^L L_{m,a}^{\frac{\rho_a-1}{\rho_a}}\right)^{\frac{\rho_a}{\rho_a-1}}, \tag{11}$$

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:

$$S_{m,a} = \left(\frac{H_{m,a}}{H_m}\right)^{-\frac{1}{\rho_a}} \beta_a^H S_m, \quad W_{m,a} = \left(\frac{L_{m,a}}{L_m}\right)^{-\frac{1}{\rho_a}} \beta_a^L W_m. \tag{12}$$

Equation (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 H that China's college expansion erected more negative effects on young workers' college premium than old workers' college premium.

[23] My finding is consistent with Card and 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.

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

4.3.2 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 $\{\varphi_n\}_{n\in\mathcal{C}}$,[25] 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 and 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:*

$$\Lambda^I_{m,n,a} = \frac{\exp(\beta U^{I'}_{n,a+1} - \tau^I_{m,n,a})^{1/\nu}}{\sum_{r\in\mathcal{C}} \exp(\beta U^{I'}_{r,a+1} - \tau^I_{m,r,a})^{1/\nu}}, \quad I \in \{H, L\}, \tag{13}$$

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

Proof: See Appendix E.1. □

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 $H^{'}_{n,a+1} = \sum_{m\in\mathcal{C}} \Lambda^H_{m,n,a} H_{m,a}$ and $L^{'}_{n,a+1} = \sum_{m\in\mathcal{C}} \Lambda^L_{m,n,a} L_{m,a}$, 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.

4.4 Equilibrium

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

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

measure of firms with state 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 E.2.

5 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.[26]

In what follows, I index China by $\mathcal{C}$ 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,

$$\hat{S}_{\mathcal{C}} - \hat{W}_{\mathcal{C}} = -\Phi_{\mathcal{C}}(\hat{H}_{\mathcal{C}} - \hat{L}_{\mathcal{C}}),$$

where the constant $\Phi_{\mathcal{C}} > 0$.

Proof: See Appendix E.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

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

has shown that an influx of college-educated workers leads to lower skill premium (e.g., Katz and Murphy 1992, Card and 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 $R_{\mathcal{C},j}$ 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 $SI_{\mathcal{C},j}$ 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.

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

(i) Proportional changes in domestic sales are:

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

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

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

where $\Pi_{\mathcal{C},\mathcal{C},j}$ 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 $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$.

(iii) With $\sigma > \theta \geq 1$ and similar $\Pi_{\mathcal{C},\mathcal{C},j}$ across industries,[27] 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 $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$.

Proof: See Appendix E.4. □

Result (i) indicates how firm sales change in response to lower skill premium, which reduces production costs by $SI_{\mathcal{C},j}\left(\hat{W}_{\mathcal{C}}-\hat{S}_{\mathcal{C}}\right)$ for industry j.[28] Firms' domestic sales change

[27] 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.

[28] Production costs of all firms also change by a common amount $\hat{W}_{\mathcal{C}}$.

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 $\Pi_{\mathcal{C},\mathcal{C},j}$. Second, firms in more skill-intensive industries enjoy lower production costs and thus gain larger market shares from 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,[29] there is larger skill upgrading of exports than domestic sales after an influx of educated labor, as I found in Section 3.2. 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 and 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 $R_{\mathcal{C},j}$ and $R_{F,j}$ as a firm's domestic sales before any innovation. By the first-order approximation, the firm's problem can be written as:

$$\max_{i} \underbrace{\frac{\sigma-1}{\sigma}\left(R_{\mathcal{C},j}+R_{F,j}\right)\exp(\eta_j)i}_{\text{expected profit growth}} - \underbrace{\phi_{1,j}\mathbf{1}_{\{i>0\}}\tilde{z}_j^{\sigma-1}P_{\mathcal{C},r} - \phi_{2,j}\frac{i^{\chi+1}}{\chi+1}z_j^{\sigma-1}P_{\mathcal{C},r}}_{\text{costs of innovation}}, \tag{14}$$

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

Proposition 4 (Interactions between Exports and Innovation).

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

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

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

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

(ii) Holding all other things constant, a new exporter increases R&D activities.

Proof: See Appendix E.5. □

As shown by Proposition 3, 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 and Linn 2004). This interaction between exports and innovation increases aggregate R&D, as more skill-intensive industries are also more innovative in reality.

6 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 5 and help me discipline key structural elasticities.

6.1 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:

$$x_m = \left(\frac{H_{m,2010} - H_{m,2005}}{H_{m,2005}} - \frac{L_{m,2010} - L_{m,2005}}{L_{m,2005}} \right), \tag{15}$$

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:

$$x_m^* = \underbrace{\frac{ENROLL_{m,1982}}{ENROLL_{1982}} \times GRAD_{-m,2006-10}}_{\text{predicted num of grads in region } m} / H_{m,2005} \tag{16}$$

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.[30] $\frac{ENROLL_{m,1982}}{ENROLL_{1982}}$ is the ratio of region m's college enrollments to national enrollments in 1982.[31] 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 2, 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 provide support for this assumption as follows. First, Appendix Figure B.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 2. 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 5.

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 6.2.3. 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 es-

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

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

timates from the model-generated data similarly. Using the implied within-industry and between-industry elasticities of substitution from the IV regressions, Section 7.4 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,[32] and other factors not captured by the model may not substantially bias the IV regressions.

6.2 Empirical Results

6.2.1 Domestic Sales and Exports Growth

I use the 2005–2010 balanced firm panel constructed in Section 3.3 to perform empirical analysis. I estimate the following regression:

$$\Delta y_{m,j}(\omega) = \beta_0 + \beta_1 SI_{m,j}x_m + \beta_2 \mathbf{Z}_{m,j}(\omega) + \iota_m + \epsilon_{m,j}(\omega). \tag{17}$$

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.[33] 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 5. 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,[34] 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[35] that cannot be directly observed,

[32] 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 and 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.

[33] 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.

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

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

Table 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 (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%.

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.

Table 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

Table 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 × 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 (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%.

China's expenses devoted to domestic goods across 2-digit manufacturing industries. The resulting θ and σ are 3.1 (3.5) and 6.9 (6.9) based on provincial (city-level) shocks.[36] As Proposition 3 was obtained using a simplified model, in Appendix F.1, I discuss robustness of the mapping between reduced-form evidence and elasticities in the full model.

In Appendix Table A.1, I assign changes in export status and the number of export destinations as dependent variables in equation (17). I find that larger exposure to the college expansion also led to more export entry, confirming Result (ii) of Proposition 3.

6.2.2 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 (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 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

[36]My estimates are comparable to Broda and 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).

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 (3)–(4) report the results for firms that did not switch export status between 2005–2010. The results are similar to Columns (1)–(2).[37]

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.[38] 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.

In Appendix Table A.2, I also explore the intensive margin of innovation, and the results are consistent with Table 2. Finally, in line with Result (ii) in Proposition 4, I find that new exporters (no exports in 2005 and positive exports in 2010) enjoyed the largest increase in the share of R&D firms (8.9%) between 2005 and 2010, compared with continuing exporters (3.1%), continuing nonexporters (0.1%), and exit exporters (-3.1%).[39]

6.2.3 Robustness Checks

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

[37]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 (Appendix Table A.1), which led to more innovation and higher coefficient in Column (1).

[38]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.

[39]I define exit exporters as those firms that had positive exports in 2005 and no exports in 2010.

arose due to political reasons (Glaeser and 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 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 1–2, and the implied within-industry and between-industry elasticities are $6.3 \sim 7.4$ and $2.0 \sim 4.9$.

Other Results. I perform pre-trend tests as suggested by Goldsmith-Pinkham, Sorkin and Swift (2018). I show that within each province, the instrumented exposure to the college expansion between 2005–2010 had no positive effects on industry-level changes in domestic sales, exports, and innovation before 2005 (when the college expansion was small in magnitude). This test lessens the concern that the distribution of college resources in 1982 may be correlated with changes in labor demand of certain industries. Finally, I also test my model predictions about processing exports and industry-level employment of college-educated and noncollege workers, and my results support these predictions.

7 Quantitative Analysis

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 H.1). In this section, I briefly discuss the model extension to incorporate processing exports, the data sources, calibration processes, and the model fit.

7.1 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 4.2, 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 G.1 for details.

7.2 Data

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

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-

[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.

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, Feng and Chen (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 and 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.

7.3 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 G.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 $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{\mathcal{C},F\}}$; productivity growth $\{g_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$; 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 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 and Parro (2015). I calibrate input-output linkages $\{\gamma^L_{u,j}, \gamma^{j'}_{u,j}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ using China's and the World Input-Output Tables in 2005. I obtain the amount of new college-educated and noncollege workers across years $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{\mathcal{C},F\}}$ directly from the data. The schedule of R&D tax incentives $\zeta_t(\cdot)$ is drawn from Chen et al. (2018).[42]

I then calibrate other parameters in three steps. First, as shown in Section 4.4, 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 $\{\gamma_j, \gamma_r, \alpha_{j(k)}, \beta^H_a, \beta^L_a, \frac{\sigma^2_\epsilon}{1-\rho^2_\epsilon}\}$, trade costs $\{d_{u,u',j}, d_{F,u,j,2005}, d_{u,F,j,2005}, f_{u,F,j}, f_{F,u,j}\}_{u,u'\in\tilde{\mathcal{C}}}$ and operation costs $\{f_{u,j}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ to target relevant parameters in 2005 (with rich data). For instance, marketing costs $\{f_{u,F,j}, f_{F,u,j}\}_{u\in\tilde{\mathcal{C}}}$ are informed by the share of exporters in each province-industry or foreign industry. International variable trade costs $\{d_{F,u,j,2005}, d_{u,F,j,2005}\}_{u\in\tilde{\mathcal{C}}}$ 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 $\{\tau^I_{u,u',a}\}_{u,u'\in\mathcal{C}}$ 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

[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) 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.

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 firms' productivity evolution and entry/exits $\{g_{u,j,t}, N_{u,j,t}, \sigma_\epsilon, \delta, \delta_p, \rho_\epsilon\}_{u\in\{\tilde{\mathcal{C}},F\}}$ and innovation $\{\chi, \sigma_\eta, \phi_{1,j}, \phi_{2,j}, A_{u,r,t}\}_{u\in\mathcal{C}}$ to target related moments between 2000–2018. Given the firm distribution in the initial year (2000), I calibrate firms' productivity drifts $\{g_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ to match changes in output over time. The amount of new firms $\{N_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ 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 (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, Lyn and Rodriguez-Clare (2017), industry-level free entry of new firms may lead to corner solutions. Appendix Section G.4 discusses how I modify equation (10) to deal with these two challenges and compute entry costs $\{f^e_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ that generate the same amount of entrants as $\{N_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$.

7.4 Model Fit

Figure 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 indus-

[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.

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

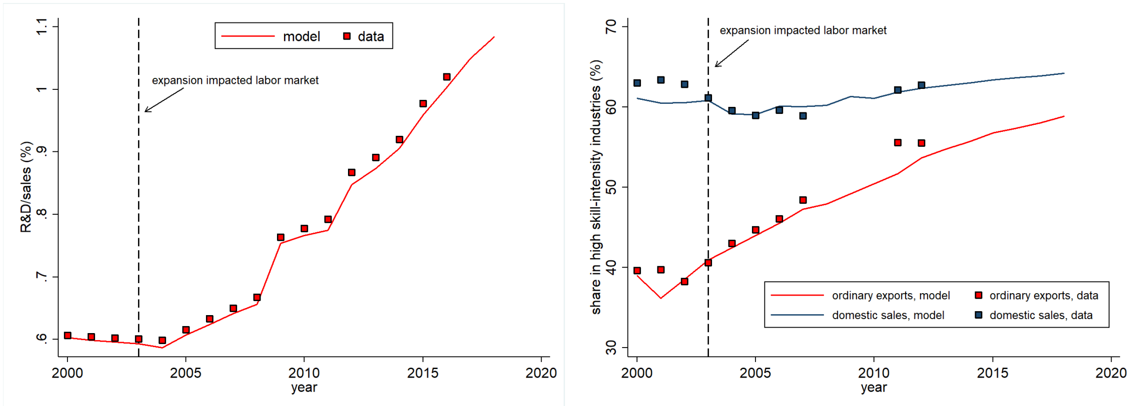
Figure 6 presents the untargeted distribution of exporting and R&D activities among manufacturing firms in 2005. Panel (a) shows that my model can replicate the shares of R&D firms and exporters across firm size percentiles. Panel (b) presents the share of R&D firms among nonexporters and exporters by 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 7 shows that my model can match observed changes in employment by provinces and education levels between 2000–2010. In Appendix H, I also estimate college wage premiums for different age groups following Card and 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.3 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 (17) and the instruments constructed in Section 6. I find that the model-generated responses are quite close to observed responses.

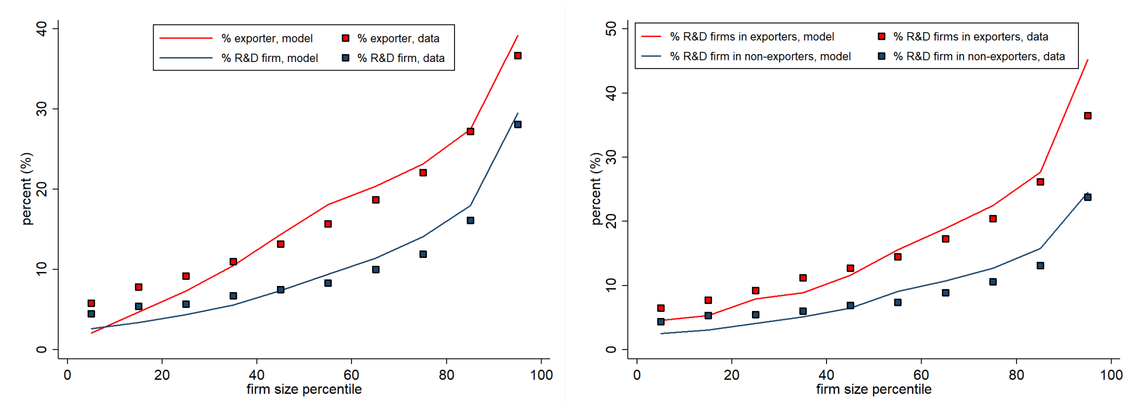
[45] As my model is calibrated to 2-digit manufacturing industries, I use 2-digit industries to define high skill-intensity industries, which are industries with skill intensities above the average across all 2-digit manufacturing industries. Industry-level skill intensities are still computed from ASM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

Figure 5: Innovation and Skill Upgrading, in Model and Data



(a) R&D sales/sales (b) Export Skill Upgrading

Figure 6: Exporting and R&D Activities by Firm Size, in Model and Data



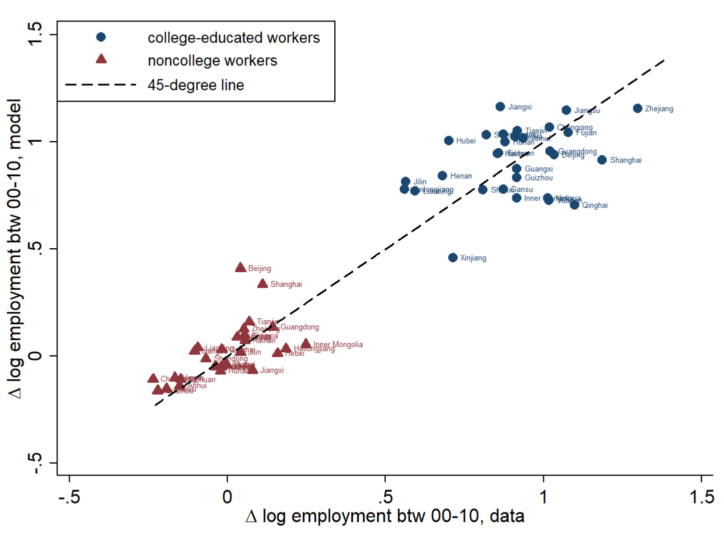
(a) Share of R&D Firms and Exporters (b) Innovative Activities by Export Status

Note: Firm size percentiles are computed based on rankings of firm sales within each province-industry pair. I only compute the shares for ordinary firms, as all processing firms export and do not innovate.

8 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

Figure 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.

accommodate this policy shock and analyze the costs and benefits of this policy change.

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

8.1 Innovation Surge

Figure 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

[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 8.5.

[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.

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 8b shows that through combined effects of innovation and labor 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 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 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]

[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 (6) in the calibrated equilibrium. I keep all other components of productivity evolution as unchanged.

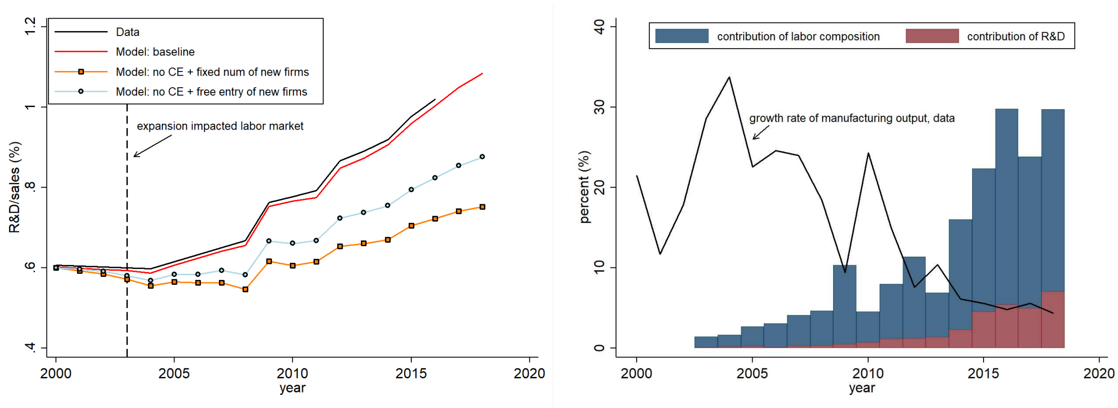
[49] Figure 8b shows that China's growth rate of manufacturing output was very high in the 2000s, mainly due to policy reforms, including the development of private enterprises (Song, Storesletten and Zilibotti 2011), loosening of migration barriers (Tombe and Zhu 2019), and embrace of globalization (Feenstra and 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 (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.

Figure 8: Effects of China's College Expansion on Manufacturing Innovation



(a) Manu R&D/sales

(b) Decomposition of Effects

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 after 2015.

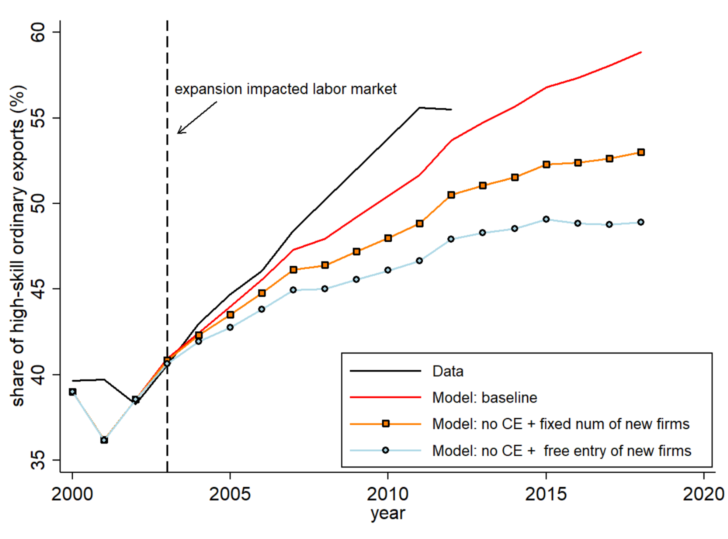
8.2 Export Skill Upgrading

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

[53] Appendix Section D.2.3 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. In comparison, China's ordinary exports are quite

Figure 9: Effects of the College Expansion on the Share of High-skill Ordinary Exports



8.3 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 5a).[54] I keep all other parameters at their baseline levels.

Table 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 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 10. More notably, Figure 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

dispersed across industries. See Appendix Figure G.1 for details.

[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 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(college 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.

skill intensities in a similar way as in the actual data.[55]

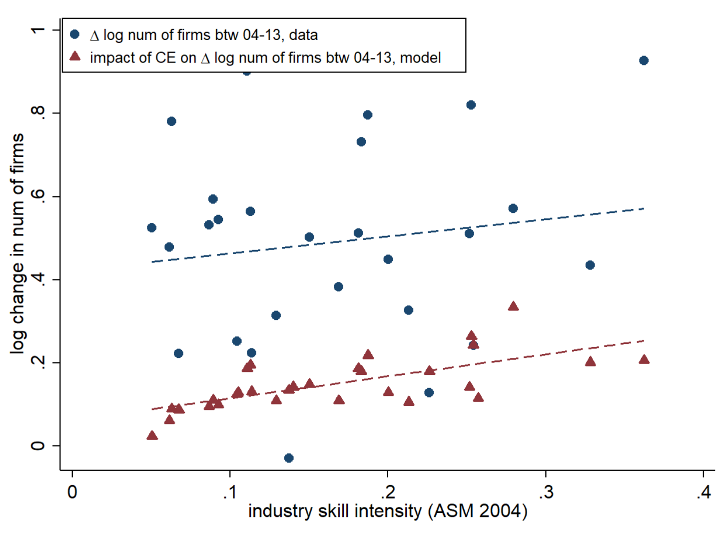
Second, trade amplified the effects of the college expansion on GDP, output and innovation. The amplification effects of trade openness on GDP and manufacturing output in 2018 were 5–10%, as trade shifted industry composition and reduced the diminishing returns of additional college-educated workers. 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 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 innovation found in Figure 4.

8.4 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

[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 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.

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.

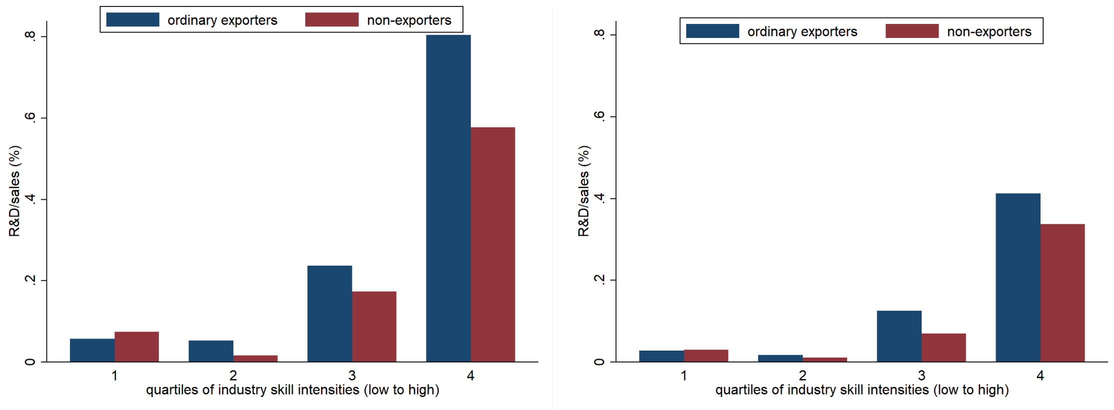
In each year, I compute increases in education expenses by multiplying additional enrollments[57] with average education expenses (including tuition and government subsidies) per college enrollment from China's Education Statistical Yearbook. I compute implicit costs by multiplying additional enrollments with average marginal products of high-school grads (aged less than 23) in the baseline equilibrium.

Figure 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 12 also finds that the increase in yearly GDP driven by the college expansion started to exceed education

[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.

Figure 11: Effects of China's College Expansion on Firms' R&D Intensities in 2018



(a) Fixed Num of New Firms

(b) Free Entry of New Firms

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.

and implicit costs of the college expansion in 2006–2009, with exact years depending on the model's assumption about firm entry.

8.5 Robustness Checks of Quantitative Analysis

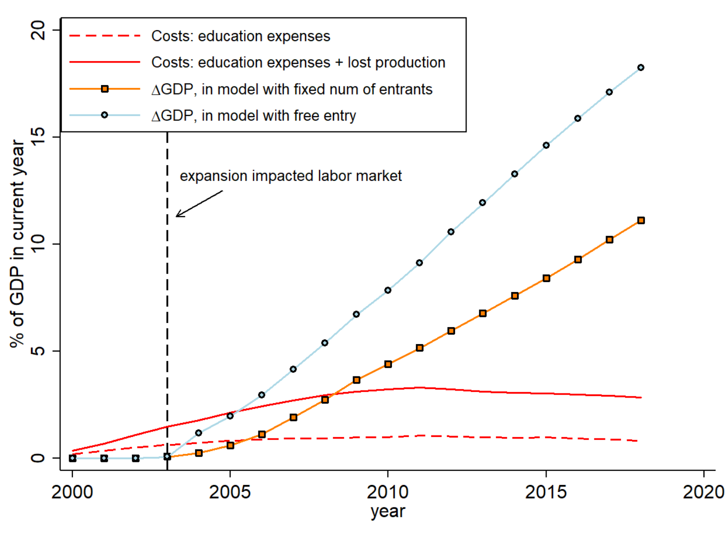
I discuss several robustness checks of my quantitative analysis. In these checks, I recalibrate time trends of aggregate research productivity such that manufacturing R&D intensity in each year is identical to the baseline calibration (Figure 5a). I keep all other parameters at their baseline levels 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

[58] The baseline economy in robustness checks still matches the export skill upgrading in Figure 5b well.

Figure 12: Costs and Benefits of China's College Expansion



the drop varies across industries of different skill intensities by estimating a regression:

$$
\begin{aligned}
y(\omega) = &\beta_0 + \beta_1 D + \beta_2 SI_j D + [\beta_3 + \beta_4 D](Z(\omega) - c) + [\beta_5 + \beta_6 D](Z(\omega) - c)^2 \\
&+ [\beta_7 + \beta_8 D](Z(\omega) - c)^3 + \beta_9 SI_j + \epsilon(\omega)
\end{aligned}
\tag{18}
$$

$y(\omega)$ 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 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 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 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.

[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.

Table 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 (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%.

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. 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 4. I iterate with these steps until the intercept and the slope from the regression match the coefficients in Column (2) of Table 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 4.

Figure 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

Figure 13: Effects of the College Expansion on Manufacturing R&D (with Misreporting)

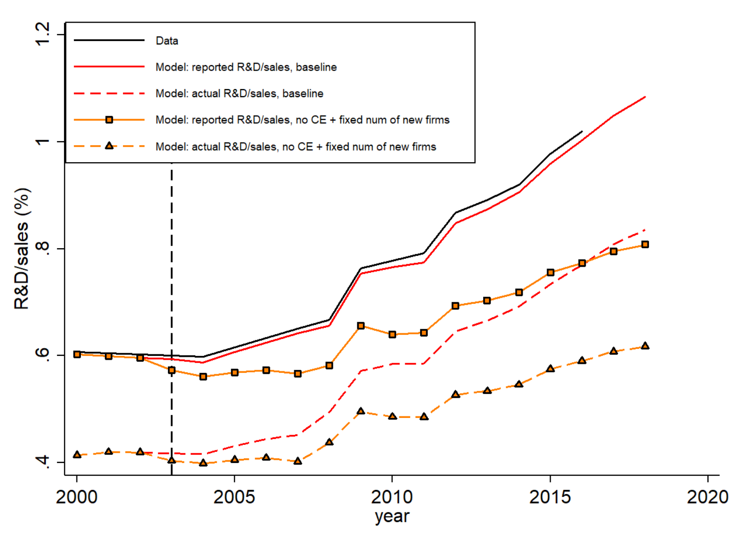


Table 5: The Impact of the College Expansion on Export Skills and Innovation, 2003–2018

	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 8. For the model with R&D misreporting, R&D intensity is the ratio of reported R&D to sales.

between 2003–2018. Third, the 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

[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 8b).

part-time colleges also experienced a threefold expansion after 1999 (see Appendix C), 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 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 parameters. To show that incorporating multiple regions within China is necessary, I recalibrate the model following the same steps in Section 7, except for no intranational regions within China.[62] Table 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 2.

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 and 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,

[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.

[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.

Sun, Tombe and Zhu (2020) who also find a substantial reduction in between-province migration costs in the same period.[64] Table 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.

9 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.

[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.

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A Additional Tables

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

Dep var:	Δ export status		Δ log(num of destinations)	
shock	provincial (1) 2SLS	city-level (2) 2SLS	provincial (3) 2SLS	city-level (4) 2SLS
Exposure to CE	0.471*** (0.073)	0.491*** (0.077)	0.798** (0.340)	0.816** (0.344)
Obs	42,808	42,712	10,160	10,136
R-squared	0.014	0.021	0.027	0.046
First-stage F	457.07	708.74	410.38	722.33

Note: This table provides estimates from regressions in equation (17). Export status is a dummy variable which equals one if a firm has positive ordinary exports. 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 A.2: Dependent Variable: Changes in R&D Intensity between 2005–2010

Dep var:	Δ R&D intensity					
	(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	0.035*** (0.006)	0.051*** (0.008)	0.027*** (0.006)	0.050*** (0.008)	0.037*** (0.005)	0.037*** (0.005)
Exposure to CE × export share					0.043** (0.018)	0.063 (0.057)
Obs	31,139	11,669	26,325	10,162	42,808	40,093
R-squared	0.012	0.042	0.008	0.047	0.018	0.017
First-stage F	428.58	413.47	456.99	410.38	224.76	224.28

Note: I replicate the regressions in Table 2, except that the dependent variable is changes in R&D/sales between 2005–2010.

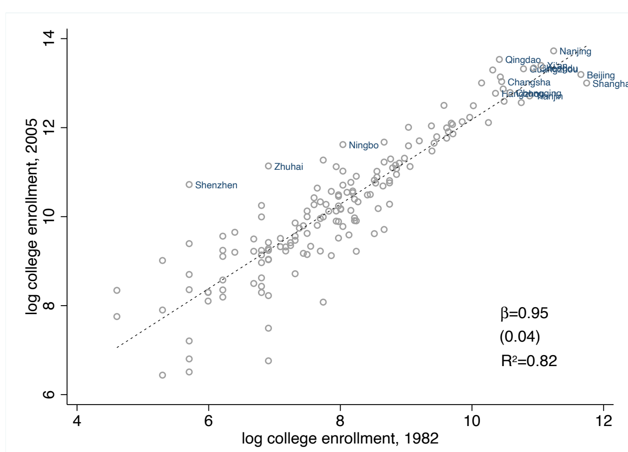
Table A.3: Dependent Variable: Province-industry-level Changes between 2005–2010

Dep var:	Δlog(domestic sales)		Δlog(ordinary exports)		Δshare of R&D firms			
					non-exporter		ordinary 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* (1.211)	2.611*** (0.847)	4.711*** (0.971)	4.974*** (1.282)	0.419*** (0.119)	0.453*** (0.081)	0.504** (0.200)	0.525*** (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 6. 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%.

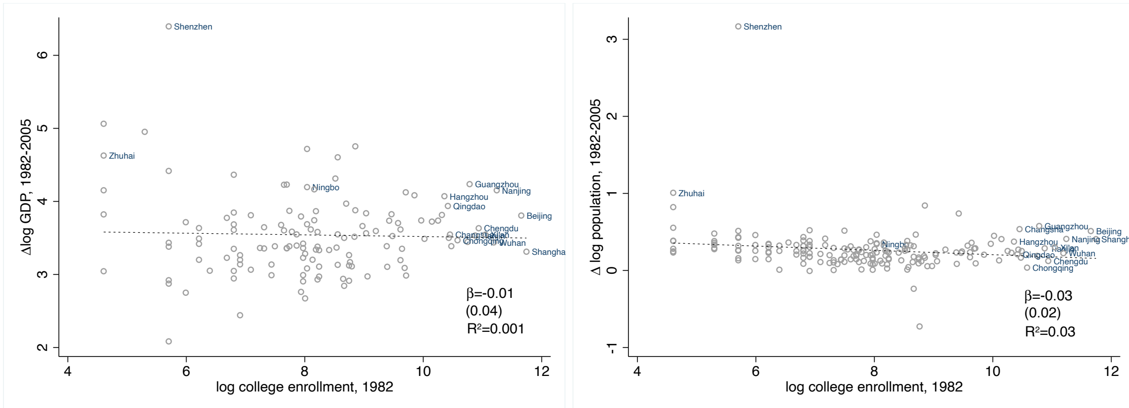
B Additional Graphs

Figure B.1: College Enrollments across Cities



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

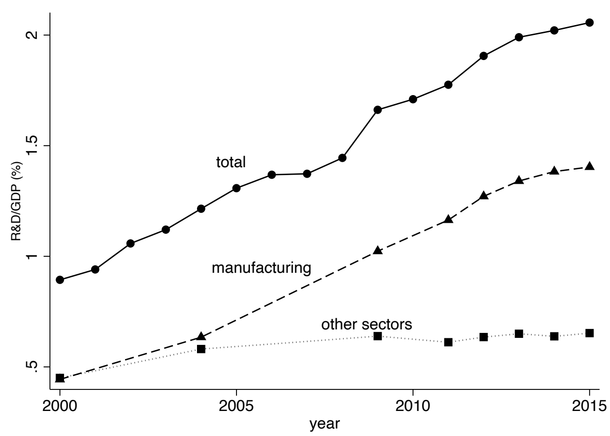
Figure B.2: College Enrollments and Changes in GDP and Population



(a) GDP (b) Population

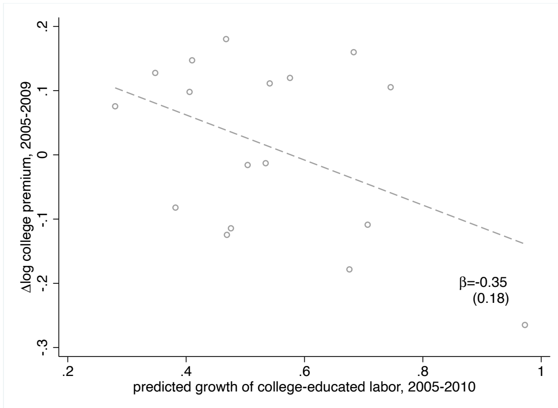
Note: The data come from multiple Provincial Statistical Yearbooks and Population Census 1982.

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

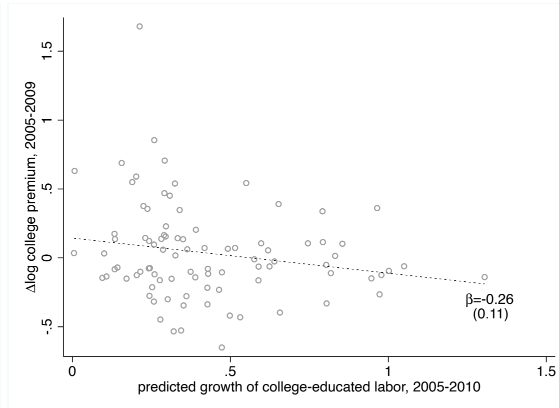


Note: The data come from China's Statistical Yearbook on Science and Technology and China's Statistical Yearbook 2000–2016.

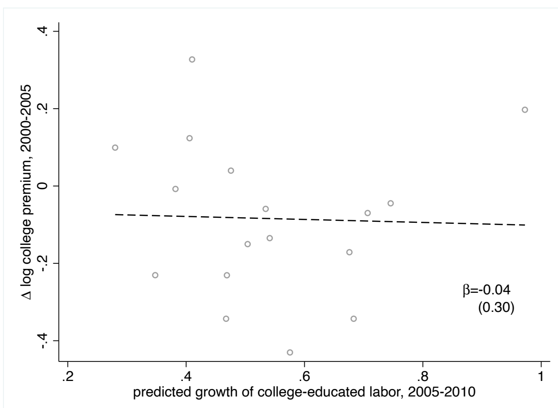
Figure B.4: IV and Changes in Young Workers' College Premium



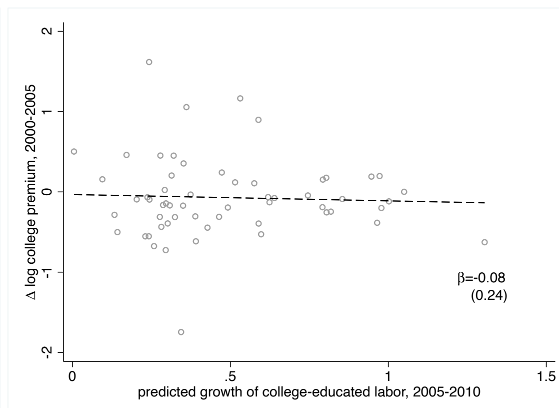
(a) Provincial, 2005–2009



(b) City level, 2005–2009



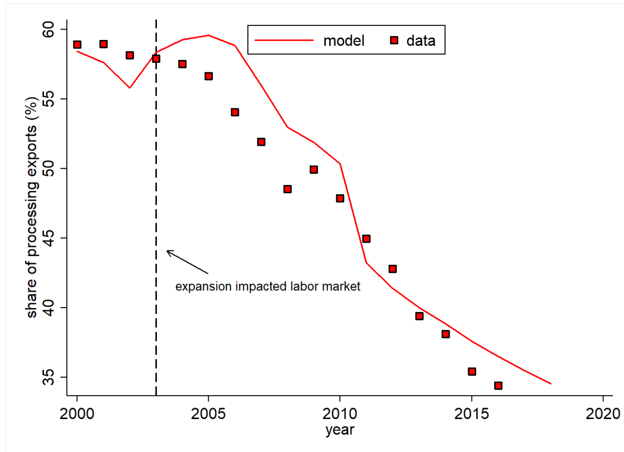
(c) Provincial, 2000–2005



(d) City level, 2000–2005

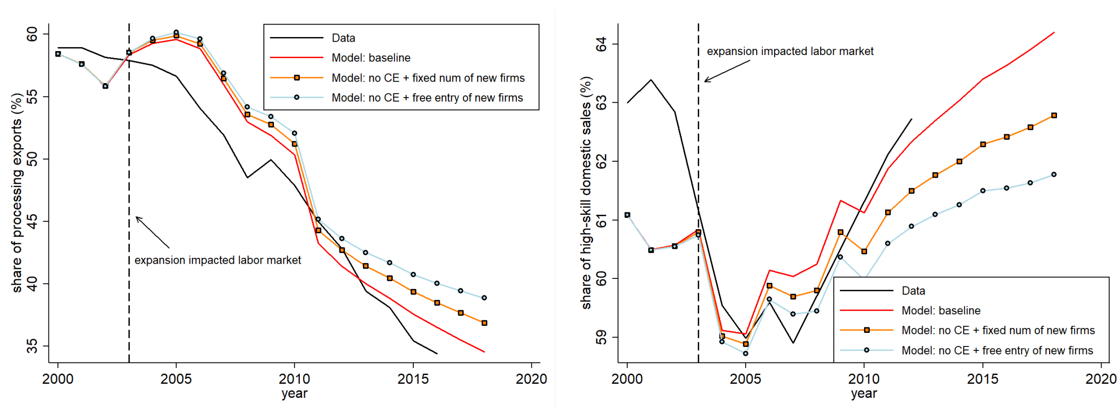
Note: I use the Urban Household Survey and measure young workers' college premium by using the average wage of college-educated workers (aged less than 28) relative to the average wage of all workers with high-school education. For older college-educated workers, the instrumented shock was uncorrelated with changes in their college premium between 2005–2009 or 2000–2005. This is because by the year 2009, college expansion had not persisted long enough to produce large effects on the supply of middle-aged and elderly people. That motivates my modelling of age-specific labor supply. See the description of data in Appendix G.3 and Appendix H for more details on changes in college premium.

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



Note: I compute the share of processing exports in total manufacturing exports using China's Customs Transactions Database 2000–2016. I define manufacturing in the customs data, using the classification of 2-digit HS products (Redding and Weinstein 2019): HS 2-digit sectors 16–96, excluding mineral products (HS 2-digit sectors 25–27) and arms and ammunition (HS 2-digit sector 93).

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



(a) Share of Processing Exports in Exports

(b) Share of High-skill Domestic Sales

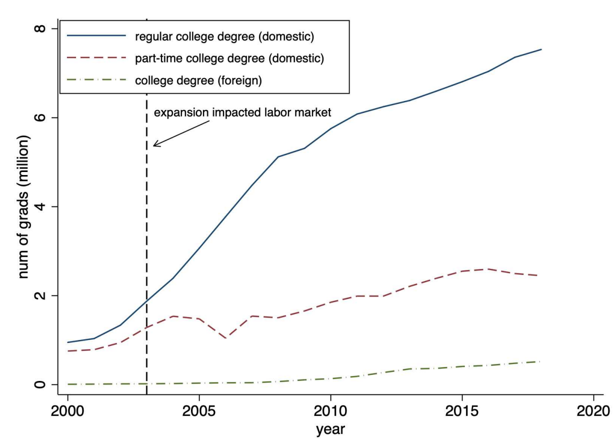
C China's College System

C.1 College Types

The college education in Figure 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 and Davey 2008). Figure C.2 shows that around 1 million obtained part-time college diploma in 2000,[65] and the amount increased to around 2 million in 2018.

Many Chinese students have obtained their college degree abroad. However, as Figure C.2 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 C.1: Number of College Grads (Annual)

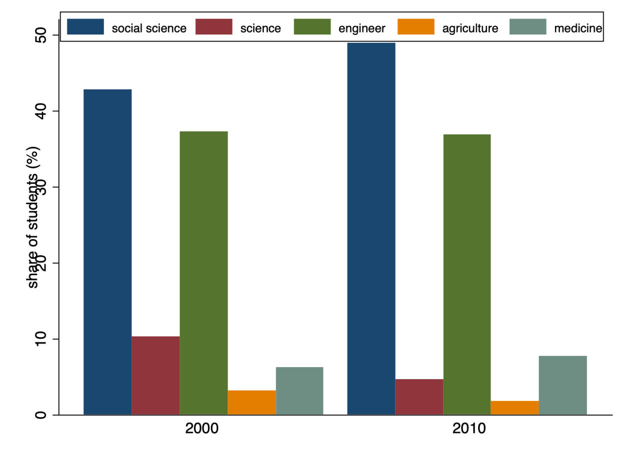


C.2 Distribution of Majors

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.

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

Figure C.2: Distribution of Field of Study Among Grads



D Robustness Checks of Section 3

D.1 Robustness Checks of Section 3.2

D.1.1 Controlling City Composition

The pattern in Figure 3 could be driven by regional economic convergence (Brandt, Kambourov and Storesletten 2018). To deal with this, I compute city-level shares of domestic sales (ordinary exports) in high skill-intensity industries. I next regress these shares on year dummies and city fixed effects, weighted by each city's share of domestic sales (ordinary exports) in the national total in 2000. I cluster the standard errors in the city level.

Figure D.1: Share of Sales in High Skill-intensity Inds (Controlling City Composition)

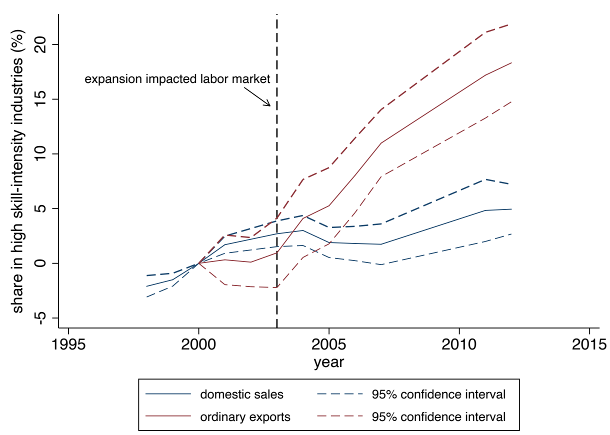


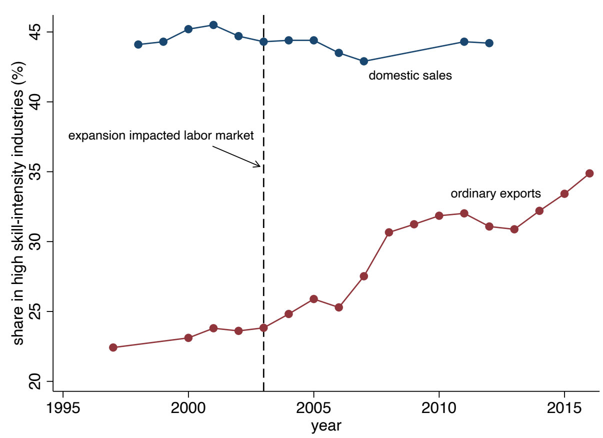
Figure D.1 illustrates the regression results. On the city level, the share of ordinary exports in high skill-intensity industries significantly increased after 2003, whereas there was only a slight change in the share of domestic sales in high skill-intensity industries.

D.1.2 Alternative Measure of Skill Intensities

I test the robustness of my results using an alternative measure of skill intensities—the ratio of nonproduction workers to employment. I compute the ratio of nonproduction workers to employment for 4-digit SIC industries (459 manufacturing industries) in the U.S. in 1990, according to the NBER Manufacturing Database. I define an industry to be a high-intensity industry if its ratio is larger than the average ratio across industries.

I convert domestic sales in ASM from China's Industry Classification (CIC) to SIC industries using the CIC-ISIC concordance from Dean and Lovely (2010) and the ISIC-SIC concordance.[66] I convert my customs data to 4-digit SIC industries using the HS-SIC concordances from the World Integrated Trade Solution (WITS). Compared to the linked ASM-Customs data used in the main text, using SIC industries provides two advantages. First, as the customs database contains all China's exports by HS products, I can thus apply the direct conversion from HS products to SIC industries for China's total exports. In other words, there is a full coverage of this skill-intensity measure on exports. Second, I have access to exports by HS products in the period 1997–2016. This allows me to extend the time series of exports to the period 1997–2016 and have longer pre-shock years.

Figure D.2: Share of Sales in High Skill-intensity Industries (Based on SIC Industries)



In Figure D.2, I plot the share of sales in high skill-intensity industries separately, based on the alternative skill-intensity measure. Clearly, there was skill upgrading of exports after 2003, whereas the skill structure of domestic sales shifted little.

[66]The ISIC-SIC concordance is drawn from Peter Schott's website on international trade data.

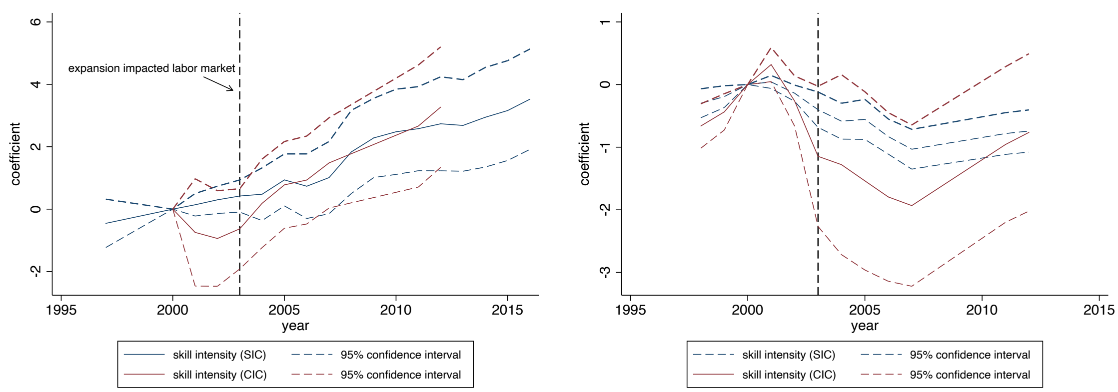
D.1.3 Statistical Tests

I show that my results in Figure 3 were not driven by the specific cutoff of high skill-intensity industries I chose. I run a regression on the 4-digit industry level as follows:

$$\log(s_{j,t}) - \log(s_{j,2000}) = \alpha_t + \beta_t SI_j + \epsilon_{j,t} \tag{D.1}$$

where $s_{j,t}$ is total domestic sales (ordinary exports) of industry j in year t. α_t is the common growth rate across industries. SI_j is the skill-intensity measure of industry j. β_t is the coefficient of interest. $\beta_t > 0$ implies that more skill-intensive industries exhibit higher growth rates in domestic sales (ordinary exports). I also control reductions in input and output tariffs due to WTO to show that the pattern is not driven by WTO accession. I apply the regression in equation (D.1) for each year I have data and cluster the standard errors by industry. In my preferred results, I weight the regression by the share of industry j's domestic sales (ordinary exports) in total domestic sales (ordinary exports) in 2000, such that β_t is informative of the shift in the distribution of domestic sales (ordinary exports). The results for unweighted regressions are similar.

Figure D.3: Coefficients of Growth in Domestic Sales and Exports on Skill Intensities



(a) Ordinary Exports

(b) Domestic Sales

The solid lines in Figure D.3 display the coefficients of estimating equation (D.1) for domestic sales and ordinary exports on two measures of skill intensities, which are the share of college-educated workers in employment for 4-digit industries in 2004 based on China's Industry Classification (CIC) and the share of nonproduction workers for 4-digit SIC industries in the U.S. in 1990. The dashed lines denote the 95% confidence intervals. Clearly, in Figure D.3a, β_t turned significantly positive after 2005 for the SIC skill-intensity measure and after 2007 for the CIC skill-intensity measure. In terms of both measures, the coefficients increased faster on average after 2003. Particularly, when I use the CIC skill-intensity measure, the turning point seems to be the year 2003 when the coefficients started to increase. This pattern is consistent with the timing of the college expansion.

Table D.1: Dependent Variable: Growth Rate of Exports

period:	1997–2003				2003–2010			
region:	China (1)	World (2)	East Asia (3)	Dev Asia (4)	China (5)	World (6)	East Asia (7)	Dev Asia (8)
skill intensity (SIC)	0.006	0.046	0.160	0.002	0.311***	0.063	0.177	0.133
	(0.095)	(0.062)	(0.100)	(0.176)	(0.076)	(0.063)	(0.126)	(0.131)
Obs	277	281	276	280	275	284	278	282
R-square	0.000	0.020	0.054	0.000	0.121	0.007	0.052	0.012

Notes: Observations are on the 4-digit SIC industry level. Each regression in Panel A is weighted by the industry's share of total exports in the initial year for that country (set of countries). Panel B shows results from unweighted regressions. The skill intensity measure is the share of nonproduction workers in employment for 4-digit SIC industries in the U.S. in the year 1990. World excludes China. East Asia includes Japan, South Korea, and Taiwan. I exclude SIC industry 3711 for East Asia because it accounts for half of East Asian exports and totally drives the results for weighted regressions. Dev Asia includes Viet Nam, Indonesia, Thailand, Cambodia, India, Malaysia, and Philippines. Standard errors are clustered by industry. Significance levels: * 10%, ** 5%, *** 1%.

D.1.4 Skill Structure of Exports in Other Regions

I show that the pattern in Figure 3 was not driven by the demand side. I obtain bilateral trade flows for 6-digit HS products from Comtrade Database. I delete the 6-digit HS products for which China's ratios of processing exports to total exports were larger than the median ratio across products in the year 2003. This allows me to avoid that China's exports are confounded by processing exports. I aggregate my data into 4-digit SIC industries using the concordance between HS products and SIC industries. I regress growth rates of exports on the SIC skill-intensity measure—the ratio of nonproduction workers to employment. I weight the regression by each industry's share of total exports in the initial year. The results for unweighted regressions are similar.

Table D.1 presents the regression results for exports from four areas and in the two periods. The coefficients for China's exports in 2003–2010 are significantly positive, indicating that exports grew faster in more skill-intensive industries. Clearly, all the coefficients for other areas in the 2003–2010 period are statistically insignificant (these results still hold if I did not delete HS products with heavy China's processing exports for other areas). Therefore, skill upgrading of exports did not seem to happen in the world, East Asia, and developing Asian countries (I exclude China from these three sets of regions).

D.1.5 Decomposition of Sales Growth into Different Margins

I denote the share of domestic sales (exports) in high skill-intensity industries as Z. Note Z is an aggregate across firms,

$$Z = \sum_{\omega \in \Omega} s(\omega) h(\omega), \tag{D.2}$$

where $s(\omega)$ is the market share of a firm's domestic sales (exports) in total national domestic sales (exports). $h(\omega)$ is the share of that firm's sales in high skill-intensity industries. I refer to $s(\omega)$ as market shares and $h(\omega)$ as the skill intensity of sales.

Following the literature (Foster, Haltiwanger and Krizan 2001, Arkolakis 2016), I can decompose the growth in the aggregate skill intensity of sales into the contribution of continuing (C), entering (N), and exiting (X) firms.

$$\begin{aligned} Z' - Z = & \underbrace{\sum_{\omega \in C} s(\omega)[h'(\omega) - h(\omega)]}_{\text{within-firm term}} + \underbrace{\sum_{\omega \in C} [s'(\omega) - s(\omega)][h'(\omega) - h(\omega)]}_{\text{cross-firm term}} \\ & + \underbrace{\sum_{\omega \in C} [s'(\omega) - s(\omega)][h(\omega) - Z]}_{\text{between-firm term}} + \underbrace{\sum_{\omega \in N} s'(\omega)[h'(\omega) - Z]}_{\text{entering firm}} + \underbrace{\sum_{\omega \in X} s(\omega)[Z - h(\omega)]}_{\text{exiting firms}} \end{aligned} \tag{D.3}$$

The first term captures within-firm changes in the skill intensity of sales with initial market shares. The second term represents the cross-firm effect of reallocation and changes in the skill-intensity of sales. The third term represents reallocating production given the initial skill intensity of sales. The final two terms are related to entry/exits.

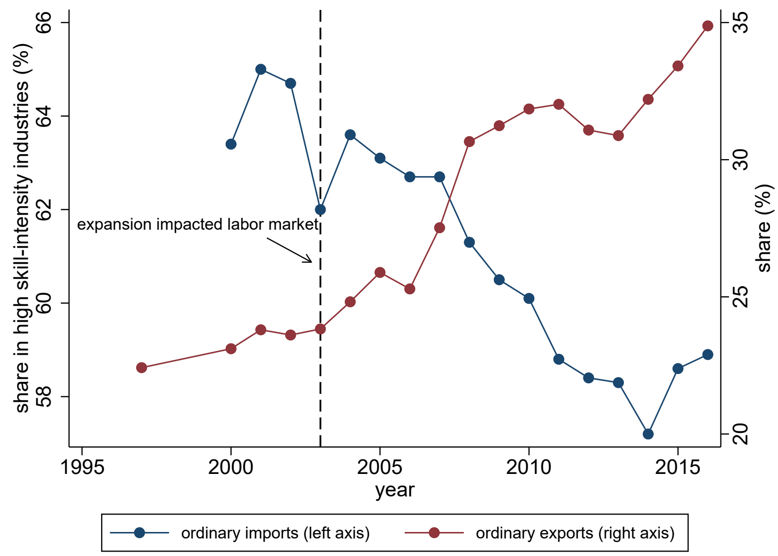
I apply the decomposition in equation (D.3) to exports for the periods 2003–2007 and 2007–2012. Columns (1)–(2) use the linked ASM-Customs data. Because every firm is associated with one industry, I do not have within-firm and cross-firm terms. I find reallocating production across firms contributed considerably to the growth in the skill intensity of exports as well as firm entry and exits.

Table D.2: Decomposition of Growth in the Skill Intensity of Exports

skill-intensity measure	share of college-educated workers		share of nonproduction workers	
period:	2003–2007 (1)	2007–2012 (2)	2003–2007 (3)	2007–2012 (4)
overall growth	12.6%	6.3%	3.7%	5.9%
decomposition				
Within-firm share			0.27	0.19
Cross-firm share			-0.20	0.00
Between-firm share	0.42	0.11	0.54	0.36
Entry-Exit share	0.58	0.89	0.39	0.45

In Columns (3)–(4), I use the alternative skill intensity—the ratio of non-production workers to employment for 4-digit SIC industries in the U.S.. I follow the definition of the skill intensity of sales in Appendix D.1.2. As the customs database covers all firm-level exports by HS products, this measure enables me to study all Chinese exporters

Figure D.4: The Skill Intensity of Ordinary Imports and Exports



using direct concordances between HS products and SIC industries. Another strength of using this measure is to investigate the within-firm term, because in principle a firm can export products that belong to multiple SIC industries. I find in both periods (2003–2007 and 2007–2012), product switching of exports within firms contributed to the skill upgrading of China's exports. The reallocation and firm entry-exit terms still contributed substantively to the increase in the skill content of exports.[67]

D.1.6 Ordinary Imports

I explore changes in the skill intensity of ordinary imports. In the customs data, I observe ordinary imports by HS products. I collapse my data on ordinary imports into SIC manufacturing industries. I then apply the SIC skill-intensity measure and define the high skill-intensity industry in the same way as I did for ordinary exports in Appendix D.1.2.

The blue line in Figure D.4 plots the share of ordinary imports in high skill-intensity industries. For ease of comparison, I also plot the changes in the share of ordinary exports in high skill-intensity industries in the red line. This graphs indicates that China's ordinary imports experienced a gradual reduction in their skill intensities after 2003, whereas China's ordinary exports enjoyed an increase in their skill intensities in the same period.

[67] The contribution of the reallocation was larger using this skill-intensity measure than using the previous skill-intensity measure. This is likely due to the fact that the customs data cover all the exporters and there are no data truncation issues, whereas there was a rise of sales thresholds in ASM data during the 2007–2012 period, from 5 million RMB in 2007 to 20 million RMB in 2012. The rise in thresholds might lead poorly performing exporters to leave the database—which were more likely to be in low skill-intensive industries—and hence raise the contribution of the firm entry-exit term in the linked ASM-Customs data.

This is consistent with that China experienced a shift in comparative advantage from low skill-intensive industries to high skill-intensive industries after 2003.

D.2 Robustness of Section 3.3

D.2.1 Construction of Balanced Panels

I construct the balanced firm panels in the following steps. First, I clean the ASM and the SAT data by dropping firms with missing or nonpositive sales and value added, as well as firms with missing or negative exports. Second, I clean and standardize firm names in the ASM, the SAT, and the customs data, following the steps in He et al. (2018). Third, I merge the different sets of data using firm names. Finally, firm-level exports reported in the ASM and the SAT may be different from the exports reported in the customs data due to imperfect match or misreporting. To ensure that the measurement of exports and domestic sales is consistent, I adjust the exports reported in the customs data proportionally (by each firm) to match firms' reported exports in the ASM or the SAT.[68] I also exclude purely processing exporters (firms that only export processing products) in the data. Table D.3 summarizes the sample statistics.

D.2.2 Robustness Checks of Figure 4

Controlling Industry Composition. The results I found in Figure 4 may be due to different industry composition between exporters and nonexporters, even though the changes in innovative activities were identical between exporters and nonexporters within the same industry. To control the industry composition, I first compute the changes in innovation activities by each 4-digit industry in the period 2001–2005 and 2005–2010, separately for exporters and nonexporters. Note that 4-digit industries are the finest industry classification in China, and there are 480 4-digit manufacturing industries. Using the number of firms (regardless of their export status) in each 4-digit industry in 2001 as weights, I compute the weighted-average changes in innovation activities in the two periods, separately for exporters and nonexporters. Row (1) in Table D.4 confirms my findings in Figure 4. I omit the results for R&D intensities because they are similar.

Using Firms Maintaining Export Status. In the second set of robustness checks, I focus on firms that did not shift their export status in my balanced firm panels. This aims to relieve the concern that better firms selected into exporting during the 2005–2010 period than the 2001–2005 period. Row (2) in Table D.4 replicates Figure 4 for firms maintaining

[68]There are some firms that report positive exports in the ASM or the SAT, but they do not have any records in the customs data—hence their exports by regimes cannot be constructed. This may be due to misreporting or noises in the matching process. I treat these firms as nonexporters. I also experimented with deleting all those firms, which led to very similar results.

Table D.3: Summary Statistics of the Balanced Firm Panels

	2001–05 matched sample				2005–10 matched sample			
	2001		2005		2005		2010	
	mean	std	mean	std	mean	std	mean	std
Panel A: all firms								
log(employment)	5.05	1.12	5.09	1.14	5.08	1.11	4.98	1.21
log(sales)	9.91	1.29	10.43	1.43	10.52	1.35	10.72	1.63
Obs	51,535		51,535		42,892		42,892	
Panel B: ordinary exporters								
log(employment)	5.50	1.18	5.60	1.13	5.54	1.14	5.42	1.20
log(sales)	10.58	1.31	11.06	1.37	11.08	1.37	11.23	1.57
log(ord. exports)	8.17	2.42	8.98	2.16	8.70	2.25	8.77	2.20
Obs	10,334		13,445		11,674		14,982	
Panel C: nonexporters								
log(employment)	4.94	1.07	4.91	1.09	4.92	1.05	4.74	1.14
log(sales)	9.74	1.22	10.21	1.38	10.31	1.28	10.44	1.59
Obs	41,201		38,090		31,218		27,910	

Note: Sales and ordinary exports are in thousands of RMB.

export status. I still have the similar findings that there was an upward shift in innovative activities after 2005, and this increase was larger among exporters.

Using Full Samples. I focus on full samples instead of the balanced firm panels. Row (3) in Table D.4 shows the share of R&D firms for 2001, 2005, and 2010 in full samples. Clearly, exporters enjoyed a larger increase in their innovative activities after 2005.

Omitting High-tech Industries. It is possible that high-tech industries may increase their innovative activities due to R&D tax incentives, as the regulations claim R&D tax incentives to be applicable to high-tech industries.[69] Row (4) in Table D.4 replicates the results excluding electoral machinery, electronics, medicine, and transportation industries, which tend to be high-tech. I find very similar findings.

Using Patent Data. I also provide a measure of innovation output, using records of firms' invention patent applications in 1998–2009 from He et al. (2018). As my patent data end at 2009 and inventing takes time, I define firms with patent applications as firms doing any patent applications in the previous two years. Row (5) in Table D.4 presents the share of firms with patent applications, using my balanced firm panels in the periods 2001–2005 and 2005–2010. Clearly, the patent applications of both exporters and nonexporters

[69]In reality, R&D tax incentives are vague regarding the applicable industries and seem to be applied broadly (Chen et al. 2018).

Table D.4: Robustness Checks of Figure 4

	ordinary exporters			nonexporters		
	2001	2005	2010	2001	2005	2010
Panel A: Share of R&D firms (%)						
(1) Control industry composition	21.0	20.7	23.7	14.6	11.6	12.2
(2) Use firms maintaining export status	20.2	20.2	23.7	13.8	11.2	11.6
(3) Use full samples	20.2	16.4	24.0	11.6	8.4	8.1
(4) Omit high-tech industries	17.7	17.7	22.1	12.2	9.3	9.2
Panel B: Share of firms with patent applications (%)						
(5) Use the baseline setting	1.8	4.7	15.8	0.6	1.7	6.7
(6) Use ASM 2005 & 2011 to compute changes	1.8	4.7	14.4	0.6	1.7	5.7

increased after 2005, when the college expansion largely impacted the labor market. This mirrors my findings in Figure 4 using R&D data.

Using ASM after 2007. My results in the main text used a balanced firm panel between 2005 and 2010, which was constructed by linking ASM 2005 with SAT 2010. I merge ASM 2005 with ASM 2011 to construct a balanced firm panel between 2005 and 2011 and redo the empirical analysis. The main motivation is to show that my results are not driven by the use of SAT after 2007. Since the R&D expenditures are not available in ASM after 2007, I report the results on patents. Row (6) in Table D.4 shows the share of firms with patent applications for 2001, 2005, and 2011.[70] Clearly, the figure exhibited the similar pattern as in Figure 4 that firms increased innovative activities after 2005 after controlling the pre-trends, and the increase was larger for exporters.

D.2.3 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 D.5 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.

[70] As my patent data ends at 2009, I use 2008 and 2009 patent applications to construct the share of firms

Table D.5: Decomposition of Sales for Each Type of Firms (ASM 2004)

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

Table D.6: 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 D.6, 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.

with patent applications for 2011.

E Proofs

E.1 Proof of Migration Probabilities and Lifetime Expected Utility

Let $f_\varphi(\varphi)$ be the density of 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 (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),

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

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.***

E.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:

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

where $\Omega_{m,n,j}$ is the set of goods sold from m to n, determined by export thresholds according to equation (7) and the distribution of state variables $N_{m,j}(\mathbf{s})$. As shown in equation (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:

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

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:

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

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

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

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 4.2.1; 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 4.3.2.

E.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:

$$h_{\mathcal{C},j}(\omega)/l_{\mathcal{C},j}(\omega) = ((1-\alpha_j)W_{\mathcal{C}}/\alpha_j S_{\mathcal{C}})^{\rho_x}$$

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

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

For each industry, I notice $H_{\mathcal{C},j}S_{\mathcal{C}} + L_{\mathcal{C},j}W_c = \frac{\sigma-1}{\sigma}(\gamma_j)^\theta \left(\frac{P_{\mathcal{C},j}}{P_{\mathcal{C}}}\right)^{1-\theta} E_{\mathcal{C}}$ from equation (1), where $E_{\mathcal{C}}$ 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:

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

where $SI_{\mathcal{C},j} = \frac{H_{\mathcal{C},j}S_{\mathcal{C}}}{H_{\mathcal{C},j}S_{\mathcal{C}} + L_{\mathcal{C},j}W_{\mathcal{C}}}$ 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:

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

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

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

where I used the definition $SI_{\mathcal{C},j}$ and $H_{\mathcal{C},j}/L_{\mathcal{C},j} = ((1-\alpha_j)W_{\mathcal{C}}/\alpha_j S_{\mathcal{C}})^{\rho_x}$.

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

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

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

Note that I do not consider innovation here, and therefore all the labor is used in production. I then have $\hat{L}_{\mathcal{C}} = \sum_j \Lambda^L_{\mathcal{C},j} \hat{L}_{\mathcal{C},j}$ and $\hat{H}_{\mathcal{C}} = \sum_j \Lambda^H_{\mathcal{C},j} \hat{H}_{\mathcal{C},j}$, where $\Lambda^H_{\mathcal{C},j}$ ($\Lambda^L_{\mathcal{C},j}$) 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 (E.9) and (E.10), I obtain:

$$\hat{S}_{\mathcal{C}} - \hat{W}_{\mathcal{C}} = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{\mathcal{C},j}(\Lambda^H_{\mathcal{C},j} - \Lambda^L_{\mathcal{C},j}))} (\hat{L}_{\mathcal{C}} - \hat{H}_{\mathcal{C}}). \tag{E.11}$$

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

$$SI_{\mathcal{C},j} = \frac{H_{\mathcal{C},j} S_{\mathcal{C}}}{H_{\mathcal{C},j} S_{\mathcal{C}} + L_{\mathcal{C},j} W_{\mathcal{C}}} = \frac{H_{\mathcal{C}} S_{\mathcal{C}}}{H_{\mathcal{C}} S_{\mathcal{C}} + L_{\mathcal{C}} W_{\mathcal{C}} \Lambda^L_{\mathcal{C},j}/\Lambda^H_{\mathcal{C},j}}$$

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

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

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

Finally, I define $\Phi_{\mathcal{C}}$ as:

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

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

E.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:

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

where $p_{\mathcal{C},\mathcal{C},j}$ is the price charged by the Chinese firm, and $P_{F,\mathcal{C},j}$ is the aggregate price index for foreign firms exporting to China. Domestic firms' aggregate price index is given by

$$P_{\mathcal{C},\mathcal{C},j}^{1-\sigma} = N_{\mathcal{C},j}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_{\mathcal{C}}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_{\mathcal{C}}^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}} \int z^{\sigma-1} dG_{\mathcal{C},j}(z). \tag{E.14}$$

where $N_{\mathcal{C},j}$ is the number of firms that are located in region $\mathcal{C}$. $G_{\mathcal{C},j}(z)$ is the productivity distribution of firms in region $\mathcal{C}$ and industry j. The aggregate price indices can be obtained as:

$$P_{\mathcal{C},j}^{1-\sigma} = P_{\mathcal{C},\mathcal{C},j}^{1-\sigma} + P_{F,\mathcal{C},j}^{1-\sigma}.$$

Note that $\Pi_{\mathcal{C},\mathcal{C},j} = \frac{P_{\mathcal{C},\mathcal{C},j}^{1-\sigma}}{P_{\mathcal{C},\mathcal{C},j}^{1-\sigma}+P_{F,\mathcal{C},j}^{1-\sigma}}$ is the share of expenditures in region $\mathcal{C}$ on domestic goods.

Log differentiating equation (E.13), I would obtain

$$\hat{R}_{\mathcal{C},j} = (1-\sigma)(1-\Pi_{\mathcal{C},\mathcal{C},j})\hat{P}_{\mathcal{C},\mathcal{C},j} + (1-\theta)\Pi_{\mathcal{C},\mathcal{C},j}\hat{P}_{\mathcal{C},\mathcal{C},j} + (\theta-1)\hat{P}_{\mathcal{C}} + \hat{E}_{\mathcal{C}} \tag{E.15}$$

Log differentiating equation (E.14) gives me proportional changes in domestic price indices:

$$\hat{P}_{\mathcal{C},\mathcal{C},j} = (1-SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}} + SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}}. \tag{E.16}$$

Combining equations (E.15) and (E.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:

$$R_{F,j} = \left(\frac{p_{\mathcal{C},F,j}}{P_{F,j}}\right)^{1-\sigma}\gamma_j^{\theta}\left(\frac{P_{F,j}}{P_F}\right)^{1-\theta} E_F, \tag{E.17}$$

where $P_{F,j}$ and P_F are industry-level and final price indices in Foreign. For a Chinese firm's price $p_{\mathcal{C},F,j}$, it can be written as:

$$p_{\mathcal{C},F,j}^{1-\sigma} = \left(\frac{\sigma}{(\sigma-1)z_j}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_{\mathcal{C}}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_{\mathcal{C}}^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}}. \tag{E.18}$$

I assumed in Section 5 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 (E.17), I can derive:

$$\hat{R}_{F,j} = (1-\sigma)\hat{p}_{\mathcal{C},F,j}, \tag{E.19}$$

where $\hat{p}_{\mathcal{C},F,j}$ can be derived by log differentiating equation (E.18),

$$\hat{p}_{\mathcal{C},F,j} = (1-SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}} + SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}}. \tag{E.20}$$

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:

$$\frac{R_{F,j}}{\sigma} - f_{\mathcal{C},F,j}P_{\mathcal{C}} = 0 \;\Rightarrow\; z_j^* = \left(\frac{\sigma f_{\mathcal{C},F,j}P_{\mathcal{C}}}{E_F P_F^{\theta-1}P_{F,j}^{\sigma-\theta}\gamma_j^{\theta}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{(\sigma-1)}\left[\frac{\alpha_j^{\rho_x}}{W_{\mathcal{C}}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_{\mathcal{C}}^{\rho_x-1}}\right]^{\frac{1}{1-\rho_x}} \tag{E.21}$$

where z_j^* is the export threshold in industry j. It is easy to show:

$$\hat{z}_j^* = (1 - SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}} + SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}} \tag{E.22}$$

Therefore, the threshold z_j^* declines more in the more skill-intensive industry when $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$. 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 $\Pi_{\mathcal{C},\mathcal{C},j} > 0$ are similar across industries, for two industries with skill intensities $SI_{\mathcal{C},j} > SI_{\mathcal{C},j'}$, from Result (i), I have:

$$\underbrace{(\sigma-1)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'})}_{\text{relative growth in exports}} > \underbrace{(\sigma-1)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'}) + (\theta-\sigma)\left(\Pi_{\mathcal{C},\mathcal{C},j}SI_{\mathcal{C},j} - \Pi_{\mathcal{C},\mathcal{C},j'}SI_{\mathcal{C},j'}\right)}_{\text{relative growth in domestic sales}}. \tag{E.23}$$

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.***

E.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.***

E.6 Proof of Proposition 6

In the case of nontradable industries, I can apply the results from proofs for Proposition 2. Combining equations (E.9) – (E.10), I obtain:

$$\hat{L}_{\mathcal{C},j} - \hat{L}_{\mathcal{C},j'} = (\theta - \rho_x)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'})(\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}}),\; j, j' \in \mathcal{O}(T)$$
$$\hat{H}_{\mathcal{C},j} - \hat{H}_{\mathcal{C},j'} = (\theta - \rho_x)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'})(\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}}),\; j, j' \in \mathcal{O}(T)$$

For a tradable industry $j \in \mathcal{O}(T)$, I have

$$H_{\mathcal{C},j}S_{\mathcal{C}} + L_{\mathcal{C},j}W_{\mathcal{C}} = \frac{\sigma-1}{\sigma}\left(\Pi_{\mathcal{C},\mathcal{C},j}\gamma_j^{\theta}\left(\frac{P_{\mathcal{C},j}}{P_{\mathcal{C}}}\right)^{1-\theta}E_{\mathcal{C}} + \Pi_{\mathcal{C},F,j}\gamma_j^{\theta}\left(\frac{P_{F,j}}{P_F}\right)^{1-\theta}E_F\right) \tag{E.24}$$

where the first term in the bracket on the right-hand side is domestic sales, and the second term denotes ordinary exports. $\Pi_{\mathcal{C},\mathcal{C},j}$ is the share of expenditures in goods produced domestically.

Using results in equation (E.15) and (E.19), I log differentiate equation (E.24):

$$\begin{aligned}
&SI_{\mathcal{C},j}(\hat{S}_{\mathcal{C}} + \hat{H}_{\mathcal{C},j}) + (1-SI_{\mathcal{C},j})(\hat{W}_{\mathcal{C}} + \hat{L}_{\mathcal{C},j}) \\
&= \Big\{D_{\mathcal{C},\mathcal{C},j}\left[(1-\sigma)(1-\Pi_{\mathcal{C},\mathcal{C},j}) + (1-\theta)\Pi_{\mathcal{C},\mathcal{C},j}\right] + (1-D_{\mathcal{C},\mathcal{C},j})(1-\sigma)\Big\}\Big(SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}} + (1-SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}}\Big) \\
&\quad + D_{\mathcal{C},\mathcal{C},j}\Big[(\theta-1)\hat{P}_{\mathcal{C}} + \hat{E}_{\mathcal{C}}\Big]
\end{aligned} \tag{E.25}$$

where $D_{\mathcal{C},\mathcal{C},j} = \frac{\Pi_{\mathcal{C},\mathcal{C},j}\left(\frac{P_{\mathcal{C},j}}{P_{\mathcal{C}}}\right)^{1-\theta}E_{\mathcal{C}}}{\Pi_{\mathcal{C},\mathcal{C},j}\left(\frac{P_{\mathcal{C},j}}{P_{\mathcal{C}}}\right)^{1-\theta}E_{\mathcal{C}} + \Pi_{\mathcal{C},F,j}\left(\frac{P_{F,j}}{P_F}\right)^{1-\theta}E_F}$ is the share of domestic sales in output. Assuming the export share of output and the share of expenditures on domestic goods are identical across tradable industries, by equation (E.5), I would obtain:

$$\hat{L}_{\mathcal{C},j} - \hat{L}_{\mathcal{C},j'} = \left[D_{\mathcal{C},\mathcal{C},j}\Pi_{\mathcal{C},\mathcal{C},j}\theta + (1-D_{\mathcal{C},\mathcal{C},j}\Pi_{\mathcal{C},\mathcal{C},j})\sigma - \rho_x\right](SI_{\mathcal{C},j} - SI_{\mathcal{C},j'})(\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}}). \tag{E.26}$$

I define $\Gamma_{\mathcal{C}} = (1-D_{\mathcal{C},\mathcal{C},j}\Pi_{\mathcal{C},\mathcal{C},j})(\sigma-\theta)$. Clearly, when $\sigma > \theta$ and $D_{\mathcal{C},\mathcal{C},j}\Pi_{\mathcal{C},\mathcal{C},j} < 1$, I obtain $\Gamma_{\mathcal{C}} > 0$. In addition, $\Gamma_{\mathcal{C}}$ increases with the export share of output $(1-D_{\mathcal{C},\mathcal{C},j})$, the share of expenditures on imports $(1-\Pi_{\mathcal{C},\mathcal{C},j})$, and the elasticity of substitution (σ). This completes the proof. ***Q.E.D.***

F Robustness of Empirical Analysis

F.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

Table F.1: 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 6. I also exclude purely processing exporters to be consistent with Section 6. 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%.

mapping between the reduced-form estimates and the structural parameters. Appendix F.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 F.1, I regress changes in the number of new entrants between 2005–2011 in each province-industry pair,[71] 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 F.1, 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.

[71] 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.

As another check, I look into how exiting firms affected industry sales. In Column (3) of Table F.1, for each province-industry pair, I regress the number of firms that exited between 2005–2011,[72] 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.

F.2 Robustness Checks of Empirical Results

F.2.1 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.[73] I then take efforts to map these data to 2-digit industries based on China's Indutsrial Classification. By doing 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 and 2. The results are quantitatively similar to my baseline results, as shown in Table F.2 and F.3, 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[74] 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 (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 and 2. The results can be found in Table F.2 and F.3. 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.

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 and 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

[72]The exiting firm is defined as a firm that showed up in ASM 2005 but disappeared in ASM 2011.
[73]The data are drawn from IPUMS International.
[74]The data can be found in https://www.naer.edu.tw/files/15-1000-7981,c1311-1.php?Lang=zh-tw.

Table F.2: Robustness Checks of Table 1

Dep var:	Δlog(ordinary exports)		Δlog(domestic sales)		Δlog(export prices)	
Geographic level:	city-level	provincial	city-level	provincial	city-level	provincial
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 enrollments 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 department reallocation to instrument for labor shocks	4.734* (2.766)	–	4.571* (2.831)	–	-0.928 (1.537)	–
Alternative Data Construction:						
(5) Use goods exported in both 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 between 2005–2007 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 the sample 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 with alternative instruments or data construction. Standard errors are clustered on the province-industry level. Significance levels: * 10%, ** 5%, *** 1%.

replicate the regressions in Table 1.[75] 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.[76] The coefficients on changes in ordinary exports or domestic sales are similar to the estimates in Table 1. I do not report the implied elasticities of substitution because the coefficients on export prices are insignificant.

F.2.2 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, and the results are shown in Table F.2. The resulting between-industry and within-industry elasticities of substitution are $3.1 \sim 3.7$ and $6.3 \sim 6.7$.

[75] I do not display results for innovation because they are all insignificant.

[76] I do not report regressions based on province-level shocks because the estimates on domestic sales, exports, and prices are all insignificant.

Table F.3: Robustness Checks of Table 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 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 and Table 2. The magnitude of the coefficients tends to be smaller, because I look into the shorter period. As suggested by Table F.2, 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.

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 is that I restrict the regression of changes in domestic sales to exporting firms as well. As suggested by Table F.2, the implied between-industry elasticity of sub-

Table F.4: Dependent Variable: Province-industry-level Annualized Changes

Dep var:					Δshare of R&D firms			
	Δlog(domestic sales)		Δlog(ordinary exports)		nonexporter		ordinary 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 6. 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%.

stitution is $4.2 \sim 4.9$, which is slightly larger than the estimates in Table 1. The implied with-industry elasticity of substitution remains identical to my baseline results.

F.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 6. Table F.4 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.

F.4 Other Model Predictions

Using the simplified model in Section 5, I can obtain two other predictions of my model and use my data to empirically test them.

F.4.1 Processing Exports

Proposition 5 (Processing Exports). Define $R_{\mathcal{P},j}$ as a firm's processing exports. If the firm always exports before and after the shock, then

$$\hat{R}_{\mathcal{P},j} \propto (\sigma-1)SI_{\mathcal{P},j}\left(\hat{W}_{\mathcal{C}}-\hat{S}_{\mathcal{C}}\right)$$

where $SI_{\mathcal{P},j}$ is the educated labor's share in total labor costs for processing exporters in China's industry j.

Proof: The proof can be similarly derived as $\hat{R}_{F,j}$ in Proposition 3. □

Proposition 5 shows that processing exports grew faster in more skill-intensive industries after the shock, even though processing exports were generally disfavored by the college expansion because of their low skill requirements. To test Proposition 5, I perform the regression in equation (17) with changes in processing exports as the dependent variable. I replace $SI_{m,j}x_m$ with $SI_{\mathcal{P},j}x_m$, where $SI_{\mathcal{P},j}$[77] is the share of college-educated workers in total employment for processing firms in industry j, obtained from ASM 2004. I instrument $SI_{\mathcal{P},j}x_m$ with $SI_{\mathcal{P},j}x^*_m$.

The results in Table F.5 confirm my prediction that processing exports grew faster in more skill-intensive industries after the shock. More notably, the coefficients in Columns (1)–(2) of Table F.5 are similar to the coefficients in Columns (1)–(2) of Table 1. This similarity supports my finding in Proposition 3 and 5 that the responses of ordinary exports and processing exports to the college expansion are both governed by $\sigma-1$.

F.4.2 "Crowding-Out" Effects

Proposition 6 ("Crowding-out Effects"). Consider two sets of industries $\mathcal{O}(g)$ $g \in \{T, N\}$. T and N denote tradable and nontradable industries respectively. For each region, the export share of total sales and the share of expenditures on domestic goods are identical within each set of industries. Then, under the assumptions of Proposition 3 (iii), there are smaller "crowding-out" effects in tradable industries, with

$$\hat{H}_{\mathcal{C},j}-\hat{H}_{\mathcal{C},j'} = (\Upsilon_{\mathcal{C}}+\theta-\rho_x)(SI_{\mathcal{C},j}-SI_{\mathcal{C},j'})\left(\hat{W}_{\mathcal{C}}-\hat{S}_{\mathcal{C}}\right),\ \forall j,j' \in \mathcal{O}(T)$$
$$\hat{H}_{\mathcal{C},j}-\hat{H}_{\mathcal{C},j'} = (\theta-\rho_x)(SI_{\mathcal{C},j}-SI_{\mathcal{C},j'})\left(\hat{W}_{\mathcal{C}}-\hat{S}_{\mathcal{C}}\right),\ \forall j,j' \in \mathcal{O}(N)$$

where the constant $\Upsilon_{\mathcal{C}}$ increases with the export share of total sales, the share of expenditures on imports, and elasticity of substitution across varieties. The same results hold if I replace $H_{\mathcal{C},j}$ with $L_{\mathcal{C},j}$.

Proof: See Appendix E.6. □

[77] I do not compute $SI_{\mathcal{P},j}$ by region because there are very few purely processing firms in some provinces.

Table F.5: College Expansion and Processing Exports, 2005–2010

Variable:	Δlog(processing exports)	
shock	city-level (1) 2SLS	provincial (2) 2SLS
Exposure to CE	3.620** (1.652)	3.535** (1.628)
Obs	3,603	3,603
R-squared	0.078	0.043
First-stage F	160.04	157.40

Note: This table provides estimates from regressions in equation (17), treating regions as cities and provinces. 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%.

Proposition 6 shows that if $\rho_x > \theta$, "crowding-out" effects occur in nontradable industries. Intuitively, more skill-intensive industries employ a higher proportion of educated labor, implying a larger output expansion in the face of an inflow of educated labor. If between-industry elasticity of substitution (θ) is low, changes in local demand are unable to accommodate expanding production in more skill-intensive industries, requiring labor to relocate away from these industries. In contrast, "crowding out" effects are lesser for tradable industries, as they can expand through foreign markets.

I test Proposition 6 by employing a first-difference regression:

$$\Delta y_{m,j} = \beta_0 + \beta_1 SI_{m,j} x_m + \beta_2 1(T) SI_{m,j} x_m + \beta_{g(j)} \mathbf{Z}_{m,j} + \iota_{m,g(j)} + \epsilon_{m,j} \tag{F.1}$$

where $\Delta y_{m,j}$ represents log changes in the employment of college-educated (noncollege) workers between 2005–2010. $SI_{m,j}$ is the share of college-educated workers in total employment for region m and industry j in 2005. I divide industries into less and more tradable industries based on the median share of exports in total sales across industries in 2005. $1(T)$ is a dummy variable for tradable sectors. Industry-level controls $\mathbf{Z}_{m,j}$ include log employment, the share of SOE workers, and log production value in 2005, as well as input and output tariff reductions due to WTO; $\iota_{m,g(j)}$ captures region-specific trends. I allow for their effects to be dependent on whether industries belong to more tradable ($g(j) = T$) or less tradable ($g(j) = N$) industries. I use the supply shock of college-educated workers x_m and the instrument x_m^* in Section 6.

I use Population Censuses 2005 and 2010 to compute $\Delta y_{m,j}$ and $SI_{m,j}$, with controls computed from ASM 2005. Due to the data availability, I estimate equation (F.1) on the provincial and 2-digit industry level. Table F.6 reports the results. Consistent with Proposition 6, for the employment of college-educated workers, there were "crowding-out" effects in less tradable industries, whereas these effects were muted in more tradable industries. For the employment of noncollege-educated workers, the "crowding-out" effects in less tradable industries were nearly negligible, whereas more tradable industries enjoyed larger inflows of noncollege employment as expected.

Table F.6: Dependent Variable: Log Change in Employment Size

Dependent variable:	Δlog(num of skilled workers)		Δlog(num of noncollege workers)	
	(1) 2SLS unweighted	(2) 2SLS weighted	(3) 2SLS unweighted	(4) 2SLS weighted
Skill intensity$\times$ shock	-9.874***	-7.491***	0.044	0.157
	(1.065)	(1.302)	(0.698)	(0.702)
Skill intensity$\times$ shock $\times$ 1(tradable industry)	4.150***	5.602***	3.218***	3.597***
	(1.462)	(1.440)	(1.060)	(1.040)
Obs	753	753	817	817
R-squared	0.418	0.493	0.418	0.450
First-stage F value	123.37	167.55	129.52	118.49

Note: This table provides estimates from regressions in equation (F.1). I control the share of SOEs, log employment, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions from Brandt et al. (2017). In Column (2) and (4), I weight the regressions by the regional employment size for that type of workers 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%.

G Calibration

G.1 Incorporating Processing Producers into the Model

I follow Liu and 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:

$$Q_{m(k),j} = \left(\int \epsilon_{F,m(k),j}(\omega)^{\frac{1}{\sigma}} q_{F,m(k),j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \sum_{n \in \mathcal{C}} \int \epsilon_{n(\mathcal{O}),m(k),j}(\omega)^{\frac{1}{\sigma}} q_{n(\mathcal{O}),m(k),j}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}.$$

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,

$$q_{m(k),j} = z_{m(k),j} \left[\alpha_{j(k)} l^{\frac{\rho_x - 1}{\rho_x}} + (1 - \alpha_{j(k)}) h^{\frac{\rho_x - 1}{\rho_x}} \right]^{\frac{\rho_x \gamma_{m(k),j}^L}{\rho_x - 1}} \prod_{j'=1}^{J} b_{j'}^{\gamma_{m(k),j}^{j'}}.$$

The following China-related parameters are regime-specific: input-output parameters $\{\gamma_{m(k),j}^L, \gamma_{m(k),j}^{j'}\}_{m \in \mathcal{C}}$, 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 $\{f_{m(k),j}^e\}_{m \in \mathcal{C}}$).

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 and Tang 2016). I thus let parameters in firm production $\{\gamma_{m(k),j}^L, \gamma_{m(k),j}^{j'}\}$ 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.

G.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 H.1. I consider agriculture, mining, and services as nontradable, whereas all manufacturing industries are tradable. Thus, only manufacturing industries produce processing exports.

G.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.[78] 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.[79] 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 and Lovely (2010).[80]

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 prod-

[78]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.

[79]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.

[80]Because the World Input-Output Table Database only records 2-digit industries, there are lots of multiple-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.

ucts. 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 and 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 and 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.

The raw data do not report export regimes, and I construct trade flows between province-regime-industries following Liu and 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.[81] 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.[82]

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[83] I adjust part-time college grads to the equivalents

[81] 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.

[82] 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 and Noguera 2016).

[83] 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 sector, given persistent differences in wage levels between agricultural and nonagricultural

of college grads with regular 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 and 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).

G.4 Calibration Procedure

I consider several sets of parameters to be 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 $\zeta_t(\cdot)$.

G.4.1 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 and 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

workers. I then use the coefficients on education levels to adjust workers of lower education levels to the equivalents of high-school grads.

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.

G.4.2 Step 1: Calibrating Production Parameters and Trade Costs

As shown in Section 4.4, 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,[84] 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 export regime. (4) Parameters $\{\beta_a^H\}$ and $\{\beta_a^L\}$ in labor supply function,[85] which pin down the relative productivity of workers across ages. (5) Variance of demand shifters $\frac{\sigma_\epsilon^2}{1-\rho_\epsilon^2}$, 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.[86] 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.

[84] I normalize $\sum_j \gamma_j = 1$ as changing $\{\gamma_j\}$ by the same proportion does not affect the relative output.

[85] 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.

[86] To rationalize wage differences between sectors, Zilibotti, Storesletten and Bo (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 and Zhu 2019).

Table G.1: 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) $\{\gamma_{u,j}^{L}, \gamma_{u,j}^{j'}\}_{u\in\{\tilde{\mathcal{C}},F\}}$		Input-output parameters, by region/industry/regime
(5) $\{H_{u,0,t}, L_{u,0,t}\}_{u\in\{\mathcal{C},F\}}$		Num of college-educated 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) $\{\beta_a^H, \beta_a^L\}$	0.07 (0.02)	Age-specific productivity in labor supply
(4) $\{\alpha_{j(k)}\}_{k\in\{\mathcal{O},\mathcal{P}\}}$	0.71 (0.09)	Skill intensities by industry and regime
(5) $\frac{\sigma_\epsilon^2}{1-\rho_\epsilon^2}$	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) $\{d_{u,F,j,2005}, d_{F,u,j,2005}\}_{u\in\tilde{\mathcal{C}}}$	3.71 (4.11)	International trade costs by region/industry/regime
(9) $\{f_{u,F,j}, f_{F,u,j}\}_{u\in\tilde{\mathcal{C}}}$	$5e{-}4(4e{-}3)$	Marketing costs by region/industry/regime
Panel C: Step 2 of Calibration		
(1) $\gamma_{age}^H, \gamma_{age}^L$	0.01, 0.04	Effects of age on migration costs, by skill type
(2) $\gamma_{dist}^H, \gamma_{dist}^L$	2.40, 2.68	Effects of distance on migration costs, by skill type
(3) $\gamma_{contig}^H, \gamma_{contig}^L$	0.21, 0.01	Effects of contiguity on migration costs, by skill type
(4.1) $\{\gamma_n^H\}_{n\in\mathcal{C}}$	2.50 (2.57)	Effects of destination-specific migration costs, college-educated
(4.2) $\{\gamma_n^L\}_{n\in\mathcal{C}}$	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) $\{g_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$	0.01 (0.18)	Exg. productivity growth, by region/industry/regime
(2) $\{N_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$	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) $\{\bar{A}_{m,r}\}_{m\in\mathcal{C}}$	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.

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.[87] (4) The relative wages of workers across age groups in China. (5) The 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.[88] (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.[89] 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 G.1 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, Guo, Li, Shi and Zhu (2020) for annual earnings and 0.24–0.37 used by Zilibotti et al. (2019).

In Table G.2, 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. Figure G.1 shows that my model matches the shares of industry-level ordinary exports in total ordinary exports in the data.

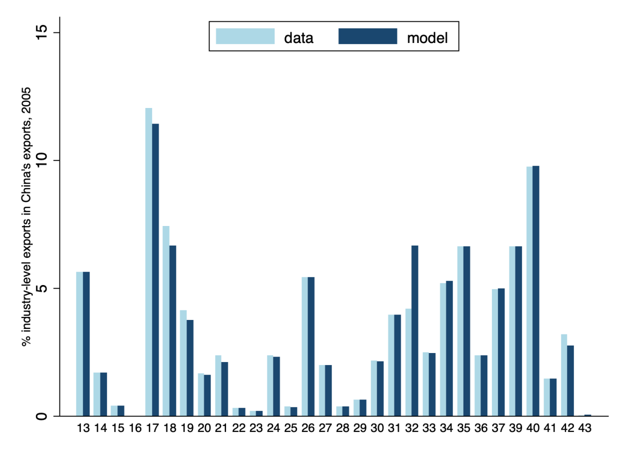
Finally, I choose firms' operation costs $\{f_{u,j}\}_{u\in\{\tilde{\mathcal{C}},F\}}$ to equal the lowest profits among operating firms for China's province-regime-industry or foreign industry. I obtain China's import and export trade costs in year t, by adjusting $\{d_{u,F,j,t}, d_{F,u,j,t}\}_{u\in\tilde{\mathcal{C}}}$ according to tariff changes between 2005 and year t.

[87] 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.

[88] 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.

[89] 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, Jensen, Redding and Schott (2007) as a proxy for the share of exporters in Foreign to each Chinese province-regime.

Figure G.1: Comparison of Export Shares in the Model and the Data



Note: This graph presents the shares of industry-level ordinary exports in China's total manufacturing ordinary exports in 2005. The label in the horizontal axis reflects the 2-digit CIC industry code (Table H.1).

G.4.3 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),

$$\tau^I_{m,n,a} = \gamma^I_{age} a + \gamma^I_{dist} \log dist_{m,n} + \gamma^I_{contig} contig_{m,n} + \mathbf{1}_{n \neq birthplace} \gamma^I_n, I \in \{H, L\},\ m, n \in \mathcal{C}. \tag{G.1}$$

$dist_{m,n}$ 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.[90] (5) Across provinces, the slope of changes in college premium on the strength

[90]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

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 6.1 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 G.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 G.1 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 and Murphy (1992) find the elasticity of substitution between college-educated and high-school workers to be 1.4, whereas Card and 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 and Lemieux (2001) but allows the model to match changes in college premium across age groups pretty well, as shown in Appendix Section H. 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 G.2 shows that the model matches the targeted data moments pretty well.

G.4.4 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 $\{g_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$. 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 $\{N_{u,j,t}\}_{u\in\{\tilde{\mathcal{C}},F\}}$. (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.[91] (9) Fixed costs $\{\phi_{1,j}\}$ and variable costs of innovation $\{\phi_{2,j}\}$. (10) The aggregate pro-

$\sum_{m\neq n}\sum_a L_{m,a}\Lambda^L_{m,n,a}/(\sum_m\sum_a L_{m,a}\Lambda^L_{m,n,a})$ for noncollege labor.

[91] 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 $\exp(-3)\approx 0.05$.

ductivity of research goods $\{A_{u,r,t}\}_{u\in\mathcal{C}}$. I set the aggregate productivity of research goods to be region-specific with a common time trend $A_{u,r,t} = \bar{A}_{u,r}a_t$.[92]

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 (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.[93] (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 $V^{'}(\mathrm{s}_{c(m),j}) = C_s\left(\sum_n \pi^{+'}_{m,n,j} - f_{m,j}P^{'}_{m,j}\right)$, 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 G.1 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 G.2 shows that my model moments match the data moments pretty well.

[92] 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 $\phi_{2,j}$.

[93] 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.

Table G.2: 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 annualized migration rates and age, for college/noncollege labor	-0.08,-0.12	-0.08,-0.12
(2) Corr btw annualized migration rates and distance, for college/noncollege labor	-0.01,-0.02	-0.01,-0.02
(3) Corr btw annualized migration rates and contiguity, for college/noncollege labor	0.09,0.13	0.13,0.13
(4.1) Share of annualized in-migrants in college-educated emp, by province	0.008 (0.007)	0.008 (0.007)
(4.2) Share of annualized in-migrants in noncollege emp, by province	0.008 (0.011)	0.007 (0.010)
(5) Slope of provincial college premium changes to strength of expansion, 2003–09	0.33	0.35
(6) Avg difference in provincial college premium between young and old, 2009	-0.45	-0.45
Panel C: Targeted Moments in Step 3		
(1.1) Output relative 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 of 2000–2018	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.

G.4.5 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 (10) to compute 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 (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 and Zidar (2016).[94] 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 $\{N_{u,j,t}\}_{u \in \{\tilde{\mathcal{C}},F\}}$.

H 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:

$$\log w_{im} = \beta_0 + \sum_{x \in X} \phi_{x,1} D^x_{it} + \sum_{x \in X} \phi_{x,2} D^x_{it} \times \mathbf{1}_{col} + \beta_1 agr_{im} + \iota_m + \epsilon_{it}$$

$\log w_{im}$ 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.

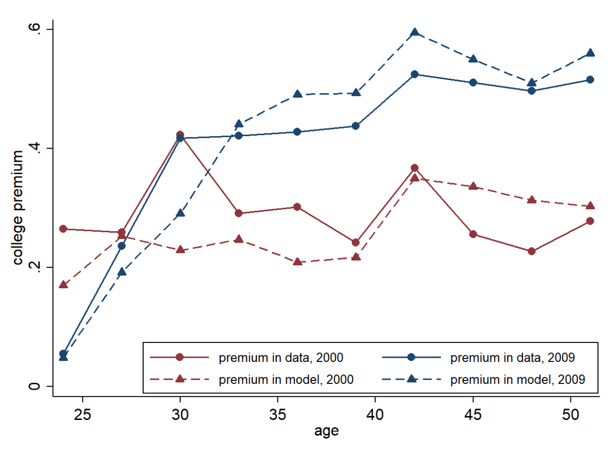
I use workers' yearly wage data in the Urban Household Survey in 2000–2009 to estimate the observed college premium.[95] I restrict the sample to workers with high-school education or above, and therefore the baseline group in the regression is workers with high-school education. In the calibrated model, I perform the same regression with noncollege labor (high-school grads) and educated labor (college-educated workers).

Figure H.1 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

[94] Although the model in Serrato and 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 $\sigma^F = 0.27$.

[95] 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.

Figure H.1: College Premium in Model and Data



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.[96] Manufacturing production in rural areas is very low-skilled. 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.[97]

[96] 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.

[97] 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, because the effects of college expansion mainly manifested after the fast growth of China's manufacturing output relative to GDP was almost over.

Table H.1: 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