College Expansion, Trade, and Innovation: Evidence from China

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Abstract

China has expanded the yearly quota on newly admitted college students by more than 7 times since 1999. How did this massive education expansion affect firms' export and innovation choices? I document that after this expansion impacted the labor market, manufacturing firms' innovation increased considerably, especially among exporting firms, accompanied by sizable skill upgrading of China's exports. I build on these insights to develop a multi-industry spatial equilibrium model, featuring skill intensity differences across industries and heterogeneous firms' innovation and export choices. Quantitatively, I find that the college expansion explained 72% of increases in China's manufacturing R&D intensity between 2003–2018 and also triggered export skill upgrading. Without trade openness, the impact of this education policy change on China's innovation and production would have declined by 10–30%.

JEL Codes: F12; O11

Key Words: international trade; innovation; college education

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1 Introduction

A notable phenomenon of China's economy is the recent surge in innovative activities, with the ratio of R&D over GDP increasing rapidly from 0.9% in 2000 to 2.1% in 2018. Understanding its causes has important policy implications for promoting innovation-led growth in developing countries. Whereas there are some explanations from the policy environment faced by firms (e.g., Chen et al. 2021, König et al. 2021), there is still a lack of understanding on how this R&D surge has been fueled from the labor market. Accompanying this R&D surge is another phenomenon regarding China's trade—the skill upgrading of "Made in China," with China gradually moving away from being a "world factory" for cheap and low-tech products. For example, China's primary export product has gradually shifted from "Clothing" to "Telecommunications Equipment" since 2000,[1] and three of the worldwide top 5 smartphone companies are now from China (IDC 2021).

This paper provides one explanation for these two possibly interacted phenomena: China's sizable expansion of college education. With strict control of the college system, the Chinese government has increased the yearly quota on newly admitted students since 1999, from 1 million in 1998 to 7–8 million in the 2010s, as shown in Figure 1. As a result of this unprecedented expansion, the number of college-educated workers more than tripled between 2000 and 2015, while the total employment only increased by 7%.

In this paper, I highlight three channels through which China's college expansion affects trade and innovation. First, the growing pool of college-educated workers lowers R&D costs and promotes innovation, as college-educated workers are intensively involved in the innovation process. Second, with elastic industry-level demand, an increasing number of college-educated workers helps China shift production and demand to more skill-intensive industries. Importantly, trade openness amplifies these adjustments of industry structure by converting the excess supply of high-skill goods into exports, which is often recognized as Rybczynski effects (Rybczynski 1955, Ventura 1997). Third, trade and innovation also interact. As more skill-intensive industries tend to be more innovative, trade-induced industry reallocation reinforces the innovation surge.

I begin my analysis by documenting several descriptive facts on innovation and trade

[1] The data on export products is drawn from the WTO Database, which decomposes exports into 10 products based on the SITC Revision 3 Industry Classification.

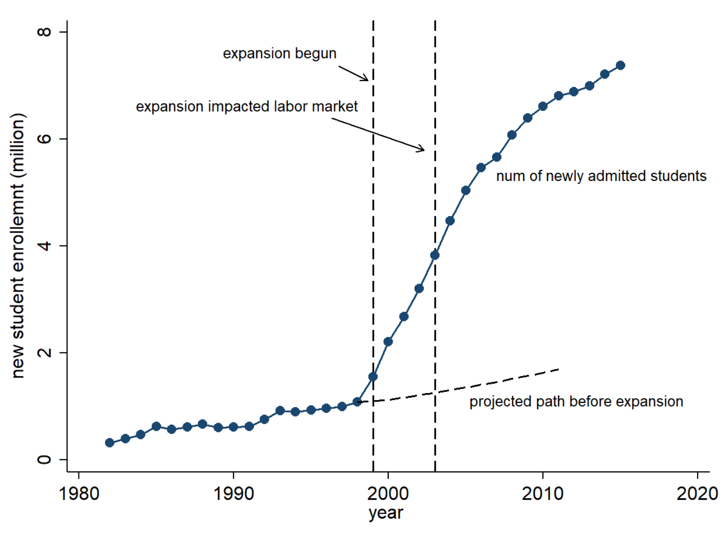


Figure 1: China's College Expansion

Note: This figure presents the yearly number of newly admitted students. The data comes from China's Statistical Yearbooks.

using aggregate and firm-level data. I find that after China's college expansion impacted the labor market: (1) Manufacturing firms' innovative activities increased sizeably—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 (ratio of R&D to sales) nearly doubled in the meantime; (2) Chinese manufacturing exports experienced a massive shift to high-skill industries, whereas manufacturing domestic sales only shifted slightly to high-skill industries; and (3) The increase in innovative activities mainly occurred among exporters, suggesting an interaction between exports and innovation.

These facts indicate a potential impact of the college expansion on firms' exports and innovation. To establish causal inference, I empirically estimate how the college expansion affected firms' production and innovation using firm-level data between 2005 and 2010. Guided by the documented facts, 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 labor supply from demand shocks, I construct instruments based on 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 find that with larger exposure to the college expansion, a firm's export prices decreased, and its exports and domestic sales both increased. The differential responses of export prices, domestic sales, and exports will be used to discipline the key structural parameters in the quantitative analysis. Furthermore, 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 then develop a model to perform the quantitative analysis. The model has the following key elements regarding production and innovation. There are two countries (China and Foreign), and in each country, there are multiple industries that host many firms within each industry. Firms employ two types of labor (educated and less-educated) with different intensities across industries and make export decisions in the face of variable and fixed trade costs (Melitz 2003). Firms can pay convex R&D costs to improve their productivity levels. I assume that educated workers are intensively used in R&D processes, following the recent growth literature (e.g., Acemoglu et al. 2018).

I analytically present the model mechanisms about how China's college expansion impacts exports and innovation. When there is an extra influx of educated workers, firms in more skill-intensive industries experience larger reductions in production costs and product prices, as they hire educated labor more intensively. Compared with the foreign market, the domestic market is supplied more heavily by Chinese firms. Thus, reductions in prices charged by Chinese firms in high-skill industries lead to larger reductions in domestic than foreign industry-level aggregate prices. As reductions in aggregate prices would tame the effect of reductions in firm prices on demand, the asymmetric responses of domestic and foreign aggregate prices lead to less demand substitution domestically than in the foreign market.[2] Thus, Chinese firms in high-skill industries expand their sales faster in the foreign market than domestically. The increase in the supply of educated workers affects innovation by directly lowering R&D costs and also by altering innovation returns through its differential impact on firms' sales growth. In particular, exporters in more skill-intensive industries experience faster sales growth and thus invest more in R&D activities, reflecting the so-called Schumpeterian effect which suggests that larger profits incentivize innovation (Schumpeter 1942). These model predictions are consistent with my empirical evidence.

I then combine data on trade flows, R&D, employment, and output from multiple

[2] Similar insights are present in other studies. For example, Atkeson and Burstein (2008) show that the demand elasticity of a firm decreases with its market share due to aggregate price responses.

sources between 2000–2018 to calibrate the model. The calibrated model matches the targeted moments well and also matches the rich interactions between firm-level export participation, innovation choices, and firm productivity levels.

I use the calibrated model to quantify the effects of China's college expansion. 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 non-college workers replace the "missing" college-educated workers. I find that the college expansion explained 72% of increases in manufacturing R&D intensity and also triggered a sizable portion of export skill upgrading between 2003–2018. Moreover, shutting down trade would reduce the impact of China's college expansion on production by 12–17% and innovation by 31%. These results highlight the amplification effects of trade openness through shifting production to high-skill industries and triggering the interaction between trade and innovation. Finally, I show that my quantitative results are robust to several model extensions, such as allowing for R&D misreporting and manipulation.

This paper makes contact with studies on China's innovation from a *macro perspective*. Few macro-level studies explore the causes of China's fast innovation increase. Ding and Li (2015) provide a comprehensive summary of government R&D policies in China. Chen et al. (2021) show that China's reform of R&D tax incentives in 2008 changed firms' R&D behavior, especially for firms near the thresholds of tax incentives. König et al. (2021) evaluate the role of output wedges in shaping Chinese firms' R&D efficiency in a stationary equilibrium. This paper complements these studies by focusing on the role of China's education policy in driving changes in China's innovation between 2000–2018.

This paper contributes to the trade literature in three aspects. First, this paper closely relates to Amiti and Freund (2010) who find no changes in China's exports' skill content before 2005, whereas I document a massive skill upgrading of China's exports after 2005 and show it is partly caused by the education expansion. Second, much empirical analysis studies how Chinese firms react to trade liberalization (e.g., Khandelwal et al. 2013, Brandt et al. 2017, Handley and Limão 2017), especially in terms of innovation (e.g., Liu and Qiu 2016, Bombardini et al. 2017, Liu et al. 2021).[3] In contrast, I emphasize the role of trade openness in amplifying the effect of a domestic education shock on innovation, in a

[3]There is also much empirical evidence showing that trade liberalization or export demand impacts firms' innovation in other countries, such as Lileeva and Trefler (2010) for Canadian firms and Aghion et al. (2018) for French firms.

similar way to Ventura (1997) who shows that trade is essential for absorbing extra capital for Asian miracle economies. Third, this paper also relates to the literature that uses quantitative models to study trade and innovation (e.g., Eaton and Kortum 2001, Grossman and Helpman 2014, Arkolakis et al. 2018). My model builds on Atkeson and Burstein (2010), enriched with industry heterogeneity and worker types to study policy shocks in China. In particular, heterogeneous skill intensities and innovative opportunities across industries, together, generate the interaction between trade and innovation.

Finally, this paper relates to studies about the effects of college education on innovation through talent supply (e.g., Aghion et al. 2009, Toivanen and Väänänen 2016, Aghion et al. 2017), especially studies focusing on China's college education (e.g., Che and Zhang 2018, Feng and Xia 2018). This paper's contributions are twofold. First, I present a new channel showing that trade can amplify the effect of college education on innovation through shifting production to high-skill industries. Second, these studies are mostly empirical, but aggregate effects are unclear. In contrast, I take reduced-form evidence to calibrate a structural model and *quantify* the aggregate impact of China's college expansion. By showing that the expansion has facilitated China's transition from a manufacturing economy to an innovation-led economy, this paper offers a lesson for developing countries and complements Porzio et al. (2022) who analyze the importance of schooling for structural transformation in developing settings. Akcigit et al. (2020) also construct a structural model to shed light on educated workers' innovative activities, and their model features the formation of research teams. In comparison, I build a model with firms' innovation and export choices to speak to the interaction between trade and innovation.

The paper proceeds as follows. Section 2 discusses the background of China's college expansion. Section 3 documents descriptive facts on the impact of the college expansion on trade and innovation, and Section 4 provides reduced-form evidence. I develop a quantitative model in Section 5 and calibrate the model in Section 6. Finally, I quantify the impact of China's college expansion in Section 7. Section 8 concludes.

2 Context

China's 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.[4] However, due to the Asian financial crisis in 1997 and the SOE layoffs in the late 1990s, China's top leadership surprisingly decided to enlarge the college system to accommodate more youth and boost education expenses (see Wang 2014, for the decision-making process). The expansion was implemented through increases in the annual quota on newly admitted students, because most of the Chinese colleges are government-owned, and China's Ministry of Education has full control over the admissions process of colleges (Jia and Li 2020).

Even though the Chinese economy bounced back after 2001, the expansion has persisted since 1999. The blue line in Figure 1 shows the yearly number of newly admitted students, which increased rapidly from 1 million in 1998 to 7–8 million in the 2010s. As a result, the share of college-educated workers in total employment increased from 4.7% in 2000 to 14.6% in 2015.[5] If college enrollments had grown at 3.8% (previous policy goal) after 2000, the number of college-educated workers would have been 46 million lower in 2015 (6% of total employment). The expansion mainly impacted the labor market after 2003, as it takes around 4 years for new students to graduate.

It is worth noting that college enrollments in Figure 1 correspond to regular education. Instead of full-time study, workers may acquire part-time college degrees through on-the-job study. Compared with regular degrees, part-time degrees are less valuable, and enrollments in part-time education experienced much less expansion after 1999 (see discussions in Appendix B). I will focus on the impact of expansion in regular college education and relegate the robustness of including expansion in part-time education to Appendix G.1. I do not consider graduates from foreign colleges (due to the lack of data), who accounted for 3% of all new college graduates in China between 2000–2018.

My empirical strategy exploits the differential magnitude of the college expansion across regions due to historical factors. This is motivated by two features of the college expansion. First, China's college expansion was attained mainly by the scale-up of enrollments in previously existing colleges (Feng and Xia 2018), which benefited regions with

[4]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).

[5]The data is from the Population Censuses in 2000 and 2015. One caveat with the Population Census and the firm-level data used later is that college-educated workers include not only college graduates in regular schools (shown in Figure 1), but also those with part-time college degrees. Between 2000 and 2015, the total amount of part-time college graduates was 24 million, whereas the total amount of regular college graduates was 66 million.

more college resources historically. Appendix Figure A.1 reveals that across cities, the relation between college enrollments in 1982 and college enrollments in 2005 is well approximated by a 45-degree line. Second, there was a mismatch between the distribution of historic regional college endowments and recent regional development levels. Coastal areas (like Guangdong and Zhejiang) became well-developed after China's transition to a market economy, but historically a large proportion of China's college resources were concentrated in inland China. Appendix Figure A.2 shows that the cities with more college resources in 1982 did not enjoy higher GDP and population growth afterward.

3 Motivating Facts

I document several facts to motivate the model developed in Section 5. Due to data availability and that China's R&D surge mainly occurred in manufacturing,[6] I focus on manufacturing industries/firms. Section 3.1 describes the aggregate pattern of China's manufacturing innovation. Section 3.2 exhibits the 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.

3.1 China's Innovation Surge

Figure 2 presents the aggregate pattern of China's manufacturing innovation from statistical yearbooks. The R&D intensity (ratio of R&D to sales) was flat at 0.6% between 2000–2004 and increased substantially after 2004, from 0.6% in 2004 to 1.1% in 2016. Given the fast sales growth of manufacturing firms (ratio of manufacturing sales to GDP increased from 73% in 2000 to 140% in 2016), the increase in China's R&D/GDP after 2000 was thus mainly driven by manufacturing (Appendix Figure A.7). In the meantime, the share of R&D workers in manufacturing employment increased from 1% in 2004 to 4% in 2016.[7]

This aggregate pattern signals the possible impact of China's college expansion on

[6] Appendix Figure A.7 shows that the increase in China's ratio of R&D to GDP after 2000 was mainly driven by the increase in manufacturing innovation.

[7] The amount of R&D workers is self-reported by firms and not inspected by the government, and thus it may be measured inaccurately in the data and needs to be interpreted with caution. Appendix G.2 discusses how this measurement issue may affect quantitative results.

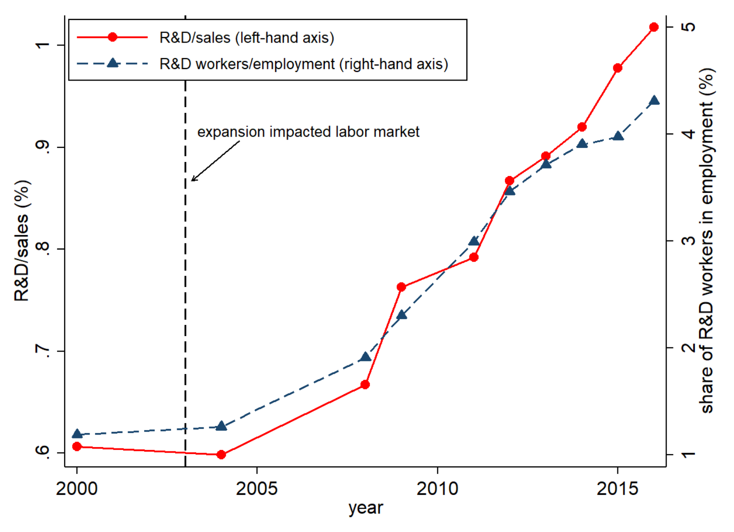


Figure 2: R&D Employment and Expenses in Manufacturing

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

innovation, given that R&D workers mostly hold a college degree,[8] and consistent with the timing of China's college expansion which unfolded in the labor market after 2003. Furthermore, the faster growth in the share of R&D workers in employment than the R&D intensity also indicates that R&D labor became cheaper over time, consistent with the large inflows of college-educated workers.

It is well-known that China has implemented many policy changes, and thus changes in innovation may reflect many factors. A major policy related to innovation is China's R&D tax incentives (Chen et al. 2021). To isolate the effects of the college expansion, in the quantitative analysis, I will explicitly model R&D tax incentives and introduce a time-variant research efficiency parameter to capture other unmodelled factors.

[8]In 2009, the share of R&D workers with at least college degrees 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 those with high-school degrees. In order to estimate the share of R&D workers with college degrees, I assume that employees with junior college degrees had the same participation rate in R&D as employees with university degrees. Appendix G.3 discusses alternative measures of the share of R&D workers with college degrees and how these alternative measures affect quantitative results.

3.2 China's Export Skill Upgrading

Data. I use China's Annual Survey of Manufacturing (ASM) for 1998–2007 and 2011–2012, with detailed financial information and 4-digit industry code for all manufacturing firms above certain sales thresholds.[9] 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.[10]

Measuring Skill Intensities. I associate domestic sales and exports of a firm with the 4-digit industry (482 manufacturing industries in total) to which it belongs. I then aggregate sales and exports by industry. I measure 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. Note that I use the measure of skill intensities that have been benchmarked to the Chinese economy to describe changes in the skill content of Chinese exports. The results are qualitatively similar if I use the US production data to measure skill intensities, as shown in Appendix C. For ease of description, I define a 4-digit industry as a high-skill industry if its college employment share lies above the employment-weighted average across all industries. I demonstrate that the results using continuous values of skill intensities are robust in Appendix C.

Chinese exports can be decomposed into ordinary and processing regimes. This decomposition is necessary for my analysis because processing exports typically embed foreign technology and provide assembly services for foreign clients (Yu 2015), and thus processing exports do not require high skills (see Appendix Table C.3 for evidence). I thus expect processing exports to benefit less from the college expansion, and pooling them together with ordinary exports would mask their different changes in the skill content of

[9] In 2000–2007, the sales threshold was 5 million RMB (roughly $600 thousand), and the sample included all state-owned firms. The sales threshold became 20 million RMB after 2011 for all firms. Because the data covers all medium-size and large firms, it is informative about aggregate manufacturing sales by industry. Brandt et al. (2012) find that below-scale firms only produced 9.9% of total industrial output in 2004.

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

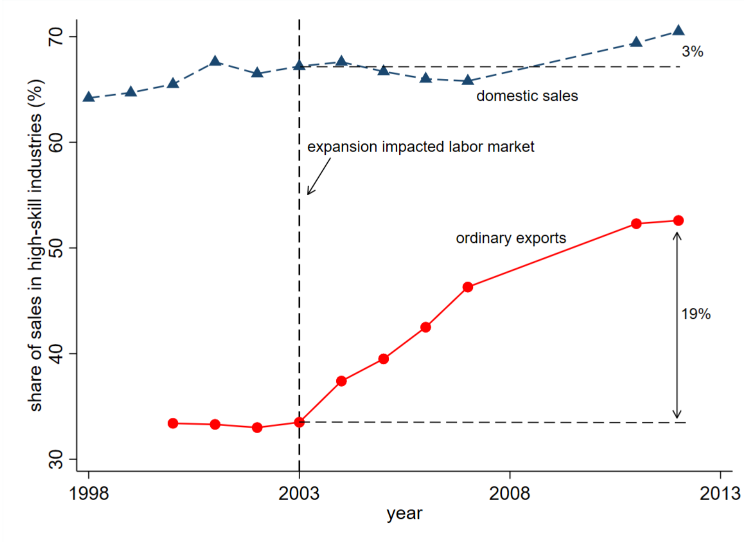


Figure 3: Skill Upgrading of Domestic Sales and Exports

Note: This figure plots the share of sales in high-skill industries separately for domestic sales and ordinary exports. The pattern is computed using ASM 1998–2007 and 2011–2012, as well as Chinese Customs Transactions Database 2000–2016.

exports.[11] Moreover, processing exporters barely innovate,[12] whereas my main focus is on the interaction between trade and innovation. Thus, my empirical results will focus on ordinary exports and exporters that perform ordinary exports (referred to as "ordinary exporters" hereafter), and I will briefly describe the results of processing exports.

Domestic Sales and Ordinary Exports. Figure 3 plots the share of sales in high-skill industries separately for domestic sales and ordinary exports, for years with available data. It shows that ordinary exports shifted strongly to high-skill industries after the college expansion impacted the labor market. In the meantime, domestic sales only moved slightly to high-skill industries. These results indicate that Chinese ordinary exports experienced sizable skill upgrading after the college expansion.

[11]Particularly, in 2005, more than half of China's processing exports were in industry "Computer, Electronic and Optical Equipment," which required high skills for ordinary production but low skills for processing production.

[12]In 2005, firms that only perform processing exports accounted for 6.8% of manufacturing sales but only 1.5% of manufacturing R&D. These two shares for exporters that perform ordinary exports were 30.5% and 44.2%. Note that by using exporters that perform ordinary exports, I do not exclude exporters that perform both ordinary and processing exports in the analysis. This is because these exporters' sales and R&D shares were 16.0% and 17.8%, and their skill intensities were similar to exporters that only perform ordinary exports (see Appendix Table C.3).

Processing Exports. Appendix Figure A.3 reports the share of processing exports in manufacturing exports. After the impact of China's college expansion unfolded in the labor market, this share declined rapidly by 20 percentage points from 55% in 2003 to 35% in 2015. This pattern is in line with the relatively low skill requirements of processing exports compared with ordinary exports. I also find that the industry composition within processing exports also became more skill-intensive over time.

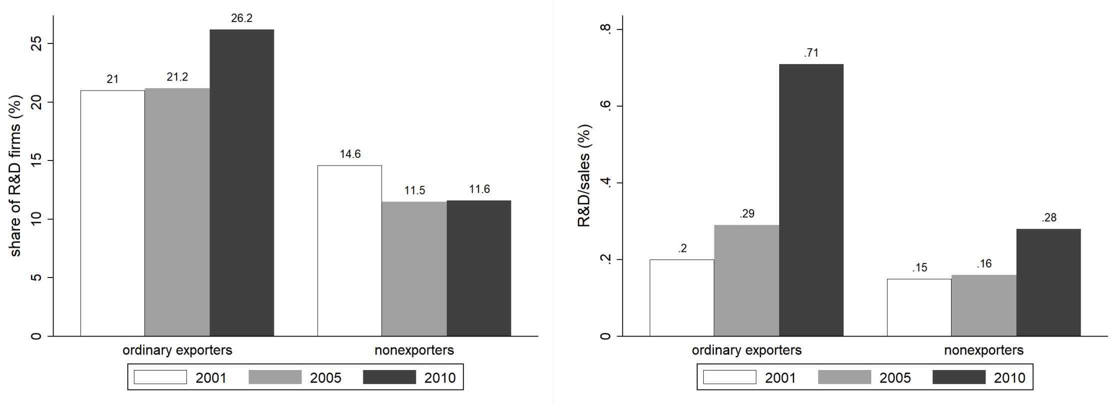
China's WTO Accession. A major policy change related to China's trade is WTO accession in 2001 (e.g., Brandt et al. 2017). Appendix Figures A.4–A.5 show that across 4-digit industries, tariff reductions due to WTO accession were uncorrelated with industry-level skill intensities and R&D intensities, indicating that tariff reductions were an unlikely driver of export skill upgrading and innovation surge. Nevertheless, in the empirical and quantitative analyses, I will explicitly control tariff reductions due to China's WTO accession to avoid its confounding effects.

3.3 Interactions between Exports and Innovation

To gauge the interaction between exports and innovation, I now investigate innovative activities performed by exporters and nonexporters respectively. Because the R&D variable in ASM is only available in 2001–2002 and 2005–2007, I supplement ASM with Chinese State Administration Survey of Tax (SAT) in 2008–2011. SAT records financial information (including R&D) for a sample of 340 thousand manufacturing firms in each year. To lessen the concerns of different sample coverages, 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 C.2 for details on matching firms in different samples).

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.[13] Innovative activities surged more among exporters than nonexporters. The share of R&D firms among exporters increased by 5.0 percentage points between 2005–2010, while the share of R&D firms among nonexporters only rose by 0.1 percentage points. The difference was more considerable in terms of increases in average R&D intensities.

[13] 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.



(a) Share of R&D Firms

(b) R&D/sales

Figure 4: Innovative Activities by Different Firms

Note: This figure plots the share of R&D firms and average R&D intensities, separately among ordinary exporters and non-exporting firms in 2001, 2005, and 2010. The data comes from the balanced firm panels in 2001–2005 and 2005–2010.

Robustness Checks. Appendix C.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 exploit patent data and find large increases in the share of firms with patent applications after 2005, especially among ordinary exporters.

4 Empirical Analysis

The documented facts suggest a potential impact of the college expansion on firms' exports and innovation. In this section, I empirically estimate how the college expansion impacted firms' production and innovation. The exercises serve two purposes. First, they establish the causal relationship and motivate the quantitative model that features firms' innovation and export choices. Second, I will use the reduced-form estimates to discipline two key structural elasticities in the quantitative analysis.

4.1 Supply Shocks of College-educated Workers and Instruments

As the Chinese government stipulated the college expansion policy to stimulate the economy, this policy is endogenous on the national level. To derive causal inference, I exploit regional variation to isolate the presumably exogenous supply changes.

Using Population Censuses, I measure changes in the relative supply of college-educated workers in region l between 2005 and 2010 as:

$$x_l = \left(\frac{H_{l,2010} - H_{l,2005}}{H_{l,2005}} - \frac{L_{l,2010} - L_{l,2005}}{L_{l,2005}} \right), \tag{1}$$

where $H_{l,t}$ ($L_{l,t}$) denotes the amount of college-educated (noncollege) workers in year t.

Region-level changes in the relative supply of college-educated workers can also be endogenous, as productive regions may attract high-skill in-migrants. To disentangle labor supply from demand shocks, I follow the trade literature (e.g., Card 2001, Burstein et al. 2020) to exploit workers' historic distribution to construct a Bartik-type instrument for the change in region l's supply of college-educated workers:

$$x_l^* = \underbrace{\frac{ENROLL_{l,1982}}{ENROLL_{1982}} \times \Delta H_{-l,2005-10}}_{\text{predicted number of graduates in region } l} / H_{l,2005}. \tag{2}$$

Here, $\Delta H_{-l,2005-10}$ represents the total inflow of college-educated workers in China, as measured by the total amount of college graduates between 2005 and 2010, reflecting the aggregate supply-push factor (the expansion of the college system). To lessen the endogeneity concern (some regions may enlarge their local college system), I adopt the leave-one-out adjustment by excluding those who attended colleges in region l from constructing $\Delta H_{-l,2005-10}$. Because the expansion mainly benefited regions with many previously existing colleges, I use the share of region l's college enrollments in national enrollments in 1982, $\frac{ENROLL_{l,1982}}{ENROLL_{1982}}$, to predict each region's benefits from the national expansion of the college system. Overall, x_l^* predicts x_l well: across cities or provinces, the slope of x_l on x_l^* is 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 uncorrelated with the distribution of college resources in 1982. I provide support for this assumption as follows. First, Appendix Figure A.6 shows that the instrument was negatively correlated with changes in local workers' college premium between 2005–2009, but uncorrelated with changes in college premium before 2005. This indicates that regions with higher exposure to the policy shock did not enjoy differential changes in labor demand for educated labor (relative to less-educated labor) before 2005. Second, I will include region fixed effects in all regressions, controlling region-specific characteristics correlated with initial shares of college endowments. Third, I find that the empirical results are robust if I use the college distribution data in 1948 or policy-induced university relocation events in the 1950s to construct alternative instruments, as discussed below.[14]

4.2 Empirical Results

4.2.1 Domestic Sales and Export Growth

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

$$\Delta y_{l,j}(\omega) = \beta_0 + \beta_1 SI_{l,j} x_l + \beta_2 \mathbf{Z}_{l,j}(\omega) + \zeta_l + \epsilon_{l,j}(\omega). \tag{3}$$

For the dependent variable, I separately use log changes in domestic sales, ordinary exports, and production costs for firm ω between 2005 and 2010. Guided by evidence in Section 3.2, I measure exposure to the college expansion for firms in region l and industry j by $SI_{l,j}x_l$, where skill intensity $SI_{l,j}$ is measured by the share of college-educated workers in employment for region l and industry j from ASM 2004. I instrument $SI_{l,j}x_l$ with $SI_{l,j}x_l^*$. I also control for firm-level initial characteristics $\mathbf{Z}_{l,j}(\omega)$, including: (1) output, employment, physical capital, and registration types in 2005; (2) two dummies indicating whether the firm was located in a high-tech zone and whether the firm was in an economic development zone in 2005, which may lead to differential changes in access to R&D subsidies between 2005–2010;[15] and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession.[16] Finally, ζ_l captures region-specific

[14] In Appendix G.6, I calibrate a model with detailed modeling of provinces in China and use province-industry-specific productivity growth to match the observed output growth across provinces and industries. Applying provincial-level college shocks and instruments as constructed by equations (1)–(2), I find that the model-generated data predicts similar regression results regarding production and innovation as in the actual data. This indicates that the IV estimates are robust if the endogeneity concern is productivity growth, and other factors not captured by the model may not substantially bias the IV regressions.

[15] Before 2008, China's R&D subsidies were only available to firms within high-tech zones, whereas starting from 2008, firms outside high-tech zones were also qualified for R&D subsidies after satisfying certain criteria. By incorporating firms' location dummies regarding high-tech zones into the regressions, I allow for changes in access to R&D subsidies to affect firms' shifts in R&D status between 2005 and 2010.

[16] Because tariff reductions were often implemented earlier than the accession agreement mandated and tariff rates barely changed after 2005 (Brandt et al. 2017), I measure tariff reductions due to WTO as changes

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	3.528*** (0.736)	3.493*** (0.742)	1.654*** (0.420)	1.841*** (0.419)	-0.600*** (0.230)	-0.580** (0.232)
Obs	10,161	10,135	40,539	40,459	8,425	8,400
R-squared	0.047	0.067	0.067	0.077	0.020	0.036
First-stage F	407.81	707.66	463.39	717.77	396.51	668.88

Note: This table provides estimates from regressions in equation (3), separately treating regions as cities and provinces. "CE" is short for "college expansion." The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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%.

trends, and hence identification of β_1 relies on within-region different responses of firms across industries (I focus on 2-digit industries to be consistent with the calibration below). This regression specification follows from Burstein et al. (2020) who study the impact of immigration shocks across different occupations in the US commuting zones.

In the model that I will develop in Section 5, the college expansion affected a firm's exports and domestic sales mainly through changes in production costs. To show evidence for this mechanism, since production costs are unobserved, I use export prices as a proxy for production costs. I use free-on-board (FOB) prices, which do not include freight costs. Using firm-level customs data, I construct changes in export prices as the weighted average of changes in firm-level ordinary export prices for each 6-digit HS product that was exported in both 2005 and 2010. The weights are firm-level ordinary export volumes across 6-digit HS products in 2005.

Table 1 presents two sets of regression results, separately treating regions as cities and provinces. The regression results are very similar regardless of the geographic levels used. 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 partic-

in actual input (output) tariffs between 1997 and 2005 (see Appendix Figure A.4). Appendix Table A.1 shows that reductions in input tariffs significantly lowered export prices, as reductions in input tariffs reduced firms' production costs. However, reductions in output tariffs did not significantly affect export prices, as output tariffs are applied to imports and mainly affect import competition in China.

ular, ordinary exports responded more strongly to the college expansion than domestic sales,[17] consistent with the evidence in Section 3.2. One standard-deviation increase in the exposure (0.04) between 2005–2010 would increase domestic sales and ordinary exports in 2010 by around 7% and 14%, while reducing export prices in 2010 by around 2%.

4.2.2 Interaction between Innovation and Exports

I next investigate how the college expansion affected firms' innovation and the interaction between innovation and exports. I perform the same regression as equation (3), but use changes in R&D status (1 if R&D is positive and 0 otherwise) as the dependent variable. Columns (1)–(2) of Table 2 report the regression results separately for firms based on export status in 2005. I only report the results using provincial variation in exposure to the expansion, as city-level results are very similar. Larger exposure to the college expansion induced more innovation, especially among ordinary exporters, confirming the interaction between exports and innovation indicated by Section 3.3. One standard-deviation increase in the exposure (0.04) between 2005–2010 increased the share of R&D firms in 2010 among initial nonexporters and ordinary exporters by 1.6 and 1.8 percentage points, respectively. To avoid the association between firm export entry/exits and changes in innovation returns, in Columns (3)–(4), I restrict the sample to firms that did not switch the export status between 2005–2010 and find similar results as in Columns (1)–(2).

I also explore the responses of the intensive margin of innovation, which is measured by changes in the ratio of R&D to sales between 2005 and 2010.[18] Consistent with Table 2, I still find that larger exposure to the college expansion induced more innovation, especially among ordinary exporters, as shown by Appendix Table A.3.

4.2.3 Robustness Checks

To corroborate the empirical results, I perform several robustness checks with details relegated to Appendix D.

[17] In Appendix Table A.2, I explore the extensive margin of trade by using changes in the export status as the dependent variable in equation (3). I find that with larger exposure to the college expansion, there were more entrants into export activity.

[18] König et al. (2021) find that the amount of R&D expenditures is measured more noisily than the R&D status in China, and thus I use the R&D status as the dependent variable in the baseline regressions.

Table 2: Dependent Variable: Changes in R&D Status between 2005–2010

Dep Var:	Changes in R&D status			
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
	export status in 2005		export status in 2005&2010	
	nonexporter	ord. exporter	nonexporter	ord. exporter
Exposure to CE	0.405***	0.453***	0.307***	0.461***
	(0.104)	(0.155)	(0.096)	(0.175)
Obs	31,139	11,668	26,325	10,161
R-squared	0.016	0.038	0.012	0.041
First-stage F	440.61	413.99	469.00	407.81

Note: This table provides estimates from regressions in equation (3), treating regions as provinces. "CE" is short for "college expansion." The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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%.

Export Product Quality. One main concern of using export prices is that changes in export prices may reflect changes in product quality (e.g., Schott 2004). Whereas it is difficult to directly observe export quality, one observation is that product quality is positively correlated with prices of imported inputs (Manova and Zhang 2012, Fieler et al. 2018). Given this observation, Appendix Section D shows that the prices of imported inputs or the number of imported inputs did not significantly change with exposure to the college expansion. This result indicates that changes in export product prices due to the college expansion may not reflect quality changes.

Feenstra and Romalis (2014) measure China's export quality for 4-digit SITC products between 1984–2011. Even though this measure is not firm-level and based on SITC products, it can be informative of quality discrepancy across industries of different skill intensities (which export different SITC products). Using this product-level quality measure, I find that firms with larger exposure to the college expansion did not experience significant changes in the average export quality of their products.

Alternative Instruments. I use several alternative ways to construct the instrument $SI_{l,j}x_l^*$ to confirm the robustness of regression results. First, as Chinese firms may change labor composition in advance of future sales growth, I use the US Population Census in 1990 to construct industry-level college employment shares $SI_{l,j}$. Second, as the college distribution in 1982 may reflect the current government's regional policies, I use the distribution of colleges in 1948 (before the current government was established) to measure the distribution of historic college resources in x_l^*. Third, I build on China's policy-induced relocation of university departments in the 1950s (Glaeser and Lu 2018) to construct another measure for the distribution of historic college resources in x_l^*. I employ these alternative instruments and find quantitatively similar results as in Tables 1–2.

Alternative Data Construction. First, to avoid firms' switches of export products, I utilize 6-digit HS products exported in both 2005 and 2010 to construct changes in ordinary exports. Second, I use the 2005–2007 data to perform all the regressions to show that my results are not due to the use of different sources of datasets (ASM and SAT). Third, I only use exporters to estimate how changes in domestic sales responded to the college expansion, because the proxy for production costs only applies to exporters. I employ these new data construction approaches in the regressions and find quantitatively similar results as in Tables 1–2. Finally, I construct firm-level exports and export prices separately for each export destination and show that the impact of exposure to the college expansion on export growth is not driven by destination factors.

Pre-trend Test. The recent literature advocates the use of pre-trend tests to corroborate the validity of Bartik instruments (e.g., Goldsmith-Pinkham et al. 2020, Borusyak et al. 2022). I perform pre-trend tests by regressing industry-level changes in sales and innovation between 2000–2005 on the instrumented exposure to the college expansion between 2005–2010. I find that exposure to the college expansion between 2005–2010 had no positive effects on industry-level changes in sales and innovation before 2005 (when exposure was small in magnitude). This result also lessens the concern that the instrument may be correlated with changes in labor demand of certain industries.

5 Quantitative Model

To understand the evidence and conduct the quantitative exercises, I develop a model of trade and innovation. There are two countries, China and Foreign. Each country hosts a number of industries $j = 1, ..., J$. Each country-industry holds many firms that differ in their productivity levels, research efficiency, and export demand. Because almost half of

China's exports were processing exports in the 2000s, I also consider that in China, firms differ in their export regimes. Firms employ two types of workers (educated and less-educated) with different intensities across industries and can pay costs to export. They decide whether to invest in R&D to improve their productivity.

I use i to index China and $i(m)$ to denote Chinese firms engaged in ordinary or processing export regime $m \in \{\mathcal{O}, \mathcal{P}\}$, where $\mathcal{O}$ and $\mathcal{P}$ denote ordinary and processing regimes respectively. I use subscript n to index Foreign and subscript t to index periods.

5.1 Aggregate-level Good Production

5.1.1 Final-good Producers

There is a nontradable final good in each country, assembled by perfectly competitive producers using industry-level intermediate goods $Y_{k,j,t}$:

$$Q_{k,t} = \left(\sum_j \gamma_j Y_{k,j,t}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \ k \in \{i, n\}. \tag{4}$$

$\gamma_j > 0$ governs the expenditure share on goods from industry j. $\theta > 0$ is the elasticity of substitution across industries. The final good can be either used for consumption or used as inputs to produce R&D inputs. The price index for the final good in country k is $P_{k,t} = \left(\sum_j \gamma_j^{\theta} P_{k,j,t}^{1-\theta} \right)^{1/(1-\theta)}$, where $P_{k,j,t}$ is the price index of industry-level goods.

5.1.2 Industry-level Good Producers

In China's industry j, there is a nontradable industry-level good produced by perfectly competitive firms according to:

$$Q_{i,j,t} = \left(\int_{\Omega_{n,i,j,t}} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \int_{\Omega_{i(\mathcal{O}),i,j,t}} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where $\Omega_{n,i,j,t}$ is the set of varieties sourced from Foreign to China, and $\Omega_{i(\mathcal{O}),i,j,t}$ is the set of varieties sourced from domestic ordinary firms. Since processing firms must sell their output overseas, the summation combines varieties sourced from foreign firms and domestic ordinary firms. σ is the elasticity of substitution between varieties within an industry. Industry-level goods $Q_{i,j,t}$ are used to assemble final goods or used as raw materials in firms' production. The price index is $P_{i,j,t} = \left(\int_{\Omega_{n,i,j,t}} p(\omega)^{1-\sigma} d\omega + \int_{\Omega_{i(\mathcal{O}),i,j,t}} p(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$, and the quantity demanded for variety ω is $q(\omega) = p(\omega)^{-\sigma} P_{i,j,t}^{\sigma} Q_{i,j,t}$.

Foreign producers can source from both processing and ordinary firms of China. The production function of industry-level goods in Foreign is given by:

$$Q_{n,j,t} = \left(\int_{\Omega_{n,n,j,t}} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega + \sum_{m\in\{\mathcal{O},\mathcal{P}\}} \int_{\Omega_{i(m),n,j,t}} \epsilon(\omega) q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}. \tag{6}$$

The price index is $P_{n,j,t} = \left(\int_{\Omega_{n,n,j,t}} p(\omega)^{1-\sigma} d\omega + \sum_m \int_{\Omega_{i(m),n,j,t}} \epsilon(\omega)^{\sigma} p(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$. The quantity demanded for a Chinese variety with price $p(\omega)$ is $q(\omega) = \epsilon(\omega)^{\sigma} p(\omega)^{-\sigma} P_{n,j,t}^{\sigma} Q_{n,j,t}$, where $\epsilon(\omega)$ is the export demand shifter, as discussed below.

5.1.3 Research Good

Following Atkeson and Burstein (2010), each country produces a research input:

$$Q_{k,t}^r = A_{k,t}^r \left(\frac{E_{k,t}^r}{1-\gamma_r}\right)^{1-\gamma_r} \left(\frac{H_{k,t}^r}{\gamma_r}\right)^{\gamma_r}, \; k \in \{i, n\}, \tag{7}$$

which requires both final goods $E_{k,t}^r$ and educated labor $H_{k,t}^r$, as R&D costs include both personnel and material costs. The research-good productivity $A_{k,t}^r$ is a residual parameter to capture all other unmodelled factors that can affect innovation levels. The unit price of research goods is $P_{k,t}^r = \frac{\left(P_{k,t}\right)^{1-\gamma_r} \left(S_{k,t}\right)^{\gamma_r}}{A_{k,r}^r}$, where $S_{k,t}$ refers to wages per educated labor.[19]

5.2 Firms' Production, Innovation and Entry/exit

5.2.1 Setup

In China's industry j and export regime m, there is a measure $N_{i(m),j,t}$ of firms. Each firm produces a unique variety indexed by ω and is engaged in monopolistic competition. The

[19] In Appendix G.3, I generalize this cost function to allow for the role of less-educated labor in R&D and imperfect substitution between labor and materials, and the quantitative results are similar.

state of a firm can be characterized by $\mathrm{s}_t(\omega) = \{z_t(\omega), \epsilon_t(\omega), \eta(\omega)\}$. For ease of description, I omit index ω when it causes no confusion. z_t and ϵ_t refer to the firm's productivity and export demand shifter, which evolve over time as typically assumed in the literature (e.g., Aw et al. 2011). η denotes research efficiency, which was drawn upon firm entry. The heterogeneity in export demand shifters and research efficiency will allow the model to match the rich interactions between export participation, innovation choices, and firm productivity levels, as I will show in Section 6.3.

Production Technology. The firm employs H units of educated labor, L units of less-educated labor, and $Q_{j'}$ units of raw materials from industry j' to produce output according to:

$$q = z_t \left[\alpha_{i(m),j} L^{\frac{\rho_x - 1}{\rho_x}} + \left(1 - \alpha_{i(m),j}\right) H^{\frac{\rho_x - 1}{\rho_x}}\right]^{\frac{\rho_x \gamma^L_{m,j}}{\rho_x - 1}} \prod_{j'=1}^{J} Q_{j'}^{\gamma^{j'}_{i(m),j}}. \tag{8}$$

$\alpha_{i(m),j}$ governs the skill intensity in industry j and export regime m, and a higher value of $\alpha_{i(m),j}$ implies more intensive use of less-educated labor in production and thus a lower skill intensity. ρ_x determines the elasticity of substitution between educated and less-educated labor. I also incorporate intermediate inputs.[20] $\gamma^{j'}_{i(m),j}$ is the share of costs spent on raw materials from industry j', and $\gamma^L_{i(m),j}$ is the share of costs spent on labor, with constant returns to scale, $\gamma^L_{i(m),j} + \sum_{j'} \gamma^{j'}_{i(m),j} = 1$.

Given these assumptions, the unit cost of the input bundle for firms with $z_t = 1$ is:

$$c_{i(m),j,t} = \Phi_{i(m),j} \left[\frac{\left(\alpha_{i(m),j}\right)^{\rho_x}}{W_{i,t}^{\rho_x - 1}} + \frac{\left(1 - \alpha_{i(m),j}\right)^{\rho_x}}{S_{i,t}^{\rho_x - 1}}\right]^{\frac{\gamma^L_{i(m),j}}{1-\rho_x}} \prod_{j'} P_{i,j',t}^{\gamma^{j'}_{i(m),j}}. \tag{9}$$

[20]Considering intermediate inputs is due to two reasons. First, China stopped publishing value-added data for manufacturing firms after 2007, and thus this paper's facts and reduced-form evidence were based on firm sales. Assuming intermediate inputs (which are included in sales) allows the model to match the evidence. Second, input-output linkages are important for understanding quantitative effects (Caliendo and Parro 2015). For this study, compared with the baseline results, assuming no intermediate inputs would quantitatively overestimate the impact of the college expansion on export skill upgrading by about 80% and innovation by about 20%. This is because, in the absence of intermediate inputs, firm production costs only rely on labor costs, and thus the decline in skill premium after the college expansion would lead to larger reductions in production costs and faster export expansion for high-skill industries.

$\Phi_{i(m),j}$ is a constant.[21] $S_{i,t}$ and $W_{i,t}$ are wage rates of educated and less-educated labor.

Operating and Trade Costs. Firms pay fixed costs $f_{i(m),j}$ per period to remain in business. Selling to the foreign market incurs additional fixed costs $f^X_{i(m),j}$. The fixed costs are in units of final goods. Firms pay iceberg costs $d_{i(m),n,j,t} \geq 1$ if exporting to the foreign market. The export iceberg costs are time-variant to incorporate tariff changes due to China's WTO accession.[22] Firms also pay iceberg costs $d_{i(m),i,j}$ if selling to the domestic market. I normalize the iceberg costs of Chinese ordinary firms for selling domestically to 1, $d_{i(\mathcal{O}),i,j} = 1$. Because processing firms cannot sell domestically, I have $d_{i(\mathcal{P}),i,j} \to \infty$.

Productivity Evolution and Innovation. The productivity of a firm in industry j and export regime m evolves in the end of the period as:

$$\Delta \log z_t = \underbrace{g_{i(m),j,t}}_{\text{aggregate growth}} + \underbrace{\xi}_{\text{idiosyncratic shock}} + \underbrace{i}_{\text{research intensity}} \times \underbrace{\eta}_{\text{research efficiency}} . \tag{10}$$

The first term $g_{i(m),j,t}$ captures exogenous productivity growth in industry j and export regime m, and the second term represents idiosyncratic productivity shocks $\xi \sim \mathcal{N}(0, \sigma_\xi)$. The third term $i \times \eta$ represents the fruits of innovation. A firm with R&D investment level i spends $\bar{z}_t^{\sigma-1}\phi_{1,j}\mathbf{1}_{\{i>0\}} + z_t^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}$ units of research goods. The fixed costs of innovation $\bar{z}_t^{\sigma-1}\phi_{1,j}$ depend on the average productivity $\bar{z}_t$ in industry j and export regime m. The dependence of variable innovation costs $z_t^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}$ on the firm's own productivity $z_t^{\sigma-1}$ aims to let innovation costs be proportional to firm sales, otherwise productive firms would have higher R&D investment level i simply because they are productive, in contrast with evidence in the literature (see Klette and Kortum 2004).[23] 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, which implies $\chi > 0$. The step size of innovation is larger for a firm with higher research efficiency η.

This innovation process builds on Atkeson and Burstein (2010), enriched to allow for

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

[22] 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 et al. (2015) and Liu and Ma (2023).

[23] The 2005 ASM data shows that the share of R&D firms increased with firm size, and the R&D intensity (R&D/sales) of actively innovating firms slightly decreased with firm size. My setup of R&D costs can generate a similar R&D pattern, as with fixed costs of innovation, only very research-efficient firms select into innovation among small firms.

fixed costs and heterogeneous costs across industries. First, with fixed costs of innovation, firms with low research efficiency opt out of innovation, in line with the fact that only a small portion of firms perform innovative activities, even among large firms (see Figure 6). Second, because more skill-intensive industries tend to be more innovative in reality, reallocating production to more skill-intensive industries can promote innovation.

Evolution of Demand Shifters. In the end of the period, export demand shifter ϵ_t evolves according to a log-normal AR(1) process, independently across firms, with autocorrelation parameter ρ_ϵ and standard deviation σ_ϵ of Gaussian white noises.

Firm Entry. In period t, an *exogenous* measure $N^e_{i(m),j,t}$ of new firms enter industry j and export regime m. As in Luttmer (2007), an entrant draws productivity z from the distribution of incumbent firms. Its productivity is given by $\exp(-\delta_p)z$, with $\delta_p > 0$ capturing imperfect imitation. Upon entry, it draws research efficiency $\log \eta \sim \mathcal{N}(0, \sigma^2_\eta)$ and export demand shifter ϵ from the ergodic distribution.

Firm Exits. After firm entry occurs, incumbent firms and new firms face an exogenous death rate δ. A firm that does not exit exogenously can still cease to operate if its value from continuing to operate is negative.

5.2.2 Solving Firm's Problem

Static Problem: Optimal Price and Export Participation. Because firms' production technology is constant-returns-to-scale, a firm in industry j and export regime m maximizes profits for each market separately. For the foreign market, the firm chooses the price p and whether to export ($\mathbf{1}_X \in \{0, 1\}$) to maximize profits:

$$\begin{aligned} \pi_{i(m),n,j,t}(\mathbf{s}_t) = \max_{p,\mathbf{1}_X} & \left(pq - \frac{c_{i(m),j,t} d_{i(m),n,j,t}}{z_t} q - P_{i,t} f^X_{i(m),j} \right) \mathbf{1}_X, \\ \text{s.t.} \quad & q = \epsilon^\sigma_t p^{-\sigma} P^\sigma_{n,j,t} Q_{n,j,t}. \end{aligned} \tag{11}$$

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

$$p^*_{i(m),n,j,t}(\mathbf{s}_t) = \frac{\sigma}{\sigma - 1} \frac{c_{i(m),j,t} d_{i(m),n,j,t}}{z_t}. \tag{12}$$

The firm will only export ($\mathbf{1}_X = 1$) if the profits from export participation are positive. I can analogously compute the profits of selling to the domestic market $\pi_{i(m),i,j,t}(\mathbf{s}_t)$, except for no fixed costs of selling. Firms in processing export regime ($m = \mathcal{P}$) cannot sell domestically with trade costs $d_{i(\mathcal{P}),i,j}$ being prohibitively large and $\pi_{i(\mathcal{P}),i,j,t}(\mathbf{s}_t) = 0$.

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

$$
\begin{aligned}
V_{i(m),j,t}(\mathbf{s}_t) = \max_{i \geq 0} \Bigg[& \underbrace{(1-\zeta_t(\mathbf{s}_t))\left(\pi_{i(m),n,j,t}(\mathbf{s}_t) + \pi_{i(m),i,j,t}(\mathbf{s}_t)\right)}_{\text{after-tax profits}} - \underbrace{f_{i(m),j} P_{i,t}}_{\text{operating costs}} \\
& - \underbrace{\left(\bar{z}_t^{\sigma-1}\phi_{1,j}\mathbf{1}_{\{i>0\}} + z_t^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}\right)P_{i,t}^r}_{\text{innovation costs}} + \frac{1-\delta}{1+r}\mathbb{E}\underbrace{\max\{V_{i(m),j,t+1}(\mathbf{s}_{t+1}),0\}}_{\text{next-period value}}\Bigg], \\
\text{s.t.} \quad & \Delta \log z_t = g_{i(m),j,t} + \xi + i \times \eta, \quad \log \epsilon_t \sim \text{AR(1)}.
\end{aligned} \tag{13}
$$

The firm's value includes after-tax profits net of operating and innovation costs in the current period, as well as the next-period value. Consistent with Chen et al. (2021), the profit tax rate $\zeta_t(\cdot)$ depends on the size of firm sales and R&D intensity (sales/R&D), reflecting the policy regarding R&D tax incentives. The term $\max\{V_{i(m),j,t+1}(\mathbf{s}_{t+1}),0\}$ is the next-period value of the firm, reflecting endogenous exits when the firm value is negative. The tax revenue collected from local firms is spent on local final goods, and firm owners also spend the net profits on local final goods.

5.2.3 Foreign Firms

In industry j, there is a measure $N_{n,j,t}$ of foreign firms. I assume that each foreign firm draws productivity z from an exogenous distribution $G_{n,j,t}(z)$, and their production technology is analogous to that of Chinese ordinary firms in equation (8) with input-output linkages $\{\gamma_{n,j}^{j'}, \gamma_{n,j}^{L}\}$. If foreign firms export to China, they need to pay iceberg costs $d_{n,i,j,t}$. For simplicity, there are no fixed costs for foreign firms. As I abstract from foreign firms' innovation, the foreign firm's problem is a static problem of deciding optimal prices for each destination and can be similarly characterized as in equations (11)–(12).

5.3 Workers

I explicitly model workers' age structure following Card and Lemieux (2001), as Figure 7 below reveals that China's college expansion had much stronger negative effects on the college premium of young workers than that of older ones.[24] Each worker lives for T periods and supplies one unit of labor inelastically in each period. At the end of each period, old workers of age T retire, and new workers enter and start working in the next period. I denote the amount of age-a educated and less-educated workers in country k as $H_{k,a,t}$ and $L_{k,a,t}$, respectively. The supply of labor services of educated (less-educated) labor in country k is a CES function of educated (less-educated) workers of different age groups,

$$H_{k,t} = \left(\sum_{a=1}^{T} \beta_a^H H_{k,a,t}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \quad L_{k,t} = \left(\sum_{a=1}^{T} \beta_a^L L_{k,a,t}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \; k \in \{i, n\}, \tag{14}$$

where $\beta_a^I, I \in \{H, L\}$ captures the relative productivity of workers of different ages. $\rho_a > 1$ governs the elasticity of substitution of workers across different ages.

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

$$S_{k,a,t} = \left(\frac{H_{k,a,t}}{H_{k,t}} \right)^{-\frac{1}{\rho_a}} \beta_a^H S_{k,t}, \quad W_{k,a,t} = \left(\frac{L_{k,a,t}}{L_{k,t}} \right)^{-\frac{1}{\rho_a}} \beta_a^L W_{k,t}. \tag{15}$$

Equation (15) 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 educated workers leads to a lower wage for young cohorts relative to that of older cohorts, in line with the evidence in Figure 7 below. I assume that workers spend all their income on final goods.

There are persistent wage differences between agriculture and non-agriculture in China (e.g., Zilibotti et al. 2019, Gai et al. 2020). Thus, I assume that wages in agriculture are a portion c_{agr} of nonagricultural wages in China and that workers are indifferent between

[24] 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 US, the UK, and Canada. Appendix G.5 provides a model extension that interprets reductions in young workers' college premium as reflecting declining workers' abilities, and quantitative findings are similar.

two sectors despite wage differences.[25] This assumption is important to match that almost half of Chinese workers were working in agriculture in the early 2000s.

5.4 Equilibrium

For year t, define $\mathcal{L}_t = \{H_{k,a,t}, L_{k,a,t}\}$ as the distribution of labor across countries and ages, and $\mathcal{N}_t = \{N_{i(m),j,t}(\mathbf{s}), N_{n,j,t}(z)\}$ as the distribution of firms across regions and industries, where $N_{i(m),j,t}(\mathbf{s})$ is the measure of Chinese firms in industry j and export regime m with state s, and $N_{n,j,t}(z)$ is the measure of foreign firms in industry j with productivity z.

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 and initial distributions: (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 the entry of new workers and retirement of old workers. I characterize the sequential equilibrium in more detail in Appendix E.1.

5.5 Main Forces at Work

This subsection solves a simplified model to highlight the model mechanisms about how a supply shock of educated labor affects exports and innovation. For analytical tractability, I abstract from firm entry, input-output linkages, and operation costs. I consider one period in which innovation will instantly improve firm productivity.[26] Finally, I assume that variables in Foreign are not affected by China's labor supply shock, given a low share of foreign expenses on China's exports in reality.[27] The firm's problem in the simplified

[25]To rationalize wage differences between agricultural and nonagricultural sectors in China, Zilibotti et al. (2019) assume that the government taxes wages in nonagriculture, and Tombe and Zhu (2019) consider migration costs from agricultural to nonagricultural work.

[26]In this simplified model, I consider a static innovation decision for tractability, which overlooks several economic forces that may affect innovation and are embedded in the quantitative model: (1) in the quantitative model with many periods, current innovative activities can change firms' productivity levels and thus affect future innovative activities; and (2) there are interactions between innovation and entry/exits of firms, as will be discussed in Section 7.5.1.

[27]Despite China being viewed as a "world factory," the share of foreign manufacturing expenses spent on Chinese goods was only around 2.6% in 2005 (which reflects cross-border trade barriers), according to

model and all the proofs of propositions are present in Appendix E.2.

In what follows, I denote $\hat{x} = \log\left(\frac{x'}{x}\right)$ as the proportional change from the initial to the current equilibrium for variable x. I omit the subscript for time.

Proposition 1 (**Wage Response**). In a closed economy with no innovation,

$$\hat{S}_i - \hat{W}_i = -\Phi_i(\hat{H}_i - \hat{L}_i),$$

where the constant $\Phi_i > 0$.

This proposition is intuitive: the skill premium (the relative wage of educated to less-educated labor) declines in response to an influx of educated labor in China. Although I imposed some assumptions for tractability, this result holds in more general scenarios: a large empirical literature shows 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 empirically that the skill premium experienced larger reductions in Chinese regions with greater exposure to the college expansion, as already discussed in Section 4.1.

Denote $R_{i,j}$ and $R_{n,j}$ as domestic sales and exports by a Chinese ordinary firm in industry j. For ease of description, I omit the index for firm productivity and export regime. Let $SI_{i,j}$ be the share of educated labor's wage bills in total labor costs for ordinary production in China's industry j. The next proposition shows that trade facilitates the shift of industry composition to accommodate the influx of educated labor.

Proposition 2 (**Domestic Sales and Export Growth**). Assume that there is no innovation and that a supply shock of educated labor alters the skill premium in China, $\hat{W}_i - \hat{S}_i > 0$.[28]

(i) Proportional changes in domestic sales and exports are:

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

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

the World Input-Output Table.

[28]As some firms may not export, Result (i) focuses on the impact of the shock on the intensive margin of exports, whereas Result (iii) focuses on the impact of the shock on the extensive margin of exports.

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

(ii) If $\sigma > \theta \geq 1$, firms in more skill-intensive industries experience faster growth in domestic sales and even faster growth in exports.

(iii) If the density of firms around the export threshold is identical in two industries, the more skill-intensive industry also enjoys more export entry.

Result (i) indicates how firm sales change in response to lower skill premium, which reduces production costs by $SI_{i,j}\left(\hat{W}_i - \hat{S}_i\right)$ for industry j.[29] Firms' domestic sales change due to two reasons. First, the cheaper aggregate prices of more skill-intensive industries 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 $\Pi_{i,i,j}$ (as all Chinese producers gain the reduction in production costs). Second, Chinese 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 firms to export more, the strength of which is governed by within-industry elasticity of substitution σ. By assumption, foreign industry-level aggregate prices do not change (see footnote 27 for an explanation), and thus exports are not affected by between-industry demand reallocation. In the next section, I will combine the reduced-form estimates in Section 4.2.1 with Result (i) to discipline the elasticities of substitution $\{\sigma, \theta\}$.

Result (ii) shows if $\sigma > \theta \geq 1$, firms in more skill-intensive industries experience faster growth in domestic sales and even faster growth in exports. Thus, there is faster skill upgrading of exports than domestic sales after an influx of educated labor, in line with the evidence in Section 3.2.[30] In the next section, I will confirm that my reduced-form evidence also implies $\sigma > \theta \geq 1$. Finally, Result (iii) shows that lower costs in more skill-intensive industries also encourage more export entry, which reinforces larger export expansion in these industries and is consistent with my evidence (Appendix Table A.2).

Finally, I look into innovation. With little abuse of notations, I interpret $R_{i,j}$ and $R_{n,j}$ as the amount of a firm's domestic sales and exports before any innovation. An influx

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

[30] 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), as empirically found in Broda and Weinstein (2006).

of educated labor alters innovation through two channels: (1) affecting research costs P_i^r uniformly across all firms; and (2) affecting innovation returns by changing before-innovation profits $\frac{R_{i,j}}{\sigma} + \mathbf{1}_X(\frac{R_{n,j}}{\sigma} - f_{i,j}^X)$, which varies across firms of different skill intensities and export exposure levels. Proposition 3 summarizes changes in innovation returns.

Proposition 3 (**Interactions between Exports and Innovation**).

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

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

which if $\sigma > \theta \geq 1$, increases with skill intensity $SI_{i,j}$ and export share $\frac{R_{n,j}}{R_{i,j}+R_{n,j}}$.

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

Faced with an influx of educated labor, firms in more skill-intensive industries enjoy faster sales growth, especially when they export intensely. The larger sales increase the returns of innovation, leading to more innovative activities. This interaction between exports and innovation increases aggregate R&D, as more skill-intensive industries are also more innovative in reality.

In the model, the interaction between trade and innovation stems from market size effects (Schumpeter 1942, Acemoglu and Linn 2004), which is supported by the extensive evidence in both China and other countries (e.g., Lileeva and Trefler 2010, Bustos 2011, Liu et al. 2021). The literature also finds that trade can affect innovation through other channels, such as competition, as technology-advanced firms and laggard firms may adopt different innovation strategies in response to trade openness (e.g., Muendler 2004, Aghion et al. 2018).[31] Quantitatively analyzing the competition channel usually requires adopting a quality-ladder model with many product quality segments and step-by-step innovation (see e.g., Akcigit et al. 2018, Lim et al. 2018). While incorporating the competition channel is limited by my model setting, it is likely that considering the competition channel may amplify the impact of the college expansion on innovation.[32]

[31] Another strand of literature focuses on the selection effects induced by competition, as low-productivity firms exit due to more competition after trade liberalization, which can facilitate technology adoption and spillovers (e.g., Sampson 2016, Impullitti and Licandro 2018, Perla et al. 2021).

[32] The quality-ladder model with step-to-step innovation usually predicts that the innovation intensity

6 Model Calibration

In this section, I discuss the procedure to calibrate the model to the data. I then describe the parameter values and the model fit.

6.1 Data

I calibrate the model to 33 industries (30 manufacturing industries, agriculture, mining, and services) in two countries—China and a constructed Rest of World—between 2000 and 2018. I combine aggregate and micro-level data on labor markets, production, innovation, and trade flows, with the data sources detailed in Appendix F.3.

In the model, there are two types of workers—educated and less-educated labor. I classify college-educated workers in the data as educated labor.[33] And I classify workers with high-school degrees or lower education levels in the data as less-educated labor. Because different education levels may imply different productivity levels, I adjust workers of education levels lower than high school to the equivalents of high-school graduates, using their relative wages in 2005.

6.2 Calibration Procedure

The model cannot be directly solved by the "Exact Hat" approach, because the model does not yield an analytical aggregation especially due to firms' heterogeneous innovation choices. I now describe my calibration procedure.

6.2.1 Exogenously Calibrated Parameters

Table 3 presents the set of pre-determined parameters. One period in the model is one year. I set $T = 45$ years for the length of the working life (aged 20–64).[34]. I obtain

becomes the highest at neck-and-neck position due to the "escape-competition" effect (e.g., Akcigit et al. 2018). As Chinese firms were probably technology laggards in the 2000s given low TFP levels (Zhu 2012), the innovation induced by the college expansion would allow Chinese firms to catch up with technology leaders, which may further intensify their innovation incentives due to the "escape-competition" effect.

[33]Because most data does not distinguish between college-educated workers with regular degrees and those with part-time degrees, I take into account college graduates with part-time degrees (adjusted to the equivalents of college graduates with regular degrees using relative wages) to target the data moments.

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

Table 3: Exogenously Calibrated Parameter Values

Notation	Value	Description	Source
(1) T	45	Workers' lifetime	Data
(2) $\{\gamma^L_{i(m),j}, \gamma^{j'}_{i(m),j}\}$		China's Input-output linkages	China I/O Table
(3) $\{\gamma^L_{n,j}, \gamma^{j'}_{n,j}\}$		World's Input-output linkages	World I/O Table
(4) $\{H_{k,a,t}, L_{k,a,t}\}$		Number of college and noncollege labor	Data
(5) $\zeta_t(\cdot)$		R&D tax incentives	Chen et al. (2021)
(6) $\{N_{n,j,t}\}$		Number of foreign firms	Data
(7) θ	3.0	Between-industry elasticity	Evidence in Table 1
(8) σ	6.9	Within-industry elasticity of substitution	Evidence in Table 1
(9) κ	6.49	Shape parameter of foreign firms' productivity dist	Axtell (2001)

the amount of college-educated and noncollege workers in each age group across years $\{H_{k,a,t}, L_{k,a,t}\}$ from the data. I calibrate input-output linkages using China's and the World Input-Output Tables in 2005. The schedule of China's R&D tax incentives in each year $\zeta_t(\cdot)$ is drawn from Chen et al. (2021).[35] I obtain the number of foreign firms in each industry and year $\{N_{n,j,t}\}$ from the data.

I use reduced-form evidence in Section 4.2.1 to discipline between-industry and within-industry elasticities of substitution (θ and σ), which govern the growth of domestic demand and exports after the college expansion. Result (i) in Proposition 2 indicates that the responses of ordinary exports, export costs, and domestic sales to the college expansion (estimated by equation (3)) have the following relationship:[36]

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

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

[35] Before 2008, firms with R&D intensity larger than 5% were qualified to enjoy a reduction in profit tax rates from 33% to 15%. After 2008, firms were qualified to reduce profit tax rates from 25% to 15% with R&D intensity: (1) larger than 6% if their sales were smaller than 50 million RMB; (2) larger than 4% if their sales were between 50–200 million RMB; or (3) larger than 3% if their sales were larger than 200 million RMB. Appendix G.4 also considers that the coverage of R&D tax incentives changed over time, and shows that quantitative results are similar.

[36] As shown in Proposition 2, when there is a supply shock of educated labor that lowers the skill premium, a firm in industry j has a reduction of $SI_{i,j}(\hat{W}_i - \hat{S}_i)$ in production costs. Its domestic sales and exports increase by $[(\theta-1)\Pi_{i,i,j} + (\sigma-1)(1-\Pi_{i,i,j})]\, SI_{i,j}(\hat{W}_i - \hat{S}_i)$ and $(\sigma-1)SI_{i,j}(\hat{W}_i - \hat{S}_i)$, respectively. The ratio of the response of domestic sales to that of production costs is $[(\theta-1)\Pi_{i,i,j} + (\sigma-1)(1-\Pi_{i,i,j})]$, and the ratio of the response of exports to that of production costs is $(\sigma - 1)$.

to the regression results based on provincial shocks in Table 1, the resulting θ and σ are 3.0 and 6.9.[37] As Proposition 2 was obtained from a simplified model, Appendix F.2 shows that Result (i) of Proposition 2 still holds in the full-fledged quantitative model when I use it to discipline the structural elasticities.

Finally, I parameterize the foreign firm's productivity to be Pareto-distributed, $G_{n,j,t}(z) = A_{n,j,t}z^{-\kappa}$. I choose $\frac{\kappa}{\sigma-1} = 1.1$ such that the Pareto parameter of foreign firms' employment distribution is 1.1, matching the evidence for the US firms (Axtell 2001).

6.2.2 Internally Calibrated Parameters

I now describe two steps to internally calibrate the remaining parameters using the simulated method of moments. Although the parameters are jointly estimated in each step, Table 4 orders data moments in a sequence that relates the moments to the most relevant parameters. I use the subscript to denote the dimension of parameter values (m: export regime; j: industry; t: time) if the parameter is multi-valued along any dimension. The details on the construction of moments are provided in Appendix F.4.

Step 1 of Calibration. As shown in Appendix E.1, given labor and firm distributions,[38] the model is a static trade model. Thus, I exploit these distributions in 2005 and calibrate production-related parameters $\{\gamma_j, \gamma_r, \alpha_{i(m),j}, c_{agr}, \beta_a^H, \beta_a^L, \frac{\sigma_\epsilon^2}{1-\rho_\epsilon^2}\}$ as well as international trade costs $\{d_{i(m),n,j,2005}, d_{n,i,j,2005}, f^X_{i(m),j}\}$ to target the relevant moments. For instance, international trade costs $\{d_{i(m),n,j,2005}, d_{n,i,j,2005}\}$ are disciplined by export and import shares in each Chinese industry and export regime in 2005, and I combine these costs with tariff changes across years to compute international trade costs in other years. Fixed export costs $f^X_{i(m),j}$ are informed by the share of exporters in each industry. After the first step of calibration, I calibrate firms' operation costs $\{f_{i(m),j}\}$ to equal the lowest profits among operating firms for each China's industry-regime pair.

[37] The resulting θ and σ from the regression results based on city-level shocks are similar (3.5 and 7.0). My estimates are comparable to Broda and Weinstein (2006) who report that the within-industry elasticity of substitution for varieties from different countries was on average 6.8 (averaged across 3-digit SITC industries) between 1972–1988.

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

Table 4: Internally Calibrated Parameter Values

Notation	Value	Description	Targeted Moments	Model	Data
			Panel A: Step 1 of Calibration		
(1) $\{\gamma_j\}_j$	0.03 (0.03)	Share of industry-level goods	Output relative to services	0.05 (0.17)	0.05 (0.17)
(2) γ_r	0.47	Cost share of college labor in R&D	Share of full-time R&D workers	0.69%	0.69%
(3) $\{\beta_a^H, \beta_a^L\}_a$	0.07 (0.02)	Age-specific productivity	Wages rel. to youngest workers	1.18 (0.13)	1.18 (0.13)
(4) $\{\alpha_{i(m),j}\}_{m,j}$	0.72 (0.09)	Skill intensities	$\{$ College employment shares	0.11 (0.06)	0.14 (0.09)
			Aggregate college premium	0.64	0.64
(5) $\frac{\sigma_\epsilon^2}{1-\rho_\epsilon^2}$	0.24	Variance of export demand	Std of export-output ratios	0.27	0.29
(6) c_{agr}	0.24	Wages in agri rel. to nonagriculture	Share of agricultural employment	0.43	0.45
(7.1) $\{d_{i(m),n,j,2005}\}_{m,j}$	1.36 (2.08)	Export costs	Share of foreign expenses on China's exports	0.02 (0.03)	0.02 (0.03)
(7.2) $\{d_{n,i,j,2005}\}_j$	6.01 (7.31)	Import costs	Share of Chinese expenses on imports	0.38 (0.35)	0.36 (0.36)
(8) $\{f_{i(m),j}^X\}_{m,j}$	$2e{-}4(3e{-}4)$	Chinese firms' marketing costs	Share of Chinese firms that export	0.17 (0.11)	0.17 (0.11)
			Panel B: Step 2 of Calibration		
(1.1) $\{g_{i(m),j,t}\}_{m,j,t}$	-0.02 (0.10)	Exg. productivity growth	$\{$ China's industry-regime-level output growth (before 2011)	0.09 (0.20)	0.08 (0.05)
			China's GDP growth rel. to foreign (after 2011)	0.08 (0.05)	0.09 (0.06)
(1.2) $\{A_{n,j,t}\}_{j,t}$	1.38 (0.98)	Productivity of foreign firms	Foreign industry-level output (before 2011)	0.05 (0.17)	0.05 (0.17)
(2) $\{N_{i(m),j,t}^e\}_{m,j,t}$	21,222 (88,497)	Num of firm entrants	Changes in num of firms	10,941 (85,214)	10,944 (85,215)
(3) σ_ξ	0.07	Std of productivity growth	Std of sales growth for upper 10% firms	0.42	0.42
(4) δ	0.1	Exogenous exit rates	Exit rates for upper 10% firms	0.10	0.10
(5) δ_p	0.08	Imperfect imitation parameter	Sales of entrants rel. to incumbents	0.68	0.66
(6) ρ_ϵ	0.8	Autocorrelation of export demand	Autocorrelation of log ord. exports	0.71	0.75
(7) σ_η	1.6	Std of research efficiency	Std of R&D intensity among R&D firms	0.024	0.022
(8) χ	0.76	Convexity of innovation costs	Slope of sales growth on R&D intensity	2	2
(9.1) $\{\phi_{1,j}\}_j$	$4e{-}5(4e{-}5)$	Fixed costs of innovation	Share of R&D firms, by industry	0.10 (0.08)	0.10 (0.08)
(9.2) $\{\phi_{2,j}\}_j$	87.26 (286.02)	Variable costs of innovation	R&D intensity, by industry	0.006 (0.006)	0.006 (0.006)
(10) $\{A_{i,t}^r\}_t$	2.86 (1.52)	Time trend of research productivity	Each year's manufacturing R&D intensity	0.008 (0.002)	0.008 (0.002)
(11) ρ_x	1.5	Elast. btw college/noncollege labor	Changes in college premium btw 2003–2009	-0.01	-0.01
(12) ρ_a	3.3	Elast. of labor across age groups	Wage difference btw young/old college labor in 2009	-0.45	-0.45

Notes: For parameters and the corresponding moments with multiple values, I report the averages across all the values, with standard deviations of these values in parenthesis.

Step 2 of Calibration. I then calibrate the parameters regarding productivity evolution and firm entry/exits $\{g_{i(m),j,t}, N^e_{i(m),j,t}, A_{n,j,t}, \sigma_\xi, \delta, \delta_p, \rho_\epsilon\}$, innovation $\{\chi, \sigma_\eta, \phi_{1,j}, \phi_{2,j}, A^r_{i,t}\}$, and the labor elasticities $\{\rho_x, \rho_a\}$. For each China's industry and regime, the productivity drift $\{g_{i(m),j,t}\}$ and the number of new firms $\{N^e_{i(m),j,t}\}$ are informed by changes in output and changes in the number of operating firms over time. 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 average R&D intensity in 2005. The convexity of innovation costs χ is mainly disciplined by the slope of sales growth on R&D intensity. I use the time-variant residual parameter $A^r_{i,t}$ to perfectly match aggregate manufacturing R&D intensity in 2000–2018, capturing unmodelled factors that affect innovation levels. Finally, as the labor elasticities ρ_x and ρ_a determine relative wages across labor types and ages, I calibrate these two parameters to target the changes in aggregate college premium between 2003–2009 and the relative wages between young (less than 28 years old) and old (aged 29+) college-educated workers in 2009.

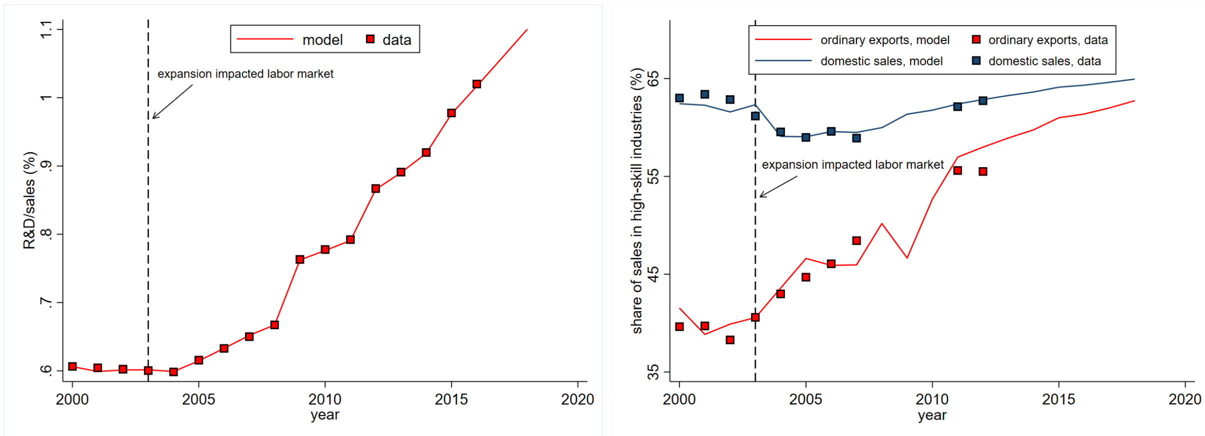
6.3 Calibration Results

Parameter Values. Table 4 reports the calibrated parameter values, which are reasonable compared with the literature. For instance, the calibrated elasticities of substitution between college-educated and high-school workers and across ages are 1.5 and 3.3 respectively, similar to the typical values found in the macro literature (e.g., Katz and Murphy 1992, Card and Lemieux 2001).[39] The convexity of innovation costs χ is 0.76, implying the elasticity of successful innovation to R&D costs is $\frac{1}{1+\chi} = 0.57$, close to 0.5 typically used in the literature (see Acemoglu et al. (2018) for a review). The share of labor costs in R&D costs is $\gamma_r = 0.47$, which is also in the ballpark of the estimates from other economies.[40]

Targeted Moments. Table 4 shows the model matches the targeted data moments well. Figure 5 shows that the model can replicate the documented pattern of China's inno-

[39]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 it to be 2.5. Card and Lemieux (2001) find the elasticity of substitution across age groups to be 5.

[40]According to enterprise data in the OECD Database, the share of labor costs in R&D (averaged between 2000–2018) was 0.61 in the US, 0.47 in the UK, 0.57 in France, and 0.60 in Germany. As for Asian economies, the share was 0.41 in Singapore, 0.41 in Japan, 0.53 in Taiwan, and 0.43 in Korea.



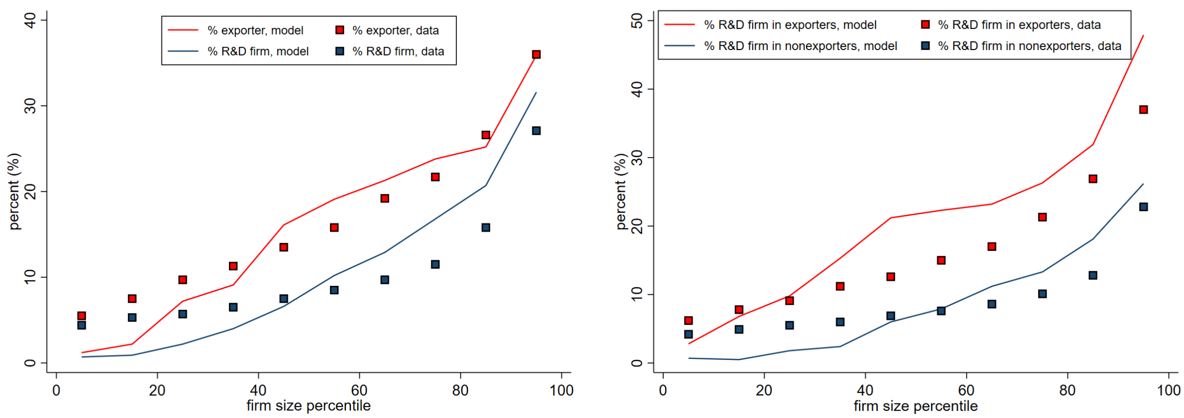
(a) R&D/sales (b) Export Skill Upgrading

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

Note: This figure plots the ratio of R&D to sales (left-hand panel) and the share of sales in high-skill industries separately for domestic sales and ordinary exports (right-hand panel), using the model-generated data and the actual data.

vation surge and export skill upgrading. Panel (a) presents yearly manufacturing R&D intensity. As I targeted the overall trend of manufacturing R&D intensity using changes in aggregate research productivity, the model replicates the data well. Panel (b) reports the time-series pattern of the share of sales in high-skill industries for domestic sales and ordinary exports, respectively. Even though I did not directly target domestic sales and ordinary exports, the model predicts similar skill upgrading patterns as in the actual data. In particular, relative to domestic sales, China's ordinary exports experienced sizable skill upgrading after the college expansion. Appendix Figure A.8 shows that the model can also replicate changes in the share of processing exports.

Untargeted Moments. Figure 6 presents the distribution of export and R&D activities among manufacturing firms in 2005. Panel (a) shows that the model can replicate the shares of R&D firms and exporters across firm size percentiles. Panel (b) shows that the model can reconcile with the observed differences in R&D activities between exporters and nonexporters. Figure 7 shows that in the 2000s, the model and the data both predict a decline in young workers' college premium and an increase in old workers' college premium. In the model, the former pattern is due to a large inflow of young college graduates which reduced their relative wages, and the latter is driven by fast growth of



(a) Share of R&D Firms and Exporters

(b) Share of R&D Firms by Export Status

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

Note: This figure plots the share of R&D firms and exporters in the left-hand panel and the share of R&D firms conditional on export status in the right-hand panel. Firm size percentiles are computed based on rankings of firm sales within each industry. I only compute the shares for ordinary firms, as all processing firms export and do not innovate.

manufacturing firms' sales which increased the overall demand for educated labor.

7 Quantitative Effects of China's College Expansion

In this section, I quantify the contribution of the college expansion to China's innovation surge and export skill upgrading. I also study the role of trade openness in helping China accommodate this policy shock and conduct a cost-benefit analysis of this policy change. Finally, I discuss how several model extensions affect my quantitative findings.

To quantify the impact of China's college expansion, I simulate the scenario of "no college expansion." Instead of using the 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 flows of college graduates after 2003. Relative to the baseline economy, the number of college-educated workers would have been 62 million lower in 2018 (8% of employment) in counterfactual exercises. I maintain the employment growth in the data, and thus high-school graduates would replace the "missing" college-educated graduates. In all years, I treat the final good in China as the numeraire, and trade is balanced for China and Foreign.[41]

[41]To isolate the effects of the expansion of regular college education, I keep each year's enrollments in

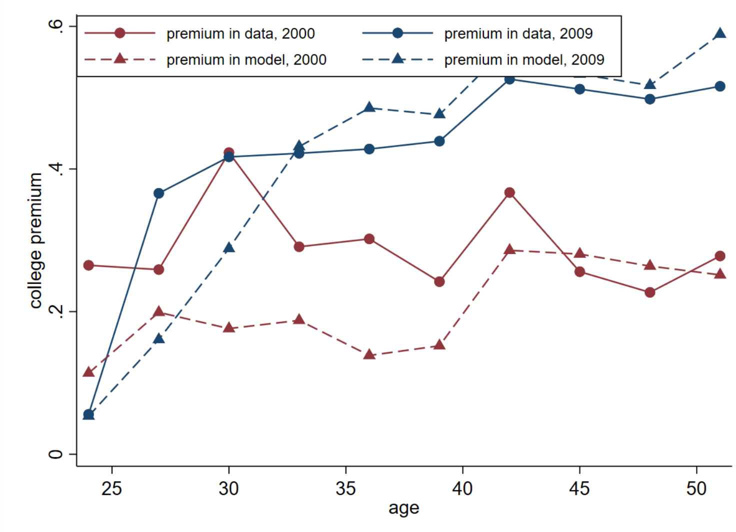


Figure 7: College Wage Premium by Age, in Model and Data

Note: This figure plots the age-specific college premium in 2000 and 2009, using the model-generated data and actual data. Appendix F.5 shows the estimation method for college premium by age, and data comes from the Urban Household Survey.

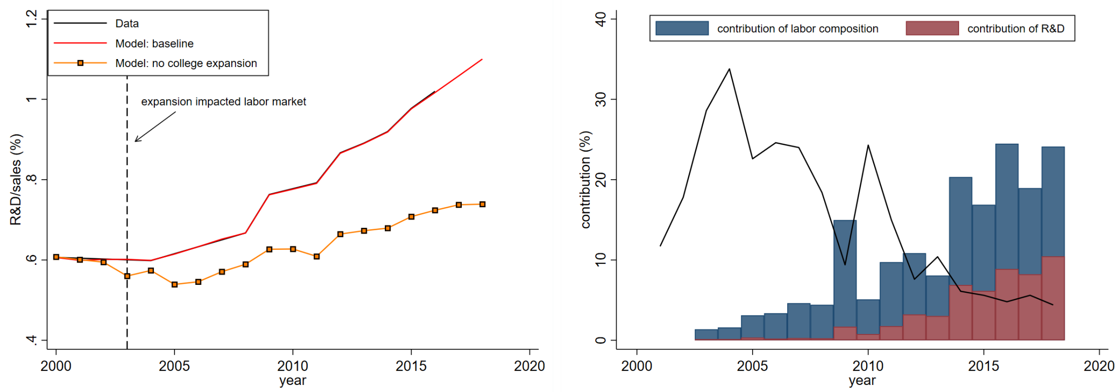
7.1 Innovation Surge

Figure 8a presents the impact of the college expansion on China's manufacturing innovation. The college expansion accounted for $\frac{0.36 \text{ p.p.}}{0.50 \text{ p.p.}} = 72\%$ of increases in manufacturing R&D intensity between 2003–2018. In principle, by stimulating more innovation, the college expansion could speed up firms' productivity growth, besides its direct productivity enhancement due to more educated workers in production. Figure 8b reports the contributions of the college expansion to manufacturing output growth through (1) more innovation and (2) changes in the composition of college-educated/noncollege labor.[42] Through the combined effects of innovation and labor composition, China's college expansion accounted for a quarter of manufacturing output growth after 2015. With the slowdown of economic reforms (Wei et al. 2017), the college expansion has become an important engine of China's manufacturing development in recent years.

It is worth comparing the differential effects of China's college expansion through

part-time colleges unchanged in all simulations. This restriction will be relaxed in Appendix Section G.1. I also experimented with foreign GDP as the numeraire except for autarky, and the results are similar.

[42] I isolate the effects of innovation by simulating the model and assuming that each firm's R&D behavior follows the "no college expansion" scenario but labor composition is the same as the baseline. I isolate the effects of labor composition by simulating the model and assuming that the firm productivity distributions are the same as the baseline but labor composition follows the "no college expansion" scenario.



(a) Manu R&D/sales

(b) Contribution to Manu Output Growth

Figure 8: Impact of China's College Expansion on Manufacturing Innovation and Output

Note: The left-hand panel plots the ratio of manufacturing R&D to sales in the data, the baseline model, and the counterfactual scenario without the college expansion. The right-hand panel plots the contributions of the college expansion to manufacturing output growth through changes in labor composition and changes in innovation, respectively. The data on manufacturing output growth comes from China's Statistical Yearbooks and is adjusted for CPI. Because there were changes in statistical methods after 2015 due to tax reforms, I use the growth of manufacturing value-added as a proxy for the growth of manufacturing output after 2015.

labor composition and innovation. Although the college expansion produces positive output effects through increases in educated workers, the rapid accumulation of college-educated workers faces declining marginal returns. In fact, the marginal product of new college-educated workers was 15% higher than that of high-school graduates of the same age in 2018, declining from 81% in 2010. Thus, the positive effects of changes in labor composition can be possibly reversed in the near future, unless there is strong skill-biased technology change (Katz and Murphy 1992).[43] 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 around 10% of manufacturing output growth in 2018, and this contribution will likely grow with China's rapid increases in innovation levels (Wei et al. 2017).

[43]The quantitative analysis abstracts from skill-biased technology changes in the production function. Even though the model matches changes in the college premium in the 2000s pretty well (see Figure 7), it is possible that skill-biased technology became important in the 2010s, for which period I do not have available data on the college premium.

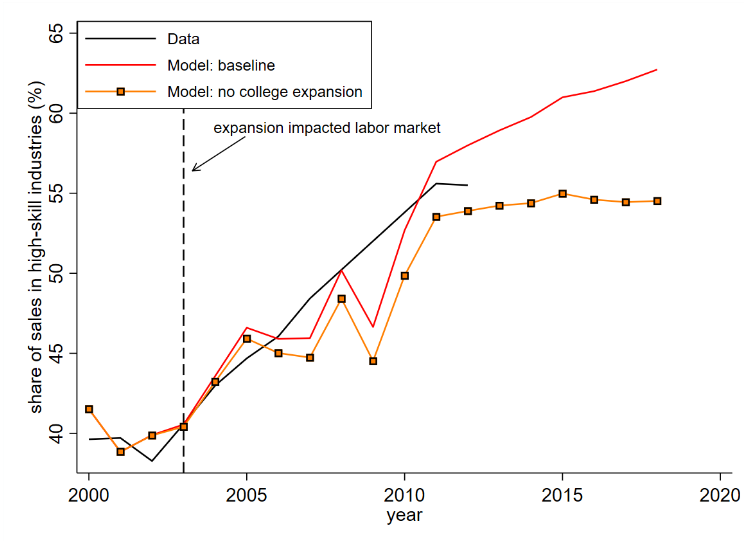


Figure 9: Effects of the College Expansion on Skill Upgrading of Ordinary Exports

Note: The figure plots the share of sales in high-skill industries for ordinary exports in the data, the baseline model, and the counterfactual scenario without the college expansion.

7.2 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 industries increased by 22.1 percentage points, from 40.6% in 2003 to 62.7% in 2018. This increase dropped to 14.1 percentage points in the absence of the college expansion; therefore, the contribution of the college expansion to skill upgrading of ordinary exports was $\frac{22.1-14.1}{22.1} = 36\%$. According to Figure 9, the college expansion has fueled China's export skill upgrading mainly since the late 2000s, echoing the lack of changes in the skill content of exports observed in the early 2000s (Amiti and Freund 2010).

Appendix Figure A.8 shows that China's college expansion explained 17% of the decline in the share of processing exports in overall manufacturing exports between 2003–2018, thus also contributing to export skill upgrading by shifting the composition between processing and ordinary exports.[44]

[44]Despite low skills of processing exports, more than half of China's processing exports are in industry "Computer, Electronic and Optical Equipment," whose processing exporters have higher skill intensities than ordinary firms in many manufacturing industries. Therefore, after China's college expansion, reallocation effects from low to high-skill industries within ordinary exports were stronger than from processing

7.3 Amplification Effects of Trade Openness

Much empirical analysis studies how Chinese firms react to trade liberalization (e.g., Khandelwal et al. 2013, Brandt et al. 2017, Handley and Limão 2017), especially in terms of innovation (e.g., Liu and Qiu 2016, Bombardini et al. 2017, Liu et al. 2021). Here, I show that trade helps China accommodate the domestic education policy change.

To explore the effects of trade openness, I simulate the impact of the college expansion in autarky (trade costs between China and Foreign go to infinity) after recalibration.[45] Table 5 compares the impact of China's college expansion on production, innovation, and college premium in 2018 between the baseline calibration and autarky. I highlight two findings. First, the college expansion increased China's GDP in 2018 by 10.01%, equalizing an annualized growth rate of 0.6–0.7% between 2003–2018. This contribution is comparable in magnitude to the contribution of reductions in migration costs, which is shown by Hao et al. (2020) to account for 0.8–1.2% annual GDP growth between 2000–2015.

Second, trade openness amplified the effects of the college expansion on production and especially innovation. If there were no trade between China and Foreign, the effects of the college expansion on GDP and manufacturing output in 2018 would have been 12–17% lower compared with the baseline results. This is because trade shifted industry composition and lessened the decline in marginal products of additional college-educated workers. Thus, trade openness also tamed the negative impact of the college expansion on the college premium by about 5%. More interestingly, without trade openness, the effects of the college expansion on innovation in 2018 would have been 31% lower compared with the baseline result, as exporters were intensively engaged in innovative activities. As supportive evidence, Figure 10 plots the impact of the college expansion on exporters and nonexporters' innovation levels in the baseline model. It shows that the college expansion increased R&D intensities in more skill-intensive industries, especially among exporters, confirming the interaction between exports and innovation.

to ordinary exports.

[45] As my focus is on GDP and R&D, I need to keep GDP and R&D expenses comparable between the baseline equilibrium and the autarkic economy. Thus, 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). I also recalibrate the productivity of college-educated workers relative to the less-educated workers such that the aggregate college premium is the same as the

Table 5: Effects of the College Expansion on Output, R&D, and Labor Income in 2018

	GDP	manu output	manu R&D/sales	log(college premium)
Baseline	10.01%	12.64%	0.36 p.p.	-0.61
Autarky	8.83%	10.45%	0.25 p.p.	-0.64
Change due to shutting down trade (% from baseline to autarky)	-11.8%	-17.3%	-30.6%	4.9%

Note: The first two rows of the table present the impact of the college expansion on GDP, manufacturing output, manufacturing R&D/sales, and college premium in 2018, respectively. The first row is under the baseline calibration, and the second row is under autarky. The last row computes the proportion change of the impact after shutting down trade (from the baseline calibration to autarky). The college premium is the average wage of college-educated workers relative to that of high-school graduates.

7.4 Costs and Benefits of China's College Expansion

China's college expansion did not come at no economic costs. First, the expansion of college education led to higher education investments, which can otherwise be used as consumption or other types of investments. Moreover, new college graduates could have entered the labor market earlier if they had not attended colleges.

I compute increases in education expenses in each year by multiplying additional enrollments[46] with average education expenses (including tuition and government subsidies) per college enrollment from China's Education Statistical Yearbooks. I compute implicit opportunity costs by multiplying additional enrollments with the average marginal products of high-school graduates (aged less than 23) in the baseline equilibrium.

Figure 11 compares the costs of China's college expansion with the GDP increase thanks to this policy. The additional education expenses represented roughly 1% of GDP in the 2010s, which was relatively small compared with the implicit loss of production (2% of GDP in the 2010s). The increase in yearly GDP driven by the college expansion started to exceed the education and implicit costs of the college expansion in 2007 when China started to enjoy net economic benefits from this large-scale education policy change.

baseline model. I keep all other parameters at their baseline levels.

[46] 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.

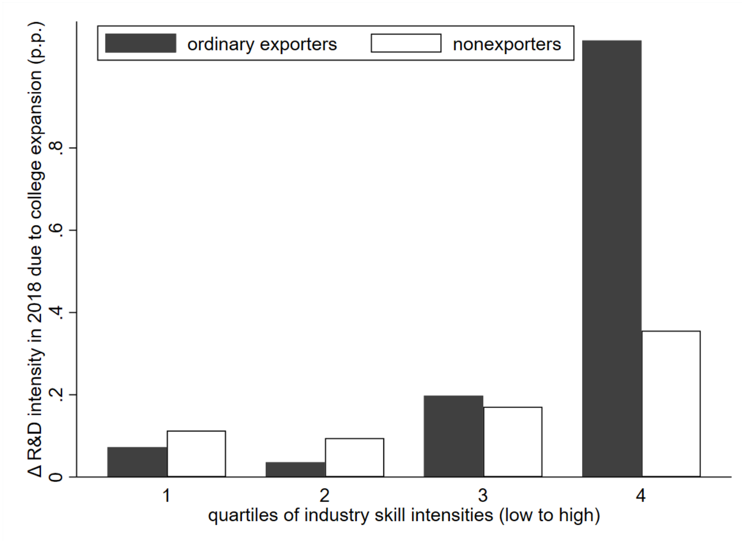


Figure 10: Effects of the College Expansion on Firms' R&D Intensities in 2018

Note: The figure shows the impact of the college expansion on R&D intensities (R&D/sales) in percentage points. 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 between the observed equilibrium and the counterfactual exercise without the college expansion.

7.5 Model Extensions

In this subsection, I extend the baseline model to incorporate: (1) endogenous entry of firms, as commonly assumed in growth models; and (2) R&D misreporting and manipulation, which matters for the accuracy of R&D expenditures in China. I discuss how quantitative results change in these two alternate settings. Appendix G provides additional quantitative results in several other model extensions.

7.5.1 Incorporating Endogenous Firm Entry

China has experienced massive entry of new firms (Brandt et al. 2012, Wei et al. 2017), which may stem from reduced R&D costs. Following the typical assumption in the growth literature (e.g., Atkeson and Burstein 2010, Grossman and Helpman 2014), I assume that an entrant needs to pay $f^e_{i(m),j,t}$ units of research goods to enter export regime m in industry j. Let $V^e_{i(m),j,t}$ be the value of a new entrant. Thus, in the equilibrium, the number of potential entrants is *endogenously* decided by the free-entry condition:

$$f^e_{i(m),j,t} P^r_{i,t} = \rho V^e_{i(m),j,t}. \tag{16}$$

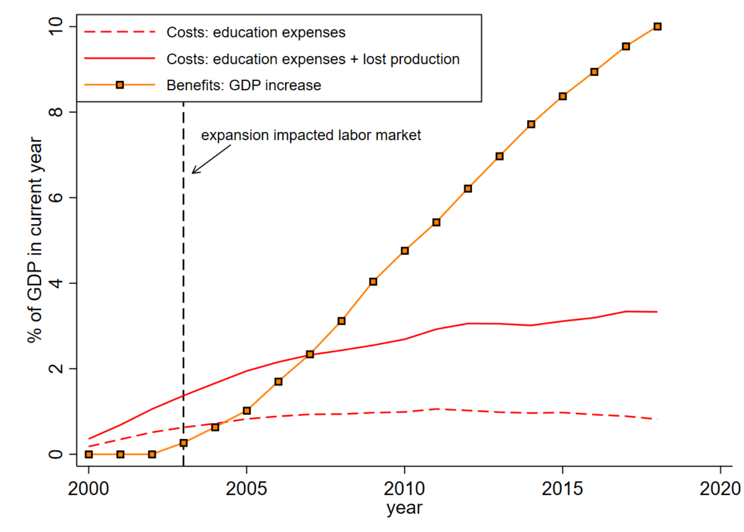


Figure 11: Costs and Benefits of China's College Expansion

Note: This figure compares the costs of China's college expansion (additional education costs and implicit opportunity costs of new college students) with the GDP increase.

I introduce parameter $0 < \rho < 1$ to capture that it is difficult to capitalize future profits to finance entry costs in China (Song et al. 2011).[47] I choose $\rho = 0.15$ so that entry costs are around one-year expected profits of an entrant. I then use this equation to calibrate entry costs $\{f^e_{i(m),j,t}\}$ that generate the same amount of entrants as $\{N^e_{i(m),j,t}\}$. I recalibrate other model parameters to match the targeted moments in Table 4.

Quantitatively, I find that incorporating endogenous firm entry reduced the contribution of the college expansion to manufacturing innovation to 56% (72% in the baseline) between 2003–2018. In particular, 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 per firm. On the other hand, with more firms in highly skill-intensive industries, the contribution of China's college expansion to skill upgrading of ordinary exports increased to 80% (36% in the baseline).

[47]China has experienced very fast growth in the number of manufacturing firms. If I assume $\rho = 1$ to compute entry costs, around half of Chinese college-educated workers were required to be used in producing research goods for entry of manufacturing firms in 2018, which was unrealistic.

7.5.2 Incorporating R&D Misreporting

One issue about China's R&D is that Chinese firms often reclassify non-R&D costs as R&D to obtain tax subsidies (e.g., Chen et al. 2021, König et al. 2021). 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. (2021) who show that firms manipulate non-R&D administrative costs and find a discontinuous drop in firms' non-R&D admin costs around the threshold of R&D incentives. I explore whether the drop varies across industries of different skill intensities by estimating a regression:

$$\begin{aligned} y(\omega) = & \beta_0 + \beta_1 D + \beta_2 SI_{i,j} D + [\beta_3 + \beta_4 D](Z(\omega) - c) + [\beta_5 + \beta_6 D](Z(\omega) - c)^2 \\ & + [\beta_7 + \beta_8 D](Z(\omega) - c)^3 + \beta_9 SI_{i,j} + \epsilon(\omega). \end{aligned} \tag{17}$$

$y(\omega)$ is the ratio of non-R&D admin expenses to the required R&D expenses for attaining the tax incentive (see footnote 35). The dummy variable D equals 1 if the firm satisfies the threshold of R&D incentives. β_1 captures the drop in non-R&D admin expenses at the threshold, and β_2 shows how the drop relies on the firm's affiliated-industry skill intensity. I control a cubic function of differences between the firm's R&D intensity $Z(\omega)$ and the threshold c, as well as industry-level skill intensity $SI_{i,j}$ to allow non-R&D expenses to differ across industries. I use SAT 2009–2011 for estimation and still measure skill intensity $SI_{i,j}$ from ASM 2004. I focus on 2-digit manufacturing industries.

Column (1) of Table 6 shows that firms at the threshold on average misreported 27.5% of the required R&D expenses from non-R&D admin costs.[48] Column (2) of Table 6 finds that the drop in non-R&D admin costs at the threshold increased with industry-level skill intensities. To test the robustness of my model, I interpret this result as reflecting that larger wage bills to college-educated workers can facilitate R&D misreporting.

In the model, I assume that Chinese firms can reclassify non-R&D costs as up to a portion $(k_1 + k_2 SI_{i(m),j,t})$ of the required R&D expenses to attain the tax incentive, where $SI_{i(m),j,t}$ is the share of payments to college-educated labor in total labor bills for export regime m and industry j in year t. I also assume that firms above the threshold do not misreport R&D, because misreporting only brings risks of being caught for them. I cal-

[48] My estimate is close to the findings in Chen et al. (2021) 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 6: Dep Var: Ratio of Non-R&D Admin Expenses to R&D Expenses, 2009–2011

	Data		Model
	(1)	(2)	(3)
R&D threshold	-0.275***	-0.187**	-0.187***
	(0.058)	(0.086)	(0.003)
R&D threshold × industry skill intensity		-0.405*	-0.402***
		(0.217)	(0.024)
Obs	22,608	22,608	30
R-squared	0.028	0.028	0.897
Avg % R&D misreported (firms at the threshold)	27.5%	27.5%	28.0%

Note: Columns (1)–(2) present the results from regression (17). I restrict the sample to firms within 2 percentage points of the required R&D intensity threshold following Chen et al. (2021). 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%.

ibrate k_1 and k_2 such that the model-generated industry-level reclassification rates between 2009–2011 match the intercept and the slope in Column (2) of Table 6. I find that with $k_1 = 0.18$ and $k_2 = 0.45$, the model-generated data matches the pattern of reclassification of non-R&D costs across industries, as shown in Column (3) of Table 6. I recalibrate other model parameters to match the targeted moments in Table 4.

Figure 12 presents the impact of the college expansion on R&D in the model extension. I highlight three findings. First, according to the model, only 78% of reported manufacturing R&D was actually spent in 2018. Second, the college expansion still accounted for $\frac{0.30 \text{ p.p.}}{0.50 \text{ p.p.}} = 60\%$ of increases in China's manufacturing reported R&D intensity between 2003–2018 (72% in the baseline). Third, the college expansion also induced more R&D misreporting. Only 80% of the increase in China's manufacturing reported R&D intensity between 2003–2018 was driven by actual increases. Given the reduced innovation efficiency due to R&D misreporting, the contribution of China's college expansion to skill upgrading of ordinary exports also declined to 30% (36% in the baseline).

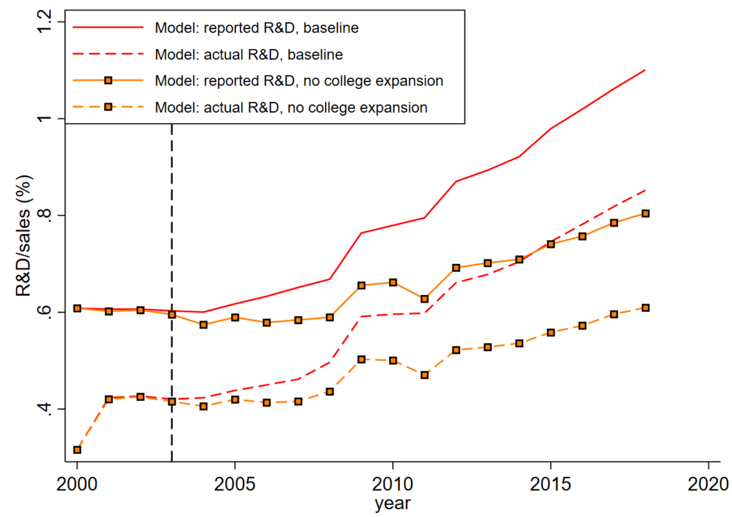


Figure 12: Effects of the College Expansion on Manufacturing R&D (with Misreporting)

Note: This figure plots the ratio of manufacturing reported (actual) R&D to sales in the baseline calibration and in the counterfactual scenario without the college expansion, respectively.

8 Conclusion

In this paper, I combine a quantitative model with empirical evidence to shed light on the contribution of China's massive college expansion to China's recent surge in innovation levels and the skill content of exports. The analysis also highlights the possible interaction between trade and innovation, as trade-induced production reallocation to high-skill industries reinforces the innovation surge. These results suggest that enlarging the higher education system serves as an effective tool for developing countries to promote innovation and growth, and that maintaining a high level of trade openness further improves the effectiveness of such an education policy in stimulating innovation.

This paper focuses on the role of the increasing supply of talent. Arguably, the expansion of college education can benefit innovation through other channels, such as more entrepreneurs or research cooperation between faculty and firms, as suggested by reduced-form evidence (e.g., Kantor and Whalley 2014, Hausman 2021). A fruitful area for future study is whether these other channels are quantitatively important, which will ultimately lead to a better evaluation of the role of college education in aggregate innovation.

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Appendix for Online Publication

A Additional Tables and Graphs

Table A.1: College Expansion and Export Prices, 2005–2010

Dep Var:	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	-0.478**	-0.462**	-0.600***	-0.580**	-0.623***	-0.600**
	(0.221)	(0.224)	(0.226)	(0.230)	(0.230)	(0.235)
Changes in applied input tariffs			1.144**	1.193**		
			(0.539)	(0.530)		
Changes in applied output tariffs			-0.186	-0.203		
			(0.220)	(0.222)		
Changes in input tariffs (based on WTO agreement)					1.206**	1.239**
					(0.554)	(0.546)
Changes in output tariffs (based on WTO agreement)					-0.155	-0.172
					(0.230)	(0.231)
Obs	8,425	8,400	8,425	8,400	8,425	8,400
R-squared	0.019	0.035	0.020	0.036	0.021	0.036
First-stage F	394.46	684.92	396.51	668.88	387.34	646.68

Notes: This table provides estimates from regressions in equation (3), separately treating regions as cities and provinces. "CE" is short for "college expansion." In Columns (3)–(4), I use changes in actual applied tariff rates. As actual tariffs may be endogenous, in Columns (5)–(6), I follow Brandt et al. (2017) to use the maximum tariff levels under the WTO agreement, which were mostly set in 1999. With the pre-determined tariff changes according to the WTO agreement, the regression results are very similar to the results in Columns (3)–(4). The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; and (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005. I also control for region-level fixed effects. 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 Export Status between 2005–2010

Dep var:	Δ export status	
Geographic level	provincial (1) 2SLS	city-level (2) 2SLS
Exposure to CE	0.441*** (0.072)	0.464*** (0.077)
Obs	42,807	42,711
R-squared	0.014	0.021
First-stage F	466.59	728.08

Note: This table provides estimates from regressions in equation (3), separately treating regions as cities and provinces. "CE" is short for "college expansion." Export status is a dummy variable that equals one if a firm has positive ordinary exports. The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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.3: 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
Exposure to CE	0.034*** (0.006)	0.047*** (0.008)	0.025*** (0.006)	0.046*** (0.009)
Obs	31,139	11,668	26,325	10,161
R-squared	0.012	0.042	0.008	0.047
First-stage F	440.61	413.99	469.00	407.81

Note: This table provides estimates from regressions in equation (3), treating regions as provinces. "CE" is short for "college expansion." The dependent variable is the change in R&D/sales between 2005–2010. The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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.4: Dependent Variable: Changes in R&D Status between 2005–2010 (Controlling for R&D Intensity in 2005)

Dep Var:	Changes in R&D status			
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
	export status in 2005		export status in 2005&2010	
	nonexporter	ord. exporter	nonexporter	ord. exporter
Exposure to CE	0.783***	0.860***	0.654***	0.905***
	(0.119)	(0.159)	(0.113)	(0.184)
R&D intensity (2005)	-4.502***	-5.791***	-4.378***	-6.321***
	(0.620)	(1.026)	(0.678)	(1.057)
Obs	31,139	11,668	26,325	10,161
R-squared	0.043	0.065	0.040	0.071
First-stage F	452.94	424.21	482.31	417.73

Note: This table provides estimates from regressions in equation (3), treating regions as provinces. "CE" is short for "college expansion." The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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.5: Impact of the College Expansion on Firm Sales and Innovation, 2005–2010 (SOEs and Other Firms)

Dep Var:	Δlog(ordinary exports)		Δlog(domestic sales)		Δlog(export prices)		ΔR&D status	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Exposure to CE	3.623***	3.637***	1.731***	1.683***	-0.586***	-0.618**	0.447***	0.467***
	(0.735)	(0.742)	(0.436)	(0.428)	(0.228)	(0.222)	(0.097)	(0.095)
Exposure to CE × SOE dummy	-10.341		-1.634*		-1.422		-0.538	
	(10.009)		(0.978)		(2.680)		(0.444)	
Exposure to CE × SOE ownership share		-2.222		-0.238		0.759		-0.727***
		(1.877)		(0.428)		(0.698)		(0.238)
Obs	10,161	10,135	40,539	40,292	8,425	8,403	42,807	42,546
R-squared	0.046	0.047	0.067	0.066	0.021	0.021	0.021	0.022
First-stage F	21.41	238.60	70.10	274.72	16.32	229.70	70.24	277.19

Note: This table provides estimates from regressions in equation (3), treating regions as provinces. "CE" is short for "college expansion." I identify a firm's SOE status in two ways: (1) I define a dummy of SOE firms based on firm registration information; and (2) I define SOE ownership share according to the share of state-owned equity in total equity. I include the interaction between exposure to the college expansion and SOE dummy in odd columns or SOE ownership share in even columns. I construct an additional instrument for the interaction term by interacting $SI_{l,j}x_l^*$ with SOE dummy in odd columns or SOE ownership share in even columns. The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after WTO accession. I also control for region-level fixed effects. 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%.

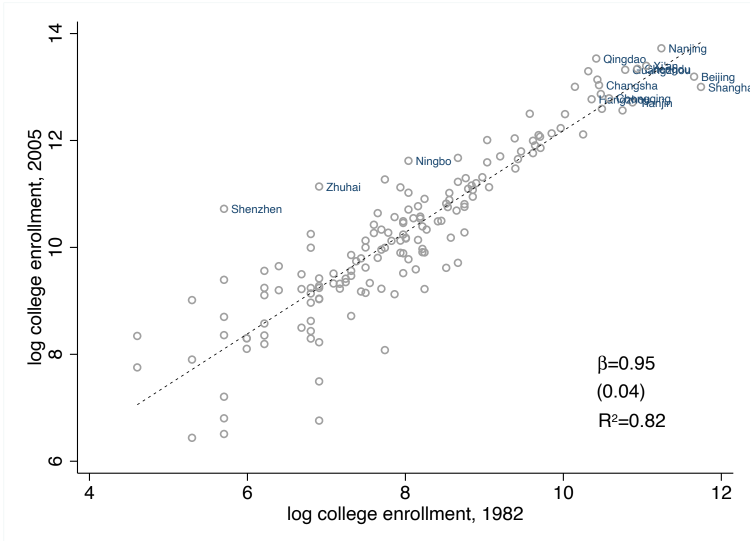
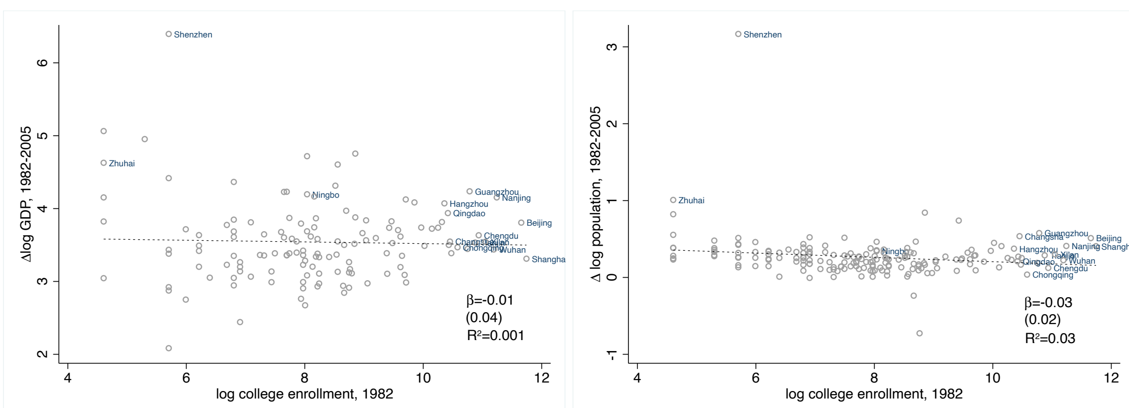


Figure A.1: College Enrollments across Cities

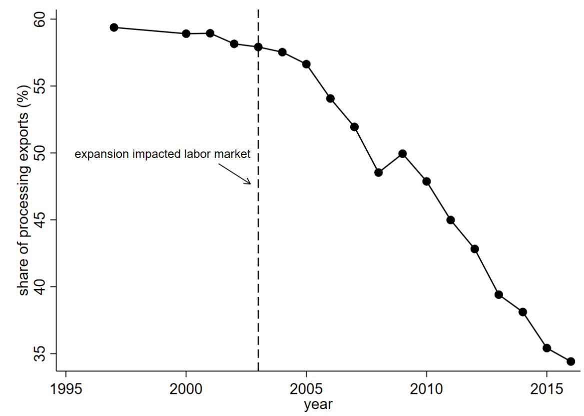
Note: This figure plots college enrollments in 1982 and 2005 across different cities. The data comes from China's City Statistical Yearbook in 2005 and Population Census in 1982.



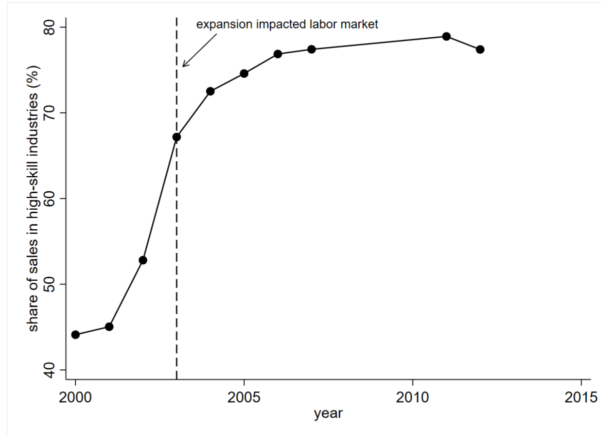
(a) GDP (b) Population

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

Note: This figure plots the relation between college enrollments in 1982 and GDP growth (left-hand panel) or population growth (right-hand panel) in 1982–2005. The data comes from multiple Provincial Statistical Yearbooks and Population Census in 1982.



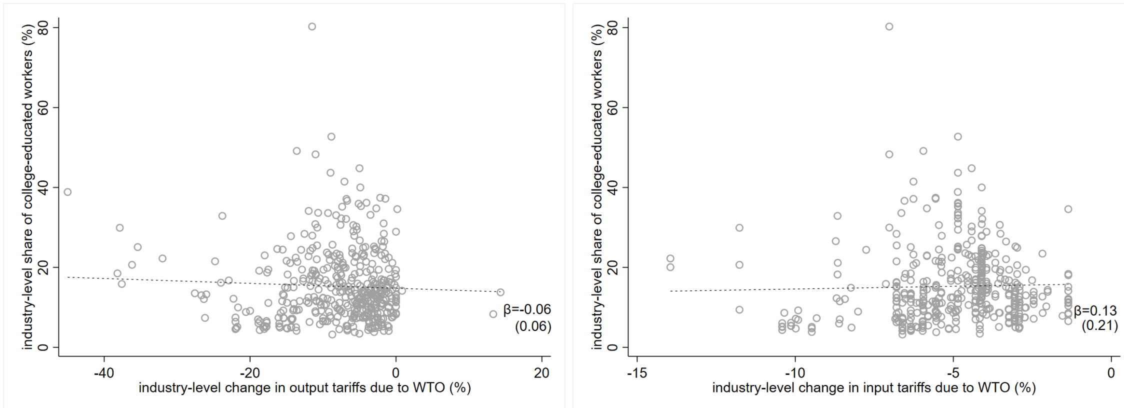
(a) % of Processing Exports in Overall Exports



(b) Within All Processing Exports, % of Processing Exports in High-skill Industries

Figure A.3: Processing Exports

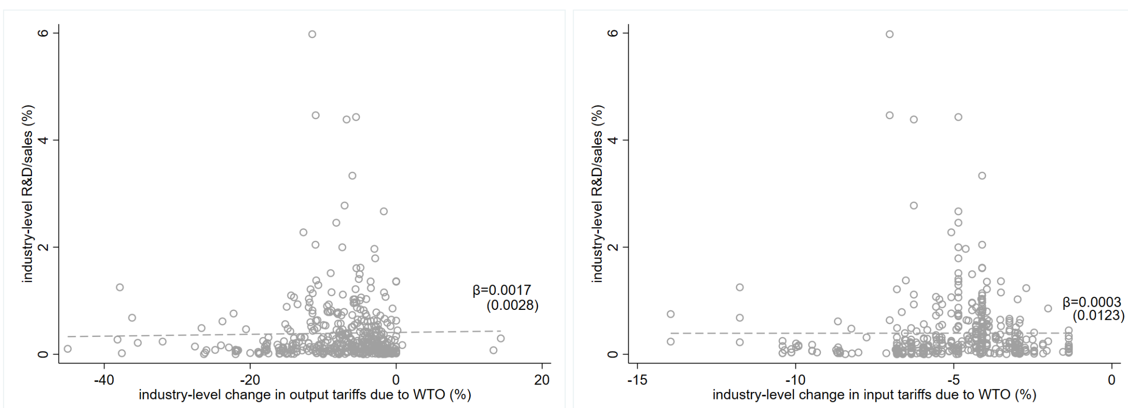
Note: Panel (a) reports the share of processing exports in China's overall manufacturing exports between 1997 and 2016. Panel (b) reports the share of exports in high-skill industries within processing exports. I measure an industry's processing-export skill intensity by the share of college-educated workers in employment for all the purely processing exporters in that industry, and this information is available from China's ASM in 2004. For ease of description, for processing exports, I also define a 4-digit industry as a high-skill industry if its college employment share lies above the employment-weighted average across all industries.



(a) Output Tariff Reductions (b) Input Tariff Reductions

Figure A.4: Industry-level Tariff Reductions and Skill Intensities

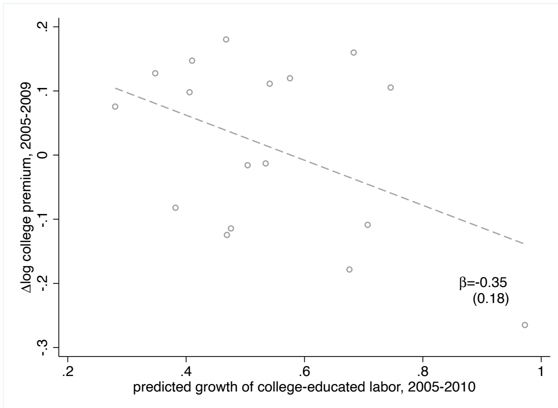
Note: The figure plots the relation between industry-level output (input) tariff reductions and industry-level skill intensities. The figure is based on 4-digit industries. Tariff data comes from Brandt et al. (2017). Because tariff reductions were often implemented earlier than the accession agreement mandated and tariff rates barely changed after 2005 (Brandt et al. 2017), I use the changes in applied input and output tariffs between 1997 and 2005. The industry's skill intensity is measured by the share of college-educated workers in employment for that industry, drawn from China's ASM in 2004.



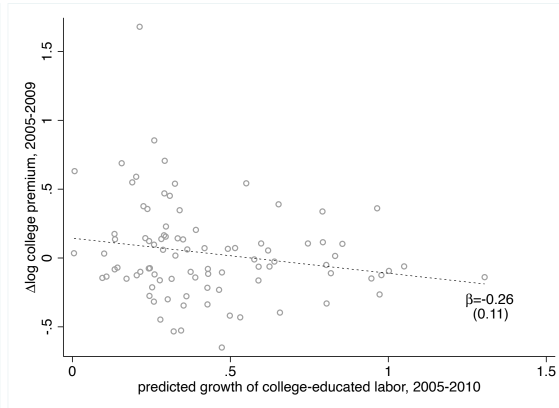
(a) Output Tariff Reductions (b) Input Tariff Reductions

Figure A.5: Industry-level Tariff Reductions and R&D Intensities

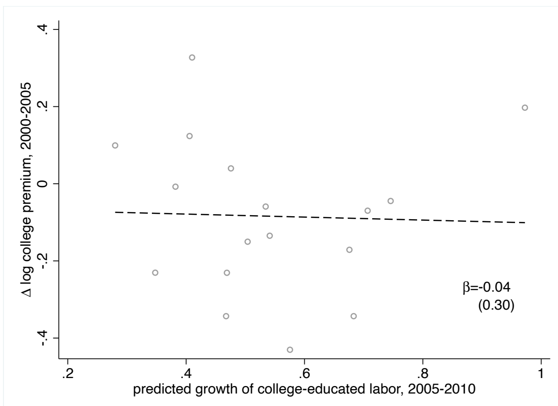
Note: The figure plots the relation between industry-level output (input) tariff reductions and industry-level R&D intensities. The figure is based on 4-digit industries. Tariff data comes from Brandt et al. (2017). Because tariff reductions were often implemented earlier than the accession agreement mandated and tariff rates barely changed after 2005 (Brandt et al. 2017), I use the changes in applied input and output tariffs between 1997 and 2005. The industry's R&D/sales is drawn from ASM 2005.



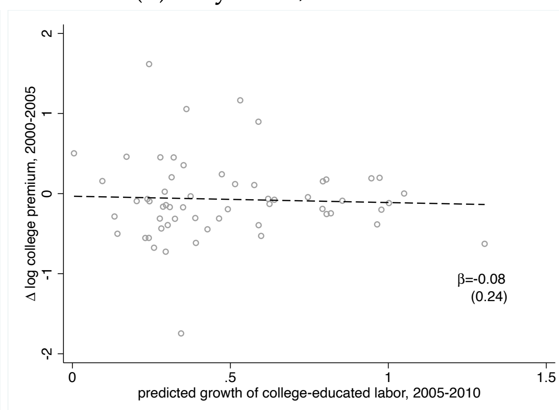
(a) Provincial, 2005–2009



(b) City level, 2005–2009



(c) Provincial, 2000–2005



(d) City level, 2000–2005

Figure A.6: IV and Changes in Young Workers' College Premium

Note: The figure plots the relation between the provincial-level (city-level) instrument and changes in the provincial-level (city-level) college premium between 2005–2009 (upper panels) or between 2000–2005 (lower panels), respectively. 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. Compared with young workers, 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, the college expansion had not persisted long enough to produce large effects on the supply of middle-aged and elderly people. This pattern motivates my modeling of age-specific labor supply in the quantitative analysis.

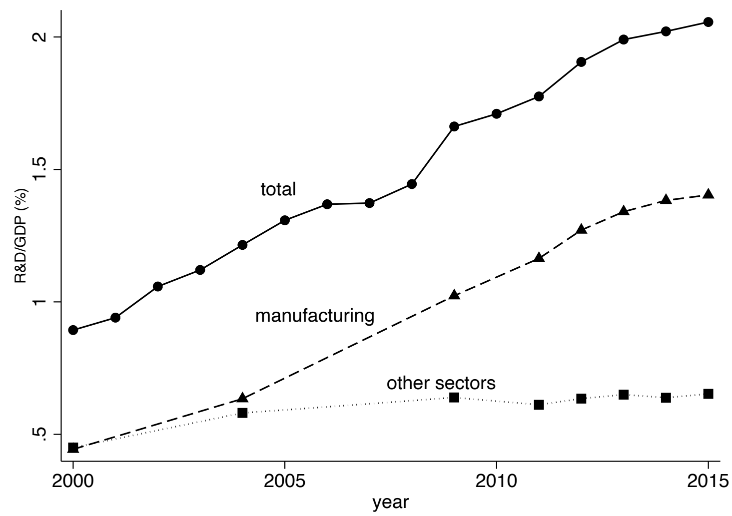
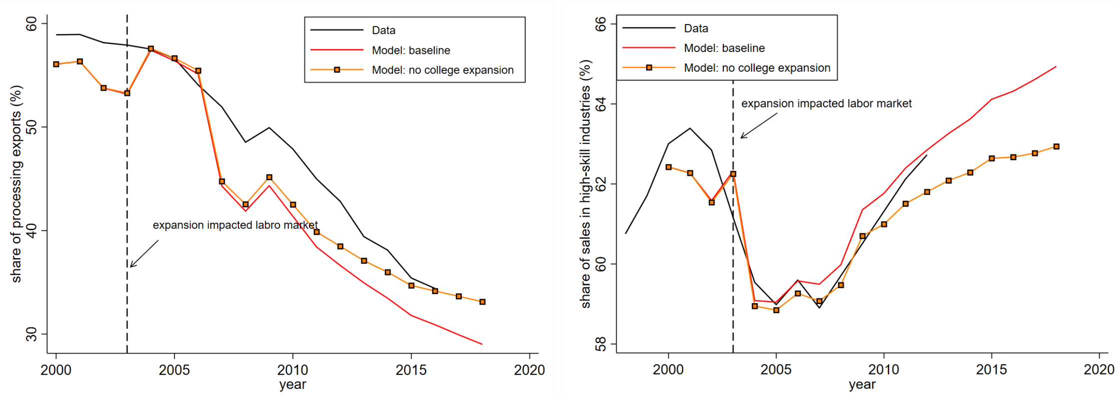


Figure A.7: China's R&D Expenses by Sectors

Note: This figure plots each year's total R&D, manufacturing R&D, and other sectors' R&D, as a share of GDP. Other sectors include all nonmanufacturing sectors. The data comes from China's Statistical Yearbooks on Science and Technology and China's Statistical Yearbooks 2000–2016.



(a) Share of Processing Exports (b) Skill Upgrading of Domestic Sales

Figure A.8: Effects of the College Expansion on Processing Exports and Domestic Sales

Note: This figure plots the share of processing exports in total manufacturing exports (left-hand panel) and the share of sales in high-skill industries for domestic sales (right-hand panel) in the data, baseline model, and the counterfactual scenario without the college expansion.

B China's College System

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 B.1 shows that around 1 million people obtained a part-time college diploma in 2000,[49] and the amount increased to around 2 million in 2018.

Many Chinese students have obtained their college degrees abroad. However, as Figure B.1 shows, the number of college graduates with foreign college degrees is still small relative to the number of domestic college graduates. Cumulatively, 2.1 million students got foreign college degrees between 2000–2015, which was only 3% of the number of domestic college graduates from regular college education in the meantime (67.2 million).

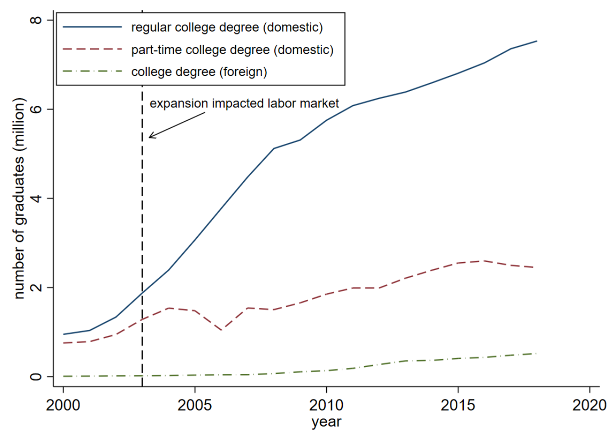


Figure B.1: Number of College Graduates (Yearly)

Note: This figure plots each year's number of graduates for different types of colleges.

C Additional Results of Descriptive Facts in Section 3

C.1 Robustness Checks of Section 3.2

C.1.1 Alternative Measure of Skill Intensities

I test the robustness of my results using an alternative measure of skill intensities—the share of nonproduction workers in employment. I compute the share of nonproduction

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

workers in employment for 4-digit SIC industries (459 manufacturing industries) in the US in 1990, according to the NBER Manufacturing Database. I define an industry to be a high-skill industry if its share is larger than the average share 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.[50] 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 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 more pre-shock years.

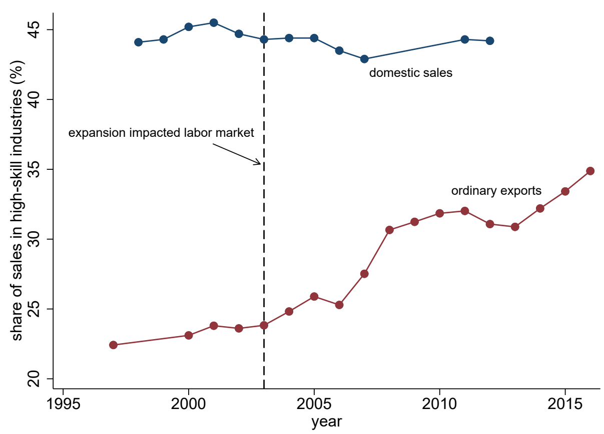


Figure C.1: Share of Sales in High-skill Industries (Alternative Skill-intensity Measure)

Note: This figure plots the share of sales in high-skill industries separately for domestic sales and ordinary exports, based on the alternative skill-intensity measure (share of nonproduction workers in employment for 4-digit SIC industries in the US).

In Figure C.1, I plot the share of sales in high-skill industries, 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.

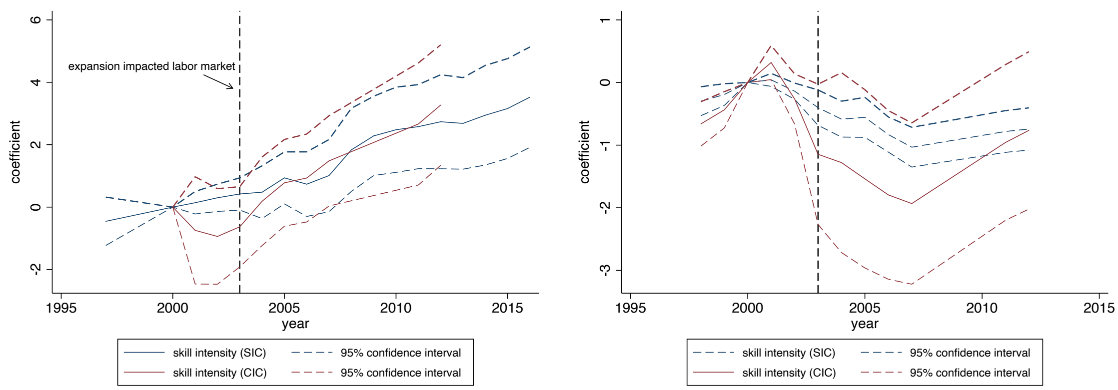
C.1.2 Statistical Tests

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

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

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

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 was not driven by WTO accession. I apply the regression in equation (C.1) for each year with available data. 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.



(a) Ordinary Exports

(b) Domestic Sales

Figure C.2: Coefficients of Growth in Domestic Sales and Exports on Skill Intensities

Note: This figure plots the coefficients of estimating equation (C.1) for domestic sales and ordinary exports on two measures of skill intensities, respectively.

The solid lines in Figure C.2 display the coefficients of estimating equation (C.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 US in 1990. The dashed lines denote the 95% confidence intervals. Clearly, in Figure C.2a, β_t turned significantly positive after 2007 for both the SIC skill-intensity measure and 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 seemed to be the year 2003 when the coefficient started to increase. This pattern is consistent with the timing of the college expansion.

C.2 Additional Results of Section 3.3

C.2.1 Construction of Balanced Panels

I construct the balanced firm panels in the following steps. First, I clean ASM and SAT 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 ASM, 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 ASM and SAT may be different from the exports reported in the customs data due to imperfect matches 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 ASM or SAT.[51] I also exclude purely processing exporters (firms that only export processing products) in the data. Table C.1 summarizes the sample statistics.

Table C.1: 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: This table provides summary statistics of the constructed 2001–05 and 2005–10 balanced firm panels. Sales and ordinary exports are in thousands of RMB.

[51] There are some firms that report positive exports in ASM or 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 C.2: 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

Note: This table provides the robustness checks of Figure 4 in different scenarios.

C.2.2 Robustness Checks of Figure 4

Controlling Industry Composition. To control the industry composition, I first compute the changes in innovative activities by each 4-digit industry in the periods 2001–2005 and 2005–2010, separately for exporters and nonexporters. 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 innovative activities in the two periods, separately for exporters and nonexporters. Row (1) in Table C.2 confirms my findings in Figure 4. I omit the results for R&D intensities because they are similar.

Using Firms Maintaining Export Status. 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 C.2 replicates Figure 4 for firms maintaining 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 C.2 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 firms in high-tech industries may increase their innovative activities due to R&D tax incentives.[52] Row (4) in Table C.2 replicates the results excluding electoral machinery, electronics, medicine, and transportation industries, which tend to be high-tech. I have very similar findings.

[52] In reality, R&D tax incentives are vague regarding the applicable industries and seem to be applied broadly (Chen et al. 2021).

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 ends in 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 C.2 shows that the patent applications of both exporters and nonexporters increased after 2005, when the college expansion largely impacted the labor market.

Using ASM after 2007. 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. Row (6) in Table C.2 shows the share of firms with patent applications for 2001, 2005, and 2011. Clearly, the numbers 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.

C.3 Purely Processing Exporters

The subsection shows that processing exports are of lower skill intensities 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 share of workers with college degrees in employment between purely processing exporters, ordinary exporters, and nonexporters. I perform this analysis using ASM 2004, in which decomposition of employment by education levels is available. A proportion of ordinary producers also perform processing exports, and hereafter I call them hybrid ordinary producers.

Table C.3: Dependent Variable: Firm-level Share of Workers with College Degrees

	(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: This table presents the estimates from regressing the firm-level share of workers with college degrees on dummies of firm types based on export status. 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 C.3, I regress the firm-level share of workers with college degrees on dummies of firm types, city fixed effects, and industry fixed effects. I also control firm-level variables, including employment, 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 degrees 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 purely ordinary exporters were more skill-intensive than nonexporters.

D Robustness of Empirical Analysis

D.1 Export Product Quality

One concern of using export prices to measure production costs is that changes in export prices may reflect changes in product quality (e.g., Schott 2004, Manova and Zhang 2012, Fan et al. 2015). Whereas it is difficult to directly disentangle firm-level export quality from export prices, one observation is that product quality is positively correlated with prices of imported inputs (Manova and Zhang 2012, Fieler et al. 2018).

Using customs data, I construct changes in import input prices as the weighted average of changes in firm-level ordinary import prices for each 6-digit HS product that was imported in both 2005 and 2010. The weights are firm-level ordinary import volumes across 6-digit HS products in 2005. I also construct changes in import input prices for the set of high-tech capital goods, following the definition of Che and Zhang (2018).[53]

Columns (1)–(2) of Table D.1 report the impact of the college expansion on the prices of import inputs, for the same sample of estimating export price changes. Larger exposure to the college expansion did not significantly change the prices of imported inputs. Columns (3)–(4) use changes in the number of imported inputs as dependent variables, showing the college expansion did not significantly change the scope of imported inputs.

Feenstra and Romalis (2014) measure China's export quality for 4-digit SITC products between 1984–2011. Even though this measure is not firm-level and based on SITC products, it can be informative of quality discrepancy across industries of different skill intensities (which export different SITC products). Using this data, I compute each firm's weighted average of log changes in export quality between 2005–2010, where weights are

[53] Che and Zhang (2018) define high-tech products by a set of Chinese key words in the description of the product ("Shebei," "Qi," "Yi," "Zidong," "Diannao," "Weiji," "Jisuanji," "Xitong," "Kongzhi," "Shuzi," "Jichuang," "Xinpian," "Shukong").

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

Dep var:	Δlog(imported input prices)		Δlog(num of imported inputs)		Δlog(export quality)
	all goods	high-tech capital	all goods	high-tech capital	
	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
Exposure to CE	-0.772	-0.892	0.232	0.073	-0.224
	(0.474)	(1.152)	(0.478)	(0.584)	(0.190)
Obs	2,877	1,607	3,872	2,183	8,328
R-squared	0.024	0.039	0.013	0.023	0.033
First-stage F	675.54	703.18	565.06	639.50	396.34

Note: This table provides estimates from regressions in equation (3). The regressions control for: (1) output, employment, physical capital, and dummies for firm registration types (e.g., SOE) in 2005; (2) dummies indicating whether the firm was located in a high-tech zone or an economic development zone in 2005; and (3) changes in applied input and output tariffs for the firm's affiliated industry after 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%.

the firm's ordinary exports in each SITC industry in 2005. In the final column of Table D.1, I find that firms with larger exposure to the college expansion did not experience significant changes in export quality.

D.2 Alternative Instruments

Using US College Employment Shares. I draw total employment and college-educated workers' employment on the three-digit industry level from the US 1990 Census.[54] I then take efforts to map these data to 2-digit industries based on China's Industrial Classification. By doing so, I obtain an alternative measure of skill intensities of Chinese industries from the US data. I replace $SI_{l,j}$ with this alternative measure in constructing the instrument $SI_{l,j}x_l^*$. I replicate the regressions in Tables 1 and 2. The results are quantitatively similar to my baseline results, as shown in Tables D.2 and D.3.

Using Instruments Based on the 1948 Distribution of Colleges. The Statistical Yearbook of Education in 1948[55] provides detailed information on locations and enrollments of each college that was operating in 1948. I digitize this yearbook and then construct two new instruments x_l^*, by replacing the share of college enrollments in the national total in 1982 in equation (2) 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 Tables 1 and 2. The results are similar to my baseline results, as shown in Tables D.2 and D.3.

[54]The data is drawn from IPUMS International.

[55]The data can be found from https://www.naer.edu.tw/files/15-1000-7981,c1311-1.php?Lang=zh-tw.

Using Instruments Based on China's Reallocation of University Departments. In the 1950s, the Chinese government implemented massive reallocation of college departments, which was 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 digitizing 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_l and replicate the regressions in Table 1.[56] I find that this instrument lacks variation and gives quite imprecise estimates, especially when I aggregate transfers by province to construct the instrument for province-level shocks.[57] The coefficients on changes in ordinary exports or domestic sales are similar to the estimates in Table 1.

D.3 Alternative Data Construction

Using Goods Exported in Both Periods to Construct Export 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 similar as shown in Table D.2.

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 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 Tables 1 and 2, and the regression results are similar to my baseline results, as shown in Tables D.2 and D.3. The magnitude of the coefficients tends to be smaller because I focus on the shorter period.

Restricting the Sample to Exporting Firms. Because my regressions of changes in ordinary exports and export prices focus on exporting firms, I restrict the regression of changes in domestic sales to exporting firms as well. As suggested by Table D.2, with larger exposure to the college expansion, ordinary exporters' domestic sales also significantly increased.

Controlling for Destination Fixed Effects. In the final two rows of Table D.2, I construct firm-level exports and export prices separately for each export destination (such as Japan and the US). Then I regress changes in firm-destination-level exports and export prices on the exposure to the college expansion. I still find faster export growth with larger exposure to the college expansion, regardless of controlling for destination fixed effects

[56] I do not display results for innovation because they are all noisy and insignificant.

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

Table D.2: Robustness Checks of Table 1

Dep var:	Δlog(ordinary exports)		Δlog(domestic sales)		Δlog(export prices)	
Geographic level:	provincial	city-level	provincial	city-level	provincial	city-level
Alternative instruments:						
(1) Use US data to measure industry-level skill intensities	5.276***	4.248***	1.148**	1.074**	-0.417*	-0.530*
	(0.929)	(0.920)	(0.489)	(0.473)	(0.255)	(0.288)
(2) Use 1948 college number to instrument for labor shocks	3.338***	2.980***	1.844***	2.170***	-0.571**	-0.547**
	(0.845)	(0.905)	(0.522)	(0.540)	(0.253)	(0.266)
(3) Use 1948 college enrollments to instrument for labor shocks	3.176***	2.936***	1.603***	2.028***	-0.486*	-0.492*
	(0.856)	(0.882)	(0.557)	(0.584)	(0.256)	(0.265)
(4) Use 1950s department reallocation to instrument for labor shocks	–	4.706*	–	4.526*	–	-0.922
		(2.767)		(2.838)		(1.522)
Alternative Data Construction:						
(5) Use goods exported in both periods to construct exports	3.470***	3.158***	1.654***	1.841***	-0.600***	-0.580***
	(0.683)	(0.719)	(0.420)	(0.419)	(0.230)	(0.232)
(6) Use changes between 2005–2007 for estimation	1.184**	1.143***	0.366***	0.514***	-0.289***	-0.268**
	(0.509)	(0.541)	(0.133)	(0.148)	(0.109)	(0.120)
(7) Restrict the sample to exporters	3.528***	3.493***	2.324***	2.623***	-0.600***	-0.580**
	(0.736)	(0.742)	(0.718)	(0.769)	(0.230)	(0.232)
(8a) Firm-destination export change	1.561**	1.396*			-0.858*	-1.173**
	(0.693)	(0.758)			(0.509)	(0.572)
(8b) Firm-destination export change (controlling for destination fixed effects)	1.462**	1.304*			-0.532	-0.865*
	(0.712)	(0.777)			(0.523)	(0.542)

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%.

or not. This indicates that shifts in destination demand are not the driving force of export growth.[58]

D.4 Pre-trend Tests

The recent literature advocates the use of pre-trend tests to corroborate the validity of Bartik instruments (e.g., Goldsmith-Pinkham et al. 2020, Borusyak et al. 2022). I regress province-industry-level trends of sales and innovation before and after 2005 on the expo-

[58]The coefficients on export growth are smaller compared with the baseline results, because the overall export growth used in the baseline results also incorporates other effects such as entry into new export destinations. I prefer to use the baseline results, which are consistent with the quantitative analysis featuring an aggregated rest of the world.

Table D.3: Robustness Checks of Table 2

Dep var:	ΔR&D status			
	nonexporter	ord. exporter	nonexporter	ord. exporter
(1) Alternative instrument: Use US data to measure industry-level skill intensities				
Exposure to CE	0.465***	0.502**	0.400***	0.573***
	(0.137)	(0.197)	(0.131)	(0.220)
(2) Alternative instrument: Use 1948 college number to instrument for labor shocks				
Exposure to CE	0.477***	0.555***	0.404***	0.590***
	(0.109)	(0.181)	(0.098)	(0.219)
(3) Alternative instrument: Use 1948 college enrollments to instrument for labor shocks				
Exposure to CE	0.454***	0.488***	0.384***	0.524**
	(0.108)	(0.178)	(0.093)	(0.217)
(4) Alternative data construction: Use changes between 2005–2007 for estimation				
Exposure to CE	0.284***	0.286***	0.228***	0.272***
	(0.061)	(0.091)	(0.062)	(0.097)

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%.

sure to the college expansion between 2005–2010, using the same constructed shock and instrument as in Section 4. Table D.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.

E Proofs

E.1 Sequential Equilibrium

I first define a static equilibrium at time t. Let $\Pi_{i(m),n,j,t}$ be the share of expenses in foreign industry j spent on goods from Chinese firms through regime m, which is given by:

$$\Pi_{i(m),n,j,t} = \frac{\int_{\Omega_{i(m),n,j,t}} \epsilon(\omega)^{\sigma} \left(\frac{c_{i(m),j,t} d_{i(m),n,j,t}}{z(\omega)}\right)^{1-\sigma} d\omega}{\sum_{m'} \int_{\Omega_{i(m'),n,j,t}} \epsilon(\omega)^{\sigma} \left(\frac{c_{i(m'),j,t} d_{i(m'),n,j,t}}{z(\omega)}\right)^{1-\sigma} d\omega + \int_{\Omega_{n,n,j,t}} \left(\frac{c_{n,j,t} d_{n,n,j,t}}{z(\omega)}\right)^{1-\sigma} d\omega}. \tag{E.1}$$

Table D.4: Dependent Variable: Annualized Province-industry-level 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	-0.917***	0.355*	0.446	0.806***	0.038	0.081***	0.039	0.101***
	(0.205)	(0.198)	(0.464)	(0.150)	(0.027)	(0.023)	(0.041)	(0.039)
Obs	786	743	600	587	785	783	600	586
R-squared	0.399	0.546	0.237	0.381	0.204	0.448	0.177	0.566
First-stage F	522.56	440.23	164.41	138.75	681.93	528.24	357.42	232.23

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 4. 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 2005–2011, because ASM is 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. The regressions control for: (1) output, employment, physical capital, and the share of SOE firms for each province-industry pair in the initial year; (2) whether there was a high-tech zone or an economic development zone for each province-industry pair in the initial year; and (3) average input and output tariff reductions for each province-industry pair after WTO accession. The regressions also control for region-level fixed effects. 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%.

where $\Omega_{i(m),n,j,t}$ is the set of goods exported by Chinese firms to Foreign through export regime m, determined by export thresholds according to equation (11) and the distribution of state variables $N_{i(m),j,t}(\mathbf{s})$. As shown in equation (9), the unit cost $c_{i(m),j,t}$ is also a function of wages and price indices. $\Omega_{n,n,j,t}$ is the set of goods sourced from local firms in Foreign. I can analogously obtain the trade shares destined to China's markets. The price index for the industry-level good in the Chinese market is given by:

$$P_{i,j,t} = \left(\int_{\Omega_{i(\mathcal{O}),i,j,t}} \left(\frac{\sigma c_{i(\mathcal{O}),j,t}}{(\sigma-1)z(\omega)} \right)^{1-\sigma} d\omega + \int_{\Omega_{n,i,j,t}} \left(\frac{\sigma c_{n,j,t} d_{n,i,j,t}}{(\sigma-1)z(\omega)} \right)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}. \tag{E.2}$$

The good market clearing in China's industry j and export regime m requires:

$$\begin{aligned} X_{i(m),j,t} = {} & \Pi_{i(m),n,j,t} \left(\frac{\sigma-1}{\sigma} \sum_{j'} \gamma^{j}_{n,j'} X_{n,j',t} + \frac{\gamma_j^{\theta} P_{n,j,t}^{1-\theta}}{\sum_{j'} \gamma_{j'}^{\theta} P_{n,j',t}^{1-\theta}} I_{n,t} \right) \\ & + \Pi_{i(m),i,j,t} \left(\frac{\sigma-1}{\sigma} \sum_{j'} \sum_{m} \gamma^{j}_{i(m),j'} X_{i(m),j',t} + \frac{\gamma_j^{\theta} P_{i,j,t}^{1-\theta}}{\sum_{j'} \gamma_{j'}^{\theta} P_{i,j',t}^{1-\theta}} I_{i,t} \right). \end{aligned} \tag{E.3}$$

The left-hand side is the total production value of Chinese firms in industry j and export regime m. The right-hand side sums up the demand from expenditures on material costs and final goods across destinations, weighted by trade shares. $I_{n,t} = \sum_j \left(\frac{1}{\sigma} + \frac{\sigma-1}{\sigma}\gamma^L_{n,j}\right) X_{n,j,t}$ is the total expenses on final goods in Foreign (by workers and firm owners). $I_{i,t} = \sum_m \sum_j \left(\frac{1}{\sigma} + \frac{\sigma-1}{\sigma}\gamma^L_{i(m),j}\right) X_{i(m),j,t}$ is the total expenses on final goods in China.

The labor market clearing in China requires:

$$W_{i,t}L_{i,t} = \sum_m \sum_j \frac{\alpha^{\rho_x}_{i(m),j} W^{1-\rho_x}_{i,t}}{\alpha^{\rho_x}_{i(m),j} W^{1-\rho_x}_{i,t} + (1-\alpha_{i(m),j})^{\rho_x} S^{1-\rho_x}_{i,t}} \frac{\sigma-1}{\sigma} \frac{\gamma^L_{i(m),j} X_{i(m),j,t}}{1-(1-c_{agr})\mathbf{1}_{\{j=agr\}}}, \tag{E.4}$$

$$S_{i,t}H_{i,t} = \sum_m \sum_j \frac{\alpha^{\rho_x}_{i(m),j} W^{1-\rho_x}_{i,t}}{\alpha^{\rho_x}_{i(m),j} W^{1-\rho_x}_{i,t} + (1-\alpha_{i(m),j})^{\rho_x} S^{1-\rho_x}_{i,t}} \frac{\sigma-1}{\sigma} \frac{\gamma^L_{i(m),j} X_{i(m),j,t}}{1-(1-c_{agr})\mathbf{1}_{\{j=agr\}}} + \gamma_r P^r_{i,t} Q^r_{i,t}, \tag{E.5}$$

where the left-hand side is the supply of labor, whereas the right-hand side is the demand for labor from production. Because wages in agriculture are a portion c_{agr} of nonagricultural wages in China, the same labor payments $\gamma^L_{i(m),j} X_{i(m),j,t}$ would generate $\frac{1}{c_{agr}}$ times of employment demand in agriculture than in nonagriculture. For educated labor, there is additional demand from R&D expenditures aggregated across all firms.

Combining equations (E.1)–(E.5), I can solve for $\{\Pi_{i(m),n,j,t}, X_{i(m),j,t}, W_{i,t}, S_{i,t}, P_{i,j,t}\}$. The equilibrium conditions for Foreign can be obtained analogously.

Given sequences of wages and prices at each time t and initial distributions, 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 5.2.1; and (2) the law of motion for labor distribution $\mathcal{L}_t$ is consistent with workers' entry and retirement.

E.2 Analytical Results of A Simplified Model

In the simplified model, I abstract from firm entry, input-output linkages, and operation costs. Without input-output linkages, a Chinese firm employs H units of educated labor and L units of less-educated labor to produce

$$q = \tilde{z}\left[\alpha_{i(m),j} L^{\frac{\rho_x-1}{\rho_x}} + (1-\alpha_{i(m),j}) H^{\frac{\rho_x-1}{\rho_x}}\right]^{\frac{\rho_x}{\rho_x-1}}, \tag{E.6}$$

where $\tilde{z}$ is the firm's productivity after innovation. The unit cost of production ($\tilde{z}=1$) is now given by:

$$c_{i(m),j} = \left[\frac{\alpha^{\rho_x}_{i(m),j}}{W_i^{\rho_x-1}} + \frac{(1-\alpha_{i(m),j})^{\rho_x}}{S_i^{\rho_x-1}}\right]^{\frac{1}{1-\rho_x}}. \tag{E.7}$$

I consider one period in which innovation will instantly improve firm productivity, and thus I omit time subscript t. For a firm with initial productivity z, the firm determines the optimal investment level i and export choices $\mathbf{1}_X$ to maximize the value of the firm. The problem is:

$$\max_{i\geq 0,\mathbf{1}_X} \underbrace{\frac{1}{\sigma}\left(\frac{\sigma c_{i(m),j} d_{i(m),i,j}}{(\sigma-1)\tilde{z}}\right)^{1-\sigma} P_{i,j}^{\sigma} Q_{i,j} + \mathbf{1}_X \left(\frac{1}{\sigma}\epsilon^{\sigma}\left(\frac{\sigma c_{i(m),j} d_{i(m),n,j}}{(\sigma-1)\tilde{z}}\right)^{1-\sigma} P_{n,j}^{\sigma} Q_{n,j} - f_{i(m),j}^{X} P_i\right)}_{\text{total profits (net of fixed export costs)}}$$
$$- \underbrace{\left(\bar{z}^{\sigma-1}\phi_{1,j}\mathbf{1}_{\{i>0\}} + z^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}\right) P_i^r}_{\text{research costs}},$$
$$\text{s.t.} \quad \log\tilde{z} = \log z + i \times \eta, \tag{E.8}$$

where I plugged in the optimal price charged in each destination market under monopolistic competition, which is a constant markup $\frac{\sigma}{\sigma-1}$ over the marginal cost of supplying one unit of good. The sales to the domestic market is $R_{i,j} = \left(\frac{\sigma c_{i(m),j} d_{i(m),i,j}}{(\sigma-1)\tilde{z}}\right)^{1-\sigma} P_{i,j}^{\sigma} Q_{i,j}$, and the sales to the foreign market is $R_{n,j} = \epsilon^{\sigma}\left(\frac{\sigma c_{i(m),j} d_{i(m),n,j}}{(\sigma-1)\tilde{z}}\right)^{1-\sigma} P_{n,j}^{\sigma} Q_{n,j}$.

E.2.1 Proof of Proposition 1

I now prove the response of relative wages to the relative supply of educated workers in the autarkic economy. In the autarkic economy, processing firms do not produce. By firms' cost minimization, I have:

$$H_{i(\mathcal{O}),j}(\omega)/L_{i(\mathcal{O}),j}(\omega) = \left((1-\alpha_{i(\mathcal{O}),j})W_i/\alpha_{i(\mathcal{O}),j}S_i\right)^{\rho_x},$$

for each ordinary firm ω in industry j. I define $H_{i,j} = \int H_{i(\mathcal{O}),j}(\omega)d\omega$ and $L_{i,j} = \int L_{i(\mathcal{O}),j}(\omega)d\omega$ as aggregate labor demand in China's industry j. Aggregating across all the firms, I still obtain $H_{i,j}/L_{i,j} = \left((1-\alpha_{i(\mathcal{O}),j})W_i/\alpha_{i(\mathcal{O}),j}S_i\right)^{\rho_x}$. Log differentiating this equation, I obtain:

$$\hat{H}_{i,j} - \hat{L}_{i,j} = -\rho_x(\hat{S}_i - \hat{W}_i). \tag{E.9}$$

For each industry, I notice $H_{i,j}S_i + L_{i,j}W_i = \frac{\sigma-1}{\sigma}(\gamma_j)^{\theta}\left(\frac{P_{i,j}}{P_i}\right)^{1-\theta} E_i$ from equation (4), where E_i is the total expenditure on the final good in China. The ratio $\frac{\sigma-1}{\sigma}$ is the share of labor costs in the total revenue. Log differentiating this equation, I further derive:

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

where $SI_{i,j} = \frac{H_{i,j}S_i}{H_{i,j}S_i + L_{i,j}W_i}$ is educated labor's share in the total wage bill for ordinary production of China's industry j. Because I abstract from new firm entry and there are no fixed costs of selling in local markets, I obtain that in Chinese regions:

$$P_{i,j}^{1-\sigma} = \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_{i(\mathcal{O}),j}^{\rho_x}}{W_i^{\rho_x-1}} + \frac{(1-\alpha_{i(\mathcal{O}),j})^{\rho_x}}{S_i^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}} \int z(\omega)^{\sigma-1}d\omega, \tag{E.11}$$

where $\int z(\omega)^{\sigma-1}d\omega$ is the aggregated productivity levels of all ordinary firms in China's industry j. Log differentiating this equation indicates:

$$\hat{P}_{i,j} = (1-SI_{i,j})\hat{W}_i + SI_{i,j}\hat{S}_i, \tag{E.12}$$

where I used the definition of $SI_{i,j}$ and $H_{i,j}/L_{i,j} = \left((1-\alpha_{i(\mathcal{O}),j})W_i/\alpha_{i(\mathcal{O}),j}S_i\right)^{\rho_x}$.

Combining equations (E.9), (E.10), and (E.12), I obtain:

$$\theta\hat{W}_i = (\rho_x-\theta)SI_{i,j}(\hat{S}_i-\hat{W}_i) - \hat{L}_{i,j} + \hat{E}_i + (\theta-1)\hat{P}_i, \tag{E.13}$$

$$\theta\hat{S}_i = (\theta-\rho_x)(1-SI_{i,j})(\hat{S}_i-\hat{W}_i) - \hat{H}_{i,j} + \hat{E}_i + (\theta-1)\hat{P}_i. \tag{E.14}$$

Note that I do not consider innovation here, and therefore all the labor is used in production. I then have $\hat{L}_i = \sum_j \Lambda_{i,j}^L \hat{L}_{i,j}$ and $\hat{H}_i = \sum_j \Lambda_{i,j}^H \hat{H}_{i,j}$, where $\Lambda_{i,j}^H$ ($\Lambda_{i,j}^L$) is the share of educated (less-educated) workers in industry j. Combining this with equations (E.13) and (E.14), I obtain:

$$\hat{S}_i - \hat{W}_i = \frac{1}{\theta + (\rho_x-\theta)\left(1-\sum_j SI_{i,j}(\Lambda_{i,j}^H - \Lambda_{i,j}^L)\right)}(\hat{L}_i - \hat{H}_i). \tag{E.15}$$

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

$$SI_{i,j} = \frac{H_{i,j}S_i}{H_{i,j}S_i + L_{i,j}W_i} = \frac{H_iS_i}{H_iS_i + L_iW_i\Lambda_{i,j}^L/\Lambda_{i,j}^H}.$$

Therefore, $SI_{i,j}$ is larger when $\Lambda_{i,j}^H/\Lambda_{i,j}^L > 1$ than when $\Lambda_{i,j}^H/\Lambda_{i,j}^L < 1$. Then, I have

$$\sum_j SI_{i,j}(\Lambda_{i,j}^H - \Lambda_{i,j}^L) = \sum_{j,\Lambda_{i,j}^H/\Lambda_{i,j}^L>1} SI_{i,j}(\Lambda_{i,j}^H - \Lambda_{i,j}^L) - \sum_{j,\Lambda_{i,j}^H/\Lambda_{i,j}^L\leq 1} SI_{i,j}(\Lambda_{i,j}^L - \Lambda_{i,j}^H) \geq 0.$$

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

Finally, I define Φ_i as:

$$\Phi_i = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{i,j}(\Lambda^H_{i,j} - \Lambda^L_{i,j}))}. \tag{E.16}$$

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

E.2.2 Proof of Proposition 2

Result (i). To prove Result (i) in Proposition 2, I note that domestic sales of a Chinese ordinary firm can be written as:

$$R_{i,j} = \frac{p^{1-\sigma}_{i,i,j}}{P^{1-\sigma}_{i,i,j} + P^{1-\sigma}_{n,i,j}} \gamma_j^\theta \left(\frac{P_{i,j}}{P_i}\right)^{1-\theta} E_i, \tag{E.17}$$

where $p_{i,i,j} = \frac{\sigma c_{i(\mathcal{O}),j} d_{i(\mathcal{O}),i,j}}{(\sigma-1)z}$ is the price charged by the Chinese firm, and $P_{n,i,j}$ is the aggregate price index for foreign firms exporting to China. Domestic firms' aggregate price index is:

$$P^{1-\sigma}_{i,i,j} = \left(\frac{\sigma c_{i(\mathcal{O}),j} d_{i(\mathcal{O}),i,j}}{\sigma - 1}\right)^{1-\sigma} \int z(\omega)^{\sigma-1} d\omega. \tag{E.18}$$

The aggregate price indices can be obtained as:

$$P^{1-\sigma}_{i,j} = P^{1-\sigma}_{i,i,j} + P^{1-\sigma}_{n,i,j}.$$

Note that $\Pi_{i,i,j} = \frac{P^{1-\sigma}_{i,i,j}}{P^{1-\sigma}_{i,i,j} + P^{1-\sigma}_{n,i,j}}$ is the share of expenditures in China on domestic goods.

Log differentiating equation (E.17) and noting that $\hat{P}_{i,i,j} = \hat{p}_{i,i,j}$ as I abstract from the extensive margin of selling to domestic markets, I obtain

$$\hat{R}_{i,j} = (1-\sigma)(1 - \Pi_{i,i,j})\hat{P}_{i,i,j} + (1-\theta)\Pi_{i,i,j}\hat{P}_{i,i,j} + (\theta - 1)\hat{P}_i + \hat{E}_i. \tag{E.19}$$

Log differentiating equation (E.18) gives me proportional changes in domestic price indices:

$$\hat{P}_{i,i,j} = \hat{c}_{i(\mathcal{O}),j} = (1 - SI_{i,j})\hat{W}_i + SI_{i,j}\hat{S}_i. \tag{E.20}$$

Combining equations (E.19) and (E.20) leads to proportional changes in domestic sales. The common trend $(\theta - 1)\hat{P}_i + \hat{E}_i$ does not vary across industries of different skill intensities and is thus absorbed by region fixed effects in my regressions.

Now consider proportional changes in exports in the intensive margin. First note that exports can be written as:

$$R_{n,j} = \epsilon^{\sigma} \left(\frac{p_{i,n,j}}{P_{n,j}} \right)^{1-\sigma} \gamma_j^{\theta} \left(\frac{P_{n,j}}{P_n} \right)^{1-\theta} E_n, \tag{E.21}$$

where $P_{n,j}$ and P_n are industry-level and final-good price indices in Foreign. For a Chinese ordinary firm's price $p_{i,n,j}$, it can be written as:

$$p_{i,n,j} = \frac{\sigma}{\sigma - 1} \frac{c_{i(\mathcal{O}),j} d_{i(\mathcal{O}),n,j}}{z}. \tag{E.22}$$

I assumed in Section 5.5 that the shock in China will not affect equilibrium outcomes in foreign regions, which indicates that $P_{n,j}$ and P_n remain constant. Therefore, log differentiating equation (E.21), I can derive:

$$\hat{R}_{n,j} = (1 - \sigma)\hat{p}_{i,n,j}, \tag{E.23}$$

where $\hat{p}_{i,n,j}$ can be derived by log differentiating equation (E.22),

$$\hat{p}_{i,n,j} = \hat{c}_{i(\mathcal{O}),j} = (1 - SI_{i,j})\hat{W}_i + SI_{i,j}\hat{S}_i. \tag{E.24}$$

Combining these two equations, I derive proportional changes in exports in Result (i).

Result (ii). From Result (i), I have:

$$\frac{\partial \hat{R}_{n,j}}{\partial SI_{i,j}} = (\sigma - 1)(\hat{W}_i - \hat{S}_i), \tag{E.25}$$

$$\frac{\partial \hat{R}_{i,j}}{\partial SI_{i,j}} = \left[(\theta - 1)\Pi_{i,i,j} + (\sigma - 1)(1 - \Pi_{i,i,j})\right](\hat{W}_i - \hat{S}_i). \tag{E.26}$$

Thus, with $\sigma > \theta \geq 1$, I have $\frac{\partial \hat{R}_{i,j}}{\partial SI_{i,j}} > 0$ and $\frac{\partial \hat{R}_{n,j}}{\partial SI_{i,j}} - \frac{\partial \hat{R}_{i,j}}{\partial SI_{i,j}} = (\sigma - \theta)\Pi_{i,i,j}(\hat{W}_i - \hat{S}_i) > 0$. Thus, firms in more skill-intensive industries experience faster growth in domestic sales and even faster growth in exports.

Result (iii). Note that the export threshold for ordinary exports of industry j can be solved as:

$$\frac{R_{n,j}}{\sigma} - f^X_{i(\mathcal{O}),j} P_i = 0 \Rightarrow z_j^* = \epsilon^{\frac{\sigma}{1-\sigma}} \left(\frac{\sigma f^X_{i(\mathcal{O}),j} P_i}{E_n P_n^{\theta-1} P_{n,j}^{\sigma-\theta} \gamma_j^{\theta}} \right)^{\frac{1}{\sigma-1}} \frac{\sigma}{\sigma - 1} \left[\frac{\alpha_{i(\mathcal{O}),j}^{\rho_x}}{W_i^{\rho_x - 1}} + \frac{(1 - \alpha_{i(\mathcal{O}),j})^{\rho_x}}{S_i^{\rho_x - 1}} \right]^{\frac{1}{1-\rho_x}}, \tag{E.27}$$

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

$$\hat{z}_j^* = (1 - SI_{i,j})\hat{W}_i + SI_{i,j}\hat{S}_i. \tag{E.28}$$

Therefore, the threshold z_j^* declines more in the more skill-intensive industry when $\hat{W}_i - \hat{S}_i > 0$. 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. ***Q.E.D.***

E.2.3 Proof of Proposition 3

Result (i) combines proportional growth of domestic sales and exports from Result (i) of Proposition 2. According to Result (i) of Proposition 2, given the export status, the overall proportional change in sales is given by:

$$\begin{aligned}
&\frac{R_{i,j}}{R_{i,j}+R_{n,j}}\hat{R}_{i,j} + \frac{R_{n,j}}{R_{i,j}+R_{n,j}}\hat{R}_{n,j} \\
&= \frac{R_{i,j}}{R_{i,j}+R_{n,j}}\left[(1-\sigma)(1-\Pi_{i,i,j})\hat{c}_{i(\mathcal{O}),j} + (1-\theta)\Pi_{i,i,j}\hat{c}_{i(\mathcal{O}),j} + (\theta-1)\hat{P}_i + \hat{E}_i\right] + \frac{R_{n,j}}{R_{i,j}+R_{n,j}}(1-\sigma)\hat{c}_{i(\mathcal{O}),j} \\
&= -\left[\sigma - 1 + (\theta-\sigma)\Pi_{i,i,j}\left(1 - \frac{R_{n,j}}{R_{i,j}+R_{n,j}}\right)\right]\hat{c}_{i(\mathcal{O}),j} + \frac{R_{i,j}}{R_{i,j}+R_{n,j}}\left[(\theta-1)\hat{P}_i + \hat{E}_i\right] \\
&= \left[\sigma - 1 + (\theta-\sigma)\Pi_{i,i,j}\left(1 - \frac{R_{n,j}}{R_{i,j}+R_{n,j}}\right)\right]\left[SI_{i,j}(\hat{W}_i - \hat{S}_i) - \hat{W}_i\right] + \frac{R_{i,j}}{R_{i,j}+R_{n,j}}\left[(\theta-1)\hat{P}_i + \hat{E}_i\right].
\end{aligned} \tag{E.29}$$

My empirical analysis focuses on the responses of firms across industries of different skill intensities to the college expansion (which affects the skill premium). Thus, the estimated response reflects the impact of $\left[\sigma - 1 + (\theta-\sigma)\Pi_{i,i,j}\left(1 - \frac{R_{n,j}}{R_{i,j}+R_{n,j}}\right)\right] SI_{i,j}(\hat{W}_i - \hat{S}_i)$.[59]

Result (ii) arises from the observation that starting to export improves revenues, thus increasing returns to innovation as shown by equation (E.8). ***Q.E.D.***

F Calibration

F.1 Industries

I calibrate a 33-industry version of my model with China and a constructed Rest of World. I group industries according to China's Industry Classification System (CIC) published in 2003. I consider agriculture, mining, services, and all 30 2-digit manufacturing industries.

[59]The remaining part is $-\left[\sigma - 1 + (\theta-\sigma)\Pi_{i,i,j}\right]\hat{W}_i + (\theta-\sigma)\Pi_{i,i,j}\frac{R_{n,j}}{R_{i,j}+R_{n,j}}\hat{W}_i + \frac{R_{i,j}}{R_{i,j}+R_{n,j}}\left[(\theta-1)\hat{P}_i + \hat{E}_i\right]$, which depends on region-level aggregate changes ($\hat{W}_i$, $\hat{P}_i$, and $\hat{E}_i$). In the empirical analysis, I control region fixed effects to capture region-level aggregate changes. As the remaining part may also depend on export shares, I also experimented with additionally controlling for export shares (with region-specific coefficients) in estimating the response of innovation, and the estimates of the response remain very similar.

F.2 Relation between Reduced-form Estimates and Structural Parameters

In Proposition 2, I abstract from input-output linkages, innovation, firm entry, and operation costs. I also do not consider productivity and demand shocks, as I focus on a one-period model. I discuss how these abstractions affect the relationship 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, modeling innovation does not affect the mapping between the reduced-form estimates and the structural parameters.

Third, modeling firm entry could bias the mapping, because more skill-intensive industries could experience more firm entry that reduces incumbent firms' sales. In Column (1) of Table F.1, I regress changes in the number of new entrants between 2005–2010, where entrants are identified by firms' establishment year, on the exposure to the college expansion. I find that larger exposure to the college expansion triggered more firm entry. In Column (3) of Table F.1, for each province-industry pair, I regress the sales share in 2010 of firms that entered between 2005–2010, on the exposure to the college expansion. The result shows that the college expansion did not significantly affect sales across industries in 2010 through firm entry between 2005–2010, as new firms tended to be small. In these regressions, I use ASM 2005 and SAT 2010 to construct dependent variables. Because SAT 2010 is only a sample of all firms, in the even columns of Table F.1, I also use ASM 2005 and 2011 to construct dependent variables as ASM provides full coverage of firms above certain sales thresholds, and the regression results are similar.

Finally, modeling operation costs and idiosyncratic shocks can 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.

As another check, I look into how exiting firms affected industry sales. In Column (5) of Table F.1, for each province-industry pair, I regress the number of firms that exited between 2005–2010,[60] 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 (7), for each province-industry pair, I regress the sales share in 2005 of

[60] The exiting firm is defined as a firm that showed up in ASM 2005 but disappeared in SAT 2010.

Table F.1: Dependent Variable: Province-industry-level Changes

Dep var:	Δlog(num of entrants)		% entrants' sales		% exiters		% exiters' sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Period	05–10	05–11	05–10	05–11	05–10	05–11	05–10	05–11
Exposure to CE	4.588***	2.136*	-0.116	-0.254	-0.473***	-0.462***	-0.635	0.143
	(1.570)	(1.205)	(0.287)	(0.244)	(0.123)	(0.110)	(0.488)	(0.451)
Obs	616	585	743	786	744	795	744	795
R-squared	0.553	0.483	0.262	0.399	0.647	0.485	0.522	0.469
First-stage F	401.68	440.11	432.49	496.63	350.72	424.00	365.57	443.87

Note: This table provides estimates from regressions, treating regions as provinces, using the same constructed shocks and instruments as in Section 4. The odd columns use ASM 2005 and SAT 2010 to construct the dependent variables, whereas the even columns use ASM 2005 and ASM 2011. I also exclude purely processing exporters to be consistent with Section 4. The regressions control for: (1) output, employment, physical capital, and the share of SOE firms for each province-industry pair in 2005; (2) whether there was a high-tech zone or an economic development zone for each province-industry pair in 2005; and (3) average input and output tariff reductions for each province-industry pair after WTO accession. The regressions also control for region-level fixed effects. Regressions in Columns (1)–(2) and (5)–(6) are weighted by the number of entrants and the total number of firms in each province-industry pair in 2005, respectively. Regressions in Columns (3)–(4) and (7)–(8) 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%.

firms that exited between 2005–2010, on the exposure to the college expansion. The result shows that exiting firms between 2005–2010 due to the college expansion were small and did not significantly affect sales across industries in 2005.

F.3 Description of Data Sources

Output and Exports. I obtain China's manufacturing output by industry between 2000–2012 from ASM. I obtain processing and ordinary exports by industry from the matched ASM-Customs Database.[61] For each industry, the difference between total output and processing exports is the output of ordinary production. I draw production in agriculture, mining, and services between 2000–2012 from input-output tables.[62]

I obtain foreign output by industry between 2000–2011 from the World Input-Output Table Database. Because the data is based on the ISIC classification, I convert the foreign industrial output to the 33 industries using concordances in Dean and Lovely (2010).

As my data does not cover China's and foreign industry-level output after 2012,[63] I

[61] As the match between ASM and Customs Database is imperfect, 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.

[62] I obtain 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.

[63] China stipulated a new standard of industry classification in 2011, which came into use in ASM in 2013. Thus, China's output in each 2-digit manufacturing industry is not fully comparable before and after 2012.

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 in Penn Table 9.1.

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 use the World Input-Output Database to compute input-output parameters for Foreign.

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 remained unchanged after 2012.

Firm Distribution. I obtain the number of firms by industry from Firm Census 2004, 2008, and 2013, and divide the number of firms in each 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. 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 and education level in 2000 from the Population Census (the labor distribution in the initial year of the quantitative analysis). The data in 2005 also provides wage data. I adjust workers of lower education levels to the equivalents of high-school graduates, using relative wages of different education groups.[64] I adjust part-time college graduates to the equivalents of college graduates with regular degrees, using their relative wages from Xu et al. (2008).

I obtain each year's amount of college graduates from Statistical Yearbooks. I infer the amount of new noncollege labor between 2000–2018 according to the amount of labor force in the corresponding cohort (age 20 population in the corresponding year net of those who were enrolled in colleges, adjusted by labor force participation rate). With the employment levels by age and education in 2000 and the number of new workers, I can obtain China's employment by education in each age group across years.

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 graduates (12 years of schooling) by assuming that the

[64] I estimate a Mincer regression of log earnings on a set of dummies of different education levels as well as province fixed effects. I also control for a dummy variable indicating whether the worker is in the agriculture sector, given persistent differences in wage levels between agricultural and nonagricultural workers. I then use the coefficients on education levels to adjust workers of lower education levels to the equivalents of high-school graduates.

returns to one year of schooling are 10%.

I use the Urban Household Survey 1988–2009 to estimate the college premium. This survey is implemented yearly 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 (30–100 thousand observations each year).

F.4 Details on Targeted Moments

Step 1. I target the following moments. (1) The relative output of each industry. (2) The share of full-time R&D workers in manufacturing employment in China. (3) The relative wages of workers across age groups in China. (4) The share of college-educated workers in employment by industry and export regime (relative to services), and aggregate college premium in China.[65] (5) The standard deviation of export-output ratios among exporters. (6) China's agricultural employment share. (7) For each industry and export regime, the share of foreign expenses sourced from China, and the share of China's expenses sourced from Foreign.[66] (8) For each industry and export regime, the share of exporting firms in China. The data moments are computed from ASM, Customs Database, 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.[67] The location parameter is specific to each province-industry-regime or foreign industry and calibrated to match the output level.

Step 2. I target the following moments. (1) Before 2011, the output in each Chinese industry-regime pair or foreign industry. After 2012, I assume that foreign industry-level productivity remained unchanged, and China's firm productivity grew at a com-

[65] 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 high-school graduates, from Population Census 2005.

[66] In reality, the imported materials used by processing exporters are duty-free, indicating that the import cost of processing producers is cheaper than that of ordinary producers and unaffected by tariffs. Therefore, for industry-level goods in equation (5), I numerically distinguish between industry-level goods used as raw materials in the production of processing exports and industry-level goods used to assemble the final good and as raw materials for ordinary production. The difference is that industry-level goods used for processing production enjoy cheaper import costs of inputs. The iceberg import costs for industry-level goods that are used for processing production are calibrated to match industry-level shares of imported materials' costs in all materials' costs for processing firms in 2005. The import costs for industry-level goods that are used to assemble the final good and as raw materials for ordinary production are calibrated to match industry-level shares of imports in all the expenses for final-good use and ordinary firms' materials in 2005, and they change over time to reflect tariff changes.

[67] I find the Pareto tail index of sales distribution is 1.1 in ASM 2005, similar to the US level (Axtell 2001).

mon yearly rate relative to foreign firms to match the relative GDP growth. (2) Changes in the number of firms in each China's industry-regime pair 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' establishment year) relative to incumbents in 2000–2007. (6) The autocorrelation parameter of a firm's ordinary exports in adjacent years, in 2000–2007. (7) The standard deviation of R&D intensity among R&D firms in 2005. (8) The slope of a firm's sales growth on its R&D intensity in the previous year, in 2001–2007.[68] (9) The share of R&D firms and the R&D intensity in 2005 for each industry. (10) Aggregate manufacturing R&D intensity in 2000–2018. (11) Changes in aggregate college premium between 2003–2009. (12) Average differences in the college premium between young (aged 20–28) and old workers (aged 29+) in 2009. 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, I compute moments (7)–(10) based on China's manufacturing industries. I set other industries' R&D expenses as given by the data. I compute moments (11)–(12) using the Urban Household Survey.

For computational tractability, I simplify the next-period's firm value as:

$$V_{i(m),j,t+1} = C_s \left[\pi_{i(m),n,j,t+1}(\mathbf{s}_{t+1}) + \pi_{i(m),i,j,t+1}(\mathbf{s}_{t+1}) - f_{i(m),j} P_{i,t+1} \right],$$

with the discount rate $C_s = \sum_{t=0}^{\infty} \frac{(1-\text{average profit tax rate})(1-\delta)^t}{(1+r)^t}$ reflecting profit taxes, death rates and interest rates. Given the data, I set the average tax rate to be 25% and the real interest rate r to be 0.01. Treating the innovation choice as a one-period decision is exploited in recent papers (e.g., Desmet et al. 2018, Chen et al. 2021).

F.5 Estimating Age-specific College Premium

To obtain the college premium in a given year, I estimate the following regression:

$$\log w_i = \beta_0 + \sum_{x \in X} \phi_{x,1} D_i^x + \sum_{x \in X} \phi_{x,2} D_i^x \times \mathbf{1}_{col} + \beta_1 agr_i + \zeta_{l(i)} + \epsilon_i.$$

$\log w_i$ is log yearly wage for worker i. 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_i is a dummy variable indicating whether the worker is in agriculture because workers' wages are much lower in agriculture than in other industries. $\zeta_{l(i)}$ captures province fixed effects.

I use workers' yearly wage in the Urban Household Survey to estimate the observed

[68] I compute this by regressing a firm's sales growth on its ratio of R&D to sales in the previous year, controlling for the deciles of the previous year's firm sales (small firms tend to grow fast), and firm and year fixed effects.

Table G.1: Contribution of College Expansion to Export Skill Upgrading and Innovation

	Contribution of College Expansion to Changes in 2003–2018	
	Δ share of high-skill ordinary exports	Δ manu R&D/sales
Baseline model	36%	72%
1. Model with expansion of part-time education	37%	66%
2. Model with alternative cost share of labor in R&D	35%	62%
3.1 Model with generalized R&D cost ($\gamma_r^H = 0.8$)	35%	62%
3.2 Model with generalized R&D cost ($\gamma_r^H = 0.65$)	34%	56%
4. Model with changes in coverage of R&D incentives	37%	70%
5. Model with changes in workers' abilities	28%	56%
6. Model with subnational regions	30%	66%

Note: This table presents the contributions of the college expansion to changes in the share of high-skill ordinary exports and changes in manufacturing R&D intensity between 2003–2018, respectively. The contributions are computed in the same way as in Sections 7.1 and 7.2.

age-specific college premium for each year. 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 less-educated labor (high-school graduates) and educated labor (college-educated workers).

G Model Extensions

In this section, I present extensions to my quantitative model and discuss how the results change in each model extension. In particular, in each subsection, I consider the robustness of quantitative results to: (1) considering expansion of part-time education, (2) considering an alternative way of calibrating the cost share of labor in R&D, (3) considering a generalized cost function of R&D inputs, (4) considering that the coverage of R&D tax incentives changes over time, (5) considering that workers' abilities change over time, and (6) considering subnational regions within China.

Table G.1 summarizes the main quantitative results in alternate model specifications, which are similar to the baseline results. In particular, across different alternate models, the college expansion can explain 56–70% of increases in manufacturing R&D intensity and 28–37% of increases in the share of high-skill ordinary exports between 2003–2018.

G.1 Expansion of Part-time College Education

The number of graduates from part-time colleges also experienced a threefold expansion after 1999 (see Appendix B), whereas my earlier analysis did not account for this. Now, in the counterfactual exercise of "no college expansion," 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, the quantitative impact of the college expansion in this extension was very similar to the baseline results, as shown in Table G.1.[69]

G.2 Measurement Quality of R&D Workers

In the baseline model, I targeted the share of R&D workers to calibrate the cost share of labor in R&D. One concern is that the amount of R&D workers is self-reported by firms and not inspected by the government, and thus it may be measured inaccurately in the data, which affects the calibration's accuracy. I thus provide an alternative calibration. The OECD Database obtains China's R&D data from the firm survey done by China's Statistical Bureau. For enterprises, the share of labor costs in R&D increased from 27% in 2003 to 33% in 2018. Thus, I set the cost share of labor in R&D to be $\gamma_r = 0.3$ instead of calibrating it using the data on R&D workers. Quantitatively, as reported by Table G.1, the college expansion can still explain 62% of increases in manufacturing innovation between 2003–2018 with this alternative calibration.

It is worth noting that China's share of labor costs in R&D drawn from the OECD Database was much lower than the estimates for other economies (see footnote 40). This issue could be due to the underreporting of labor costs in China's firm data, as discussed in the literature (e.g., Hsieh and Klenow 2009). Thus, this alternative calibration of the cost share of labor in R&D may underestimate the importance of educated labor for R&D.

G.3 Cost Function of R&D Inputs

The baseline model considers that the cost of R&D inputs is a Cobb-Douglas function of educated labor's wage and final goods' price. In this subsection, I consider a generalized cost function of R&D inputs:

$$P^r_{k,t} = \frac{\left[\gamma_r \left(S_{k,t}^{\gamma_r^H} W_{k,t}^{1-\gamma_r^H}\right)^{1-\zeta} + (1-\gamma_r) P_{k,t}^{1-\zeta}\right]^{\frac{1}{1-\zeta}}}{A^r_{k,t}}, \; k \in \{i, n\}. \tag{G.1}$$

In this function, I extend the baseline model in two aspects: (1) both educated and less-educated workers are used in the R&D process, with γ_r^H governing the share of educated workers' labor costs in total R&D labor costs (the baseline model is a special case with $\gamma_r^H = 1$); and (2) labor and materials are imperfect substitutes in producing R&D, with ζ

[69]Considering expansion of part-time college education further reduced the college premium, thus reinforcing export skill upgrading. However, it also lowered aggregate income, as additional part-time graduates were already much less productive than noncollege workers of the same age in later years. Thus, the impact of the college expansion on innovation became slightly lower compared with baseline results.

governing the elasticity of substitution between labor and materials and the share of labor costs in R&D costs given by $\gamma_r\left(S_{k,t}^{\gamma_r^H}W_{k,t}^{1-\gamma_r^H}\right)^{1-\zeta} / \left[\gamma_r\left(S_{k,t}^{\gamma_r^H}W_{k,t}^{1-\gamma_r^H}\right)^{1-\zeta} + (1-\gamma_r)P_{k,t}^{1-\zeta}\right]$, and the baseline model is a special case with $\zeta \to 1$.

In this model extension, I consider two alternative calibrations of γ_r^H to allow for the role of less-educated workers in the R&D process: (1) I calibrate $\gamma_r^H = 0.8$, as researchers account for 80% of all the R&D personnel (the remaining are supporting staff), according to China's Survey of Industrial R&D Firms in 2008; and (2) in the R&D Census, I now assume that employees with junior college degrees had the same participation rate in R&D as employees with high-school degrees[70] and calibrate γ_r^H to match this conservatively reestimated share of R&D workers with college degrees, which implies $\gamma_r^H = 0.65$.

As ζ governs how the share of labor costs in overall R&D costs changes over time, in either calibration of γ_r^H, I calibrate ζ to match proportional changes in the share of labor costs in R&D costs between 2003–2018, according to the OECD Database. I recalibrate other model parameters to match the targeted moments in Table 4.

Table G.1 suggests that the contribution of the college expansion to the innovation surge becomes lower in this model extension (compared with the baseline), as a result of a lesser role of educated labor in R&D (with $\gamma_r^H < 1$). Nevertheless, the college expansion still explained 56–62% of increases in manufacturing R&D intensity between 2003–2018.

G.4 Coverage of R&D Tax Incentives

In the baseline model, all firms can apply for R&D tax incentives. In reality, before 2008, only firms in high-tech zones can apply for R&D incentives, and foreign-invested firms were not motivated to apply for R&D incentives due to their preferential tax treatments. The tax reform in 2008 not only changed the tax rates, but also extended the coverage of R&D incentives to all firms. As a model extension, I consider that before 2008, only a portion of firms could enjoy R&D tax incentives (randomly assigned). For each year, I choose the portion to match the share of firms that were located in high-tech zones and not foreign-invested firms.[71] I recalibrate other model parameters to match the targeted moments in Table 4.

Table G.1 suggests that the quantitative results of this model extension are very similar to my baseline results. This is because, in both the baseline model and the model

[70] As the R&D Census did not separate R&D workers with junior college degrees and those with high-school degrees, I assumed that employees with junior college degrees had the same participation rate in R&D as employees with university degrees and obtained that the share of R&D workers with at least college degrees was 99% in manufacturing in the baseline (see footnote 8).

[71] I identify whether a firm was located in a high-tech zone based on whether the corresponding words showed up in the firm's address, following Li and Wu (2018). The portion of firms that were located in high-tech zones and were not foreign-invested firms was 0.2% in 2000 and 0.7% in 2007. The quantitative results are similar if I choose the portion to match the share of firms that were located in high-tech zones and were not foreign-invested firms conditional on being R&D firms.

Table G.2: Manufacturing R&D Intensity in Baseline and Counterfactual Scenarios

	Manufacturing R&D/sales in 2018
Baseline	1.10%
Without R&D tax changes in 2008	0.74%
Without college expansion	0.74%
Without both tax changes & college expansion	0.41%

Note: This table presents manufacturing R&D intensity in 2018 in the baseline calibration and in different counterfactual scenarios (without the college expansion or without tax changes in 2008), respectively.

extension, there is full coverage of R&D tax incentives after 2008, when the college expansion had a large impact on the labor market. In Table G.2, I compare manufacturing R&D intensity between the baseline calibration and the scenarios without tax changes in 2008. The effect of R&D tax changes on manufacturing R&D intensity is comparable to that of the college expansion. Without both tax changes in 2008 and the college expansion, China's manufacturing R&D intensity would have been 63% lower in 2018.

G.5 Ability of Workers

The baseline model considers that workers of the same age have homogeneous skills. One natural concern is that with the massive expansion of the college system, college students' average abilities may be lower. In light of this, the decline in college premium for young workers (relative to old workers) shown in Figure 7 may reflect the decline in young college-educated workers' average abilities instead of imperfect substitution between workers of different ages.

I consider a model extension to allow for changes in workers' average abilities and perfect substitution between educated workers of different ages. Specifically, I consider that the supply of educated and less-educated labor in country $k \in \{i, n\}$ is given by:

$$H_{k,t} = \sum_{a} \beta_a^H (\Lambda_{k,a,t}^H)^{-\lambda} H_{k,a,t}, \quad L_{k,t} = \sum_{a} \beta_a^L (\Lambda_{k,a,t}^L)^{-\lambda} L_{k,a,t}, \quad \lambda > 0.$$

The human capital of educated labor of age a is given by $\beta_a^H (\Lambda_{k,a,t}^H)^{-\lambda}$. Here, β_a^H captures age-specific productivity levels (Lagakos et al. 2018). $\Lambda_{k,a,t}^H$ is the share of educated labor in the corresponding cohort, $\Lambda_{k,a,t}^H = 1 - \Lambda_{k,a,t}^L$. $(\Lambda_{k,a,t}^H)^{-\lambda}$ captures that the average abilities of educated labor may decline if more workers in the same cohort sort into being educated, and this setting follows the literature studying workers' sorting based on abilities (e.g., Lagakos and Waugh 2013, Hsieh et al. 2019). Finally, the aggregate supply of labor services from educated labor sums up the number of educated workers across different age groups, after adjusting for their relative skill levels. The modeling for labor services from less-educated labor is analogous.

I still calibrate $\beta_a^I, I \in \{H, L\}$ to match relative wages across ages and education levels in 2005. As λ governs the magnitude of declining abilities, I calibrate λ to match the college premium for the youngest cohort in 2009 as shown in Figure 7. I recalibrate other model parameters to match the targeted moments in Table 4.

Although the declining abilities of college-educated workers lower the impact of the college expansion, the contributions of the college expansion to China's R&D surge and export skill upgrading are still sizable. As shown in Table G.1, the college expansion still accounted for 56% of increases in manufacturing R&D intensity between 2003–2018.

G.6 Subnational Regions within China

As my empirical analysis exploited regional variation, I also consider a model extension with detailed modeling of within-China regions (with cross-regional trade and migration networks). This model extension draws on the quantitative literature on China's economic geography (e.g., Fan 2019, Tombe and Zhu 2019, Hao et al. 2020).

Cross-regional Trade Networks. There are multiple regions within China, and I denote subnational regions by $l \in i$. The modeling of aggregate production and firms in each region l is analogous to that in Sections 5.1–5.2. One difference is that I consider productivity growth and firm entry to be region-specific. Another difference is that ordinary firms in Chinese region l can also sell to another domestic region l' with iceberg costs $d_{l,l',j}$. I model the export and import costs for region l as inter-provincial trade costs to the nearest port multiplied by national-level export costs and import costs, respectively.

Cross-regional Trade Networks. I follow Artuc et al. (2010) to model migration of Chinese workers between subnational regions within China. A worker has per-period log utility on the final good and discounts the future utility by rate β. In each period, a worker draws location preferences $\{\varphi_l\}_{l\in i}$ 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 l to l', she incurs migration costs $\tau^H_{l,l',a}$ ($\tau^L_{l,l',a}$). A forward-looking worker trades off between the gains from migration (location preferences and changes in the utility from future real wage flows) against migration costs. These assumptions yield an analytical solution of migration probabilities $\Lambda^I_{l,l',a,t}$ $I \in \{H, L\}$ for age-a workers from region l to l'. The labor supply of Chinese region l in $t+1$ can be computed as $H_{l,a+1,t+1} = \sum_{l'\in i} \Lambda^H_{l',l,a,t} H_{l',a,t}$ and $L_{l,a+1,t+1} = \sum_{l'\in i} \Lambda^L_{l',l,a,t} L_{l',a,t}$.

Calibration. Due to data availability, I consider within-China regions as provinces. I calibrate parameters regarding productivity growth and firm entry to match province-industry-regime-level output growth and changes in the number of firms. I model inter-provincial trade costs from ordinary producers as a function of distance and contiguity, $\log d_{l,l',j} = \beta_{1,j} \log dist_{l,l'} + \beta_{2,j} contig_{l,l'},\ \forall l, l' \in i, l \neq l'$ with $d_{l,l,j} = 1\ \forall\ l, j$. $dist_{l,l'}$ is the distance between capitals of provinces l and l', and the dummy $contig_{l,l'}$ captures the effect of contiguity between provinces l and l'. For each industry, I calibrate $\{\beta_{1,j}, \beta_{2,j}\}$ to

Table G.3: Dep Var: Annualized Province-industry-level Changes between 2005–2010

Dep var:	Δlog(domestic sales)		Δlog(ordinary exports)		Δshare of R&D firms			
					nonexporter		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	0.355*	0.340**	0.806***	0.703***	0.081***	0.120***	0.101***	0.177***
	(0.198)	(0.150)	(0.150)	(0.168)	(0.023)	(0.025)	(0.039)	(0.031)
Obs	743	785	587	600	783	787	586	599
R-squared	0.546	0.458	0.381	0.314	0.448	0.521	0.566	0.619
First-stage F	440.23	442.76	138.75	140.58	528.24	528.86	232.23	233.08

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 4. For the data moments, I use ASM 2005 and ASM 2011 to construct province-industry-level trends of domestic sales and ordinary exports, and I use ASM 2005 and SAT 2010 to construct province-industry-level changes in the share of R&D firms between 2005–2010. The regressions control for: (1) output, employment, physical capital, and the share of SOE firms for each province-industry pair in the initial year; (2) whether there was a high-tech zone or an economic development zone for each province-industry pair in the initial year; and (3) average input and output tariff reductions for each province-industry pair after WTO accession. The regressions also control for province-level fixed effects. 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 in 2005. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments. Significance levels: * 10%, ** 5%, *** 1%.

match the sum of trade shares to nonself provinces and the sum of trade shares to nearby provinces in industry j, using China's inter-provincial trade data in 2005.

As for workers' migration decisions, I set discount rate $\beta = 0.95$, and I consider the scale parameter in location preferences as $\nu = 2$ following Caliendo et al. (2019). I assume that for movers, migration costs are a function of age, distance, contiguity, and a destination-specific term (if the destination is not birthplace),[72]

$$\tau^I_{l,l',a} = \gamma^I_{age} a + \gamma^I_{dist} \log dist_{l,l'} + \gamma^I_{contig} contig_{l,l'} + \mathbf{1}_{l' \neq birthplace} \gamma^I_{l'}, I \in \{H, L\},\ l, l' \in i. \quad \text{(G.2)}$$

I thus group workers based on age, education level, current residence, and birthplace, with available information from Population Census 2000. I choose parameters in migration costs to target the effects of age, distance, and contiguity on bilateral migration rates, as well as the share of in-migrants in a destination's employment. The data moments are computed for the year 2000 from Population Census. I recalibrate other parameters to

[72]The motivation for the destination-specific term is as follows. First, in 2000, among migrant workers who migrated from non-birthplace provinces, 53% went back to their birthplace provinces, indicating that migration costs are possibly higher to non-birthplace areas. Second, there are frequent temporary transfers of the Hukou status, as China allows enrolled college students to move their Hukou to the location of their colleges temporarily during the period of their study. Thus, I follow Fan (2019) to model the Hukou policy according to birthplaces instead of the Hukou status.

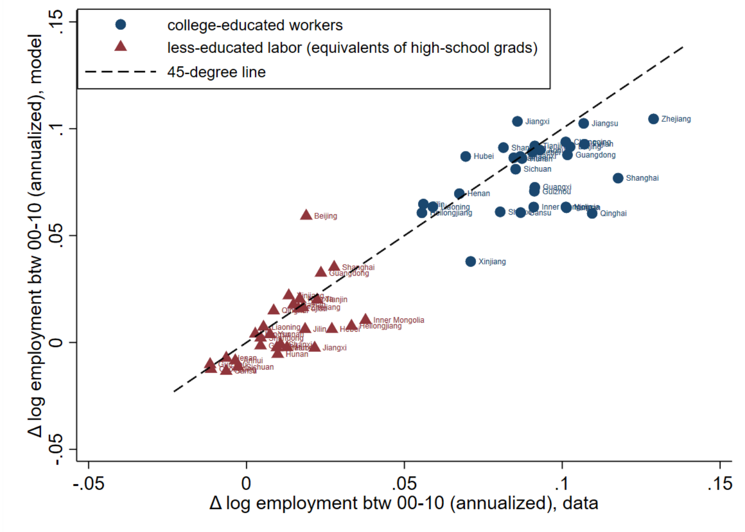


Figure G.1: Employment Changes between 2000–10 in Data and Model

Note: The figure plots annualized employment changes between 2000–2010 in the data and the model, respectively. Data on employment by education level and province comes from Population Censuses in 2000 and 2010.

match the targeted moments in Table 4.

Untargeted Moments. Table G.3 compares the model-generated and the observed responses of province-industry-level exports, domestic sales, and R&D activities to the college expansion between 2005–2010, using regression (3) and the instrument constructed in Section 4. The model and the data both predict a stronger response of ordinary exports to the college expansion than that of domestic sales and a stronger response of exporters' innovation than that of nonexporters' innovation. The model-generated responses are similar in magnitude to the observed responses, which provides additional validation to the model. Figure G.1 shows that the model with subnational regions can match the observed changes in employment across provinces and education levels between 2000–2010.

Quantitative Results. Table G.1 suggests that the quantitative results of this model extension are similar to the baseline results. In particular, compared with the baseline, modeling China's subnational regions slightly reduced the impact of the college expansion on innovation and export skill upgrading. This indicates that the geographic distribution of college graduates was unfavorable for aggregate productivity, confirming the mismatch between college enrollments and regional development levels discussed in Section 2.