College Expansion, Trade and Innovation: Evidence from China

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February 2022

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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 college expansion affect firms' export and innovation choices? I document that after this expansion impacted the labor market, Chinese manufacturing firms' innovation strongly increased, especially among exporting firms, accompanied with sizable skill upgrading of China's exports. Guided by these facts, I develop a two-country multi-industry spatial equilibrium model, featuring skill intensity differences across industries and heterogeneous firms' innovation and export choices. Using firm-level data over time, I empirically validate the model predictions by exploiting differential supply shocks of college-educated workers across regions. 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 10–20%.

JEL Codes: F12; O11

key Words: international trade; innovation; college education

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*Email: xiaomaecon@gmail.com This paper is based on a chapter of my doctoral dissertation. I am grateful to my advisors, Gordon Hanson and Natalia Ramondo, for their invaluable support and guidance. I thank Hanming Fang, Ruixue Jia, David Lagakos, Marc Muendler, Tommaso Porzio, Zheng (Michael) Song, Alon Titan, Fabian Trottner, Daniel Yi Xu, Xiaodong Zhu, and seminar participants at China International Conference in Macroeconomics 2021, CUHK Shenzhen, HKU, HKUST, Jinan University, Peking University, Renmin University, Shanghai Tech, and Shanghai Jiaotong University for their helpful discussions. I am also grateful to Binkai Chen for generously sharing data. All potential errors are my own.

1 Introduction

"Made in China" is often viewed as low-skilled. Largely neglected is the recent skill upgrading of China's exports. For example, China's primary export product has gradually shifted from "Clothing" to "Telecommunications Equipment" since 2000,[1] and three of the worldwide top 5 smartphone companies are nowadays from China (IDC 2021). Most of these smartphone companies' workers are well-educated college graduates. Another notable trend of the Chinese economy is the fast growth of firms' innovative activities (Wei et al. 2017), with the ratio of R&D to GDP more than doubling since 2000.[2] Whereas the macro literature has proposed several causes for China's innovation from the policy environment faced by firms (e.g., Chen et al. 2021, König et al. 2021), how this R&D boom has been fueled from the labor market is still understudied.

This paper offers one explanation for these two trends: China's expansion of college education. With a 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%.

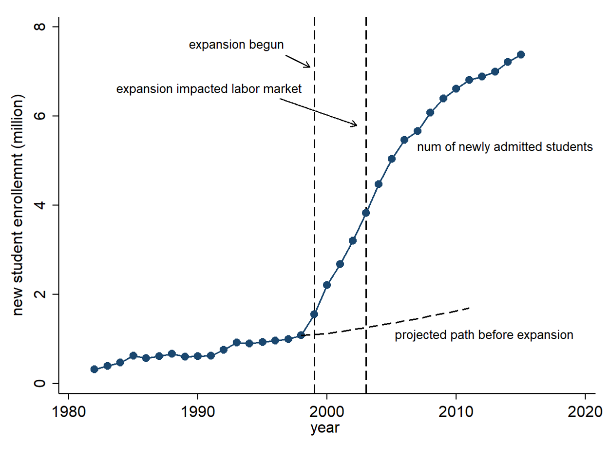
In this paper, I highlight three channels through which China's college expansion affects trade and innovation. First, the growing pool of college-educated workers lowers R&D costs and promotes innovation, as college-educated workers are intensively involved in the innovation process. Second, with an 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, often recognized as Rybczynski effects in the literature (Rybczynski 1955, Ventura 1997). Third, trade and innovation also interact. As skill-intensive industries tend to be more innovative, trade-induced industry reallocation reinforces the innovation surge.

I begin my analysis by documenting several descriptive facts on innovation and trade using aggregate and firm-level data. I find that after China's college expansion impacted

[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.

[2] The ratio of R&D to GDP increased from 0.9% in 2000 to 2.1% in 2018.

Figure 1: China's College Expansion



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

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.

To understand the facts, I develop an analytical model with two countries (China and Foreign) and 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 educated workers are intensively used in R&D processes, following the growth literature (e.g., Acemoglu et al. 2018, Akcigit et al. 2018).

Using the model, 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. Because foreign markets feature more demand substitution than domestic markets (in domestic markets, most sellers experience the shock, and thus there is little reallocation of market shares), Chinese firms in high-skill industries can expand their sales faster in foreign markets than in domestic markets, in line with the documented aggregate pattern. The increase in the supply of educated workers affects innovation by directly lowering R&D costs and also 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).

Using firm-level data for 2005 and 2010, I empirically validate the model mechanisms about exports and innovation. Guided by my analytical model, I measure a firm's exposure to the college expansion by growth in the local supply of college-educated workers, interacted with the firm's affiliated-industry skill intensity. To disentangle 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 allow me to discipline the key structural parameters that govern substitution of demand for exports and domestic sales. 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 combine data on migration flows, trade flows, R&D, employment, and output from multiple sources between 2000–2018 to calibrate a quantitative model. The calibrated model matches the targeted moments well and produces similar regression results as in the empirical analysis.

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, by shifting production to high-skill industries and triggering the interaction between trade and innovation, I find that trade openness amplified the impact of China's college expansion on production by 10–15% and innovation by 16%. It is noteworthy that the college expansion did not come at no costs, as it incurred larger education expenses and also reduced the amount of production workers in the economy. I find that the yearly GDP increase due to the college expansion started to exceed yearly education expenses and opportunity costs of additional college enrollments in 2007. Finally, I show that my quantitative results are robust to several model extensions, such as allowing for R&D misreporting.

Previous Literature. I contribute to the trade literature in three aspects. First, I closely relate 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 suggest 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, similar to Ventura (1997) who shows that trade is essential for absorbing extra capital for Asian miracle economies. Aside from directly lowering innovation costs, I show that the college expansion also affects innovation through the Schumpeterian effect, which is supported by evidence on tariff reductions and innovation in China (Liu et al. 2021). Third, I also relate to the literature that uses quantitative models to study trade and innovation (e.g., Eaton and Kortum 2001, Grossman and Helpman 2014, 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. Given reduced-form evidence based on cross-regional variation, I incorporate this model with a detailed modelling of within-China regions (with cross-regional trade and migration networks), drawing on the quantitative literature of China's economic geography (e.g., Fan 2019, Tombe and Zhu 2019, Hao et al. 2020).

I also make 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, and

[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, Bergeaud, Lequien and Melitz (2017) for French firms.

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. I complement these studies by focusing on the the role of expansion of college education in driving changes in China's innovation between 2000–2018.

Finally, I relate to studies about the effects of college education on innovation through more talents (e.g., Aghion et al. 2009, Toivanen and Väänänen 2016, Aghion, Akcigit, Hyytinen and Toivanen 2017), especially those studying China's college education (e.g., Che and Zhang 2018, Feng and Xia 2018). My 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. Akcigit et al. (2020) construct a general equilibrium model, in which they model occupational choices and research teams to shed light on R&D subsidy policies in Denmark. In comparison, I build a model with heterogeneous firms' innovation and export choices to speak to the interaction between trade and innovation.

The paper proceeds as follows. Section 2 sketches the background of China's college expansion. Section 3 documents descriptive facts which motivate the model in Section 4. In Section 5, I empirically validate the model mechanisms and apply reduced-form evidence to calibrate key structural elasticities. I calibrate other parameters in Section 6 and 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

[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).

implemented through increases in the annual quota on newly admitted students, because most of Chinese colleges are government-owned, and China's Ministry of Education has a 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 be 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 a 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 role of expansion of regular college education and briefly discuss robustness of including expansion in part-time education quantitatively. I abstract from foreign colleges' graduates (due to lack of data), who accounted for 3% of all 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 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

[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. Compared with regular degrees, part-time degrees are less valuable, and enrollments in part-time education experienced less expansion. Between 2000 and 2015, the total amount of part-time college graduates was 24 million, whereas the amount of regular college graduates was 66 million.

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 4. Due to data availability and that China's R&D rise 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. In the meanwhile, the share of R&D workers in manufacturing employment increased from 1% in 2004 to 4% in 2016.

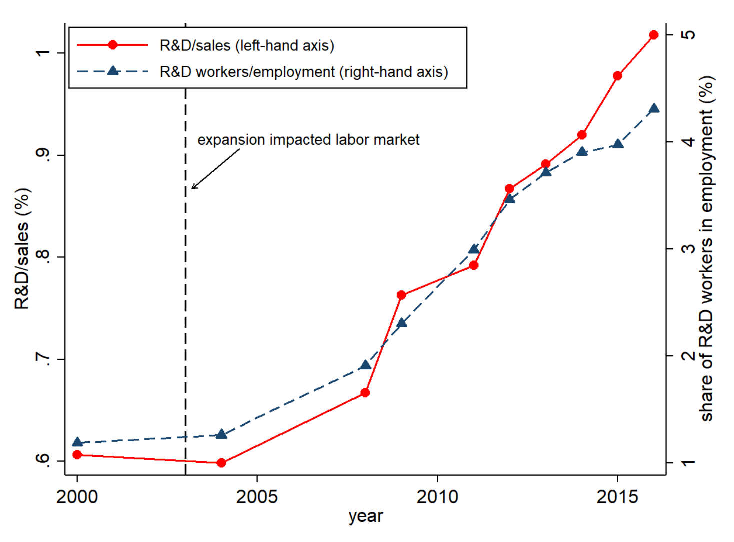
This aggregate pattern signals the possible impact of China's college expansion on innovation, given that R&D workers mostly hold a college degree,[7] and consistent with the timing of China's college expansion which unfolded in the labor market after 2003. Furthermore, the faster growth in the share 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 experienced many policy changes, and thus changes in innovation may reflect many factors. Two major policy changes related to trade and

[6] Appendix Figure A.4 shows that the rise in China's ratio of R&D to GDP after 2000 was mainly due to the increase in manufacturing innovation.

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

Figure 2: R&D Employment and Expenses



Note: 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 are China's WTO accession in 2001 and changes in R&D tax incentives in 2008 (Chen et al. 2021). To isolate the effects of the college expansion, in the quantitative analysis, I will explicitly model these two major confounding policy changes and introduce a time-variant research efficiency parameter to capture other unmodelled factors.

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.[8] 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.[9]

[8] In 2000–2007, the sales threshold was 5 million RMB (roughly $60 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.

[9] 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

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 U.S. 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-intensity 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 exports.[10] Moreover, processing exporters barely innovate,[11] whereas my main focus is the interaction between trade and innovation. Thus, my empirical results will focus on ordinary exports and exporters that perform ordinary exports (referenced as "ordinary exporters" hereafter), and I will briefly describe the results of processing exports.

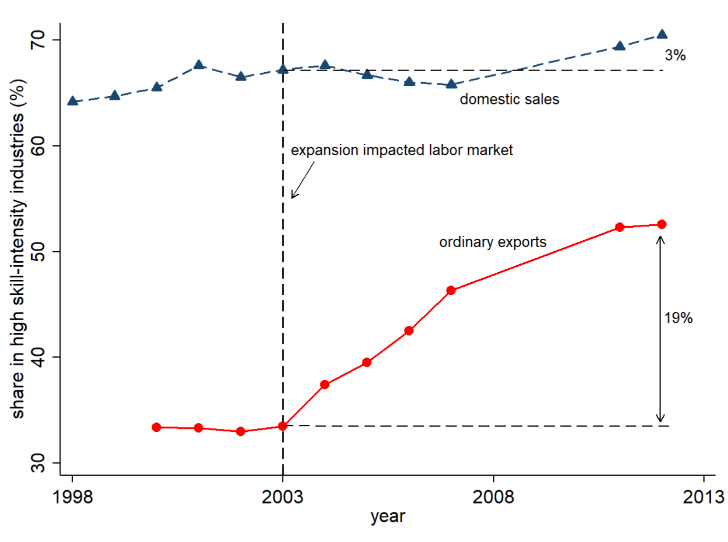
Domestic Sales and Ordinary Exports. Figure 3 plots the share of sales in high skill-intensity industries separately for domestic sales and ordinary exports, for years with available data. It shows that ordinary exports shifted strongly to high skill-intensity industries after the college expansion impacted the labor market. In the meantime, domes-

reported in ASM can be matched with customs data.

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

[11]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).

Figure 3: Skill Upgrading of Domestic Sales and Exports



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

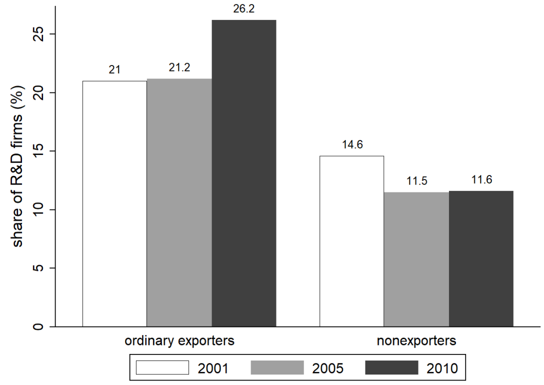
tic sales only moved slightly to high skill-intensity industries. These results indicate that Chinese ordinary exports experienced sizable skill upgrading after the college expansion.

Processing Exports. Appendix Figure A.5 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.

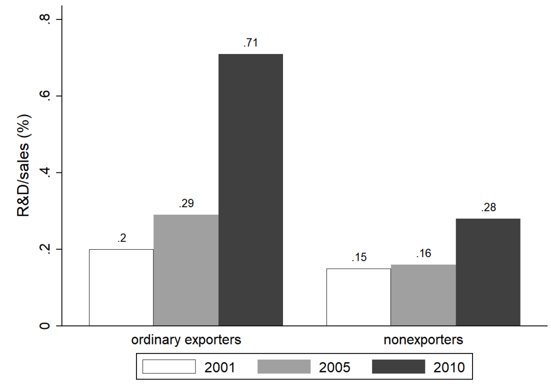
3.3 Interactions between Exports and Innovation

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. The SAT records financial information (including R&D) for a sample of 340 thousand manufacturing firms in each year. Note that I use ASM data before 2007. 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

Figure 4: Innovative Activities by Different Firms



(a) Share of R&D Firms



(b) R&D/sales

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.[12] 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.

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 Analytical Model

To understand the motivating facts, I develop a model of trade and innovation. There are two countries, China $\mathcal{C}$ and Foreign $\mathcal{F}$. I consider multiple regions within China and treat Foreign as a single region. Each region-industry holds many firms that differ in pro-

[12] 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.

ductivity levels and research efficiency. 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 which involves the use of educated labor. For analytical tractability, I consider one period, and the fruits of innovation arrive *contemporarily*. I also abstract from processing exports to focus on the interaction between trade and innovation. These simplifications will be relaxed in the quantitative analysis. I index regions by m and n, industries by j, and the set of Chinese regions as $\mathcal{C}$.

4.1 Aggregate-level Good Production

4.1.1 Final-good Producers

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

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

Parameter $\gamma_j > 0$ governs the expenditure share on goods from industry j. Parameter $\theta > 0$ is the elasticity of substitution across industries, which decides the strength of between-industry demand reallocation after the college expansion, as shown below.

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

4.1.2 Industry-level Good Producers

The industry-level intermediate good in region m and industry j is produced competitively by:

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

composed of quantities of varieties sourced from different origins. $\Omega_{n,m,j}$ is the set of varieties selling from region n to m. Parameter σ is the elasticity of substitution between varieties within an industry, which governs the strength of firm-level export expansion after the college expansion, as shown below. The quantity demanded for a variety with price p is $q = p^{-\sigma} P_{m,j}^{\sigma} Q_{m,j}$, where the industry-level price index is $P_{m,j} = \left(\sum_n \int p_{n,m,j}(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$. Industry-level goods are used to assemble final goods.

4.1.3 Research Good

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

$$Q_{m,r} = A_{m,r} \left(\frac{E_{m,r}}{1-\gamma_r}\right)^{1-\gamma_r} \left(\frac{H_{m,r}}{\gamma_r}\right)^{\gamma_r}. \tag{3}$$

Producing research inputs requires both final goods $E_{m,r}$ and educated labor $H_{m,r}$, as R&D costs include both personnel and material costs. The research-good productivity $A_{m,r}$ is a residual parameter to capture all other unmodelled factors that can affect innovation levels. The unit price of research goods is $P_{m,r} = \frac{(P_m)^{1-\gamma_r}(S_m)^{\gamma_r}}{A_{m,r}}$, where S_m refers to wages per educated labor. The college expansion has a direct impact on R&D costs through changes in educated labor's wages.

4.2 Firms' Production and Innovation

4.2.1 Setup

In region m and industry j, there is a measure $N_{m,j}$ of firms. I leave the incorporation of firm entry/exits to the quantitative analysis, as they do not affect analytical results. Each firm produces a unique differentiated variety indexed by ω, and I omit ω when it causes no confusion. A firm's state is $\{z, \eta\}$, where productivity z and research efficiency η are randomly drawn from the cumulative distribution $G_{m,j}(z, \eta)$ with density $g_{m,j}(z, \eta)$.

Productivity Evolution and Innovation. The productivity of each firm is determined by the initial draw z and R&D investment level i:

$$\log \tilde{z} = \log z + \underbrace{i}_{\text{R\&D investment level}} \times \underbrace{\eta}_{\text{research efficiency}}. \tag{4}$$

The term $i \times \eta$ represents the fruits of innovation. A firm with R&D investment level i spends $\bar{z}_{m,j}^{\sigma-1}\phi_{1,j}\mathbf{1}_{\{i>0\}} + z^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}$ units of research goods. The fixed costs of innovation $\bar{z}_{m,j}^{\sigma-1}\phi_{1,j}$ depend on the average productivity $\bar{z}_{m,j}$ in region m and industry j. The dependence of variable innovation costs $z^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}$ on firms' own productivity $z^{\sigma-1}$ 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).[13] 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 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.

Production Technology. Firms employ educated labor h and less-educated labor l to produce

$$q = \tilde{z}\left[\alpha_j l^{\frac{\rho_x-1}{\rho_x}} + (1-\alpha_j)h^{\frac{\rho_x-1}{\rho_x}}\right]^{\frac{\rho_x}{\rho_x-1}}. \tag{5}$$

Parameter α_j governs the skill intensity in industry j, and parameter ρ_x determines the elasticity of substitution between educated and less-educated labor.

Given these assumptions, the unit cost of the input bundle for firms with $\tilde{z} = 1$ is:

$$c_{m,j} = \left[\frac{\alpha_j^{\rho_x}}{W_m^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_m^{\rho_x-1}}\right]^{\frac{1}{1-\rho_x}}, \tag{6}$$

where S_m and W_m are wage rates of educated and less-educated labor.

Trade Costs. Firms compete monopolistically and pay iceberg costs $d_{m,n,j} \geq 1$ if selling to market n. Firms also pay marketing costs $f^X_{m,j}$ units of final goods when they export. The extensive margin of selling domestically will be captured by firm entry/exits quantitatively.

[13] 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.

4.2.2 Solving Firm's Problem

I solve the firm's problem in two steps. I first solve the firm's optimal price in each market given productivity $\tilde{z}$, and then solve optimal innovation and export decisions.

Optimal Selling Price. Because production technology is constant-returns-to-scale, a firm chooses prices to maximize profits (gross of marketing costs) for each market n separately:

$$\begin{aligned} \pi_{m,n,j}(\tilde{z}) &= \max_p pq - \frac{d_{m,n,j}c_{m,j}}{\tilde{z}}q, \\ \text{s.t.} \quad & q = p^{-\sigma}P_{n,j}^{\sigma}Q_{n,j}, \end{aligned} \tag{7}$$

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

$$p^*_{m,n,j}(\tilde{z}) = \tilde{\sigma}\frac{c_{m,j}d_{m,n,j}}{\tilde{z}}, \tag{8}$$

where $\tilde{\sigma} = \frac{\sigma}{\sigma-1}$ is the markup ratio. Thus, $\pi_{m,n,j}(\tilde{z}) = p^*_{m,n,j}(\tilde{z})^{1-\sigma}P^{\sigma}_{n,j}Q_{n,j}/\sigma$, and the corresponding sales is $\sigma\pi_{m,n,j}(\tilde{z})$.

Optimal Export and R&D Choices. A firm determines the optimal investment level i and export choices $\mathbf{1}_X$ to maximize the value of the firm. For a Chinese firm ($m \in \mathcal{C}$), its problem is written as:

$$\begin{aligned} \max_{i\geq 0,\mathbf{1}_X} & \underbrace{\sum_{n\in\mathcal{C}} \pi_{m,n,j}(\tilde{z}) + \mathbf{1}_X\left(\pi_{m,\mathcal{F},j}(\tilde{z}) - f^X_{m,j}P_m\right)}_{\text{total profits (net of marketing costs)}} - \underbrace{\left(\bar{z}^{\sigma-1}_{m,j}\phi_{1,j}\mathbf{1}_{\{i>0\}} + z^{\sigma-1}\phi_{2,j}\frac{i^{\chi+1}}{\chi+1}\right)P_{m,r}}_{\text{research costs}}, \\ \text{s.t.} \quad & \log\tilde{z} = \log z + i\times\eta, \end{aligned} \tag{9}$$

where $\mathbf{1}_X \in \{0,1\}$ and $\mathbf{1}_{\{i>0\}} \in \{0,1\}$ denote the export and innovation statuses respectively. The problem for foreign firms is analogous. I denote the optimal innovation level as $i^*_{m,j}(z,\eta)$. Firm owners spend the net profits on local final goods.

4.3 Workers

I denote the amount of educated and less-educated labor in region m as H_m and L_m. I abstract from workers' period-to-period migration, which will be incorporated in the quantitative version with multiple periods. Workers spend all the income on final goods.

4.4 Equilibrium

The trade is balanced for each region m. Let $Y_{m,j}$ be the total production value of industry j in region m. Then, the market clearing for industry j in region m requires:

$$Y_{m,j} = \sum_n \Pi_{m,n,j} \frac{\gamma_j^\theta P_{n,j}^{1-\theta}}{\sum_{j'} \gamma_{j'}^\theta P_{n,j'}^{1-\theta}} \sum_j Y_{n,j}, \tag{10}$$

where $\frac{\gamma_j^\theta P_{n,j}^{1-\theta}}{\sum_{j'} \gamma_{j'}^\theta P_{n,j'}^{1-\theta}} \sum_j Y_{n,j}$ is the expenses on industry j in region n, captured by the share of expenses spent on industry j, $\frac{\gamma_j^\theta P_{n,j}^{1-\theta}}{\sum_{j'} \gamma_{j'}^\theta P_{n,j'}^{1-\theta}}$, and the total expenses $\sum_j Y_{n,j}$ (which equal the total production value). $\Pi_{m,n,j}$ is the share of expenses in region n sourced from region m,

$$\Pi_{m,n,j} = \frac{\int \int_{\Omega_{m,n,j}} \left(\frac{c_{m,j} d_{m,n,j}}{z \exp(i^*_{m,j}(z,\eta)\eta)} \right)^{1-\sigma} g_{m,j}(z,\eta) dz d\eta}{\sum_{m'} \int \int_{\Omega_{m',n,j}} \left(\frac{c_{m',j} d_{m',n,j}}{z \exp(i^*_{m',j}(z,\eta)\eta)} \right)^{1-\sigma} g_{m',j}(z,\eta) dz d\eta}. \tag{11}$$

And the price index for industry j in region n is:

$$P_{n,j} = \left(\sum_m \int \int_{\Omega_{m,n,j}} \left(\frac{\tilde{\sigma} c_{m,j} d_{m,n,j}}{z \exp(i^*_{m,j}(z,\eta)\eta)} \right)^{1-\sigma} g_{m,j}(z,\eta) dz d\eta \right)^{1/(1-\sigma)}. \tag{12}$$

The labor market clearing requires:

$$W_m L_m = \sum_j \frac{\alpha_j^{\rho_x} W_m^{1-\rho_x}}{\alpha_j^{\rho_x} W_m^{1-\rho_x} + (1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}} \frac{\sigma - 1}{\sigma} Y_{m,j}, \tag{13}$$

$$S_m H_m = \sum_j \frac{(1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}}{\alpha_j^{\rho_x} W_m^{1-\rho_x} + (1-\alpha_j)^{\rho_x} S_m^{1-\rho_x}} \frac{\sigma - 1}{\sigma} Y_{m,j} + \gamma_r P_{m,r} Q_{m,r}, \tag{14}$$

where the left-hand side is the labor supply, and the right-hand side includes the demand for production labor. For educated labor, there is an extra labor demand from research:

$$Q_{m,r} = \sum_j N_{m,j} \int \int \left(\bar{z}_{m,j}^{\sigma-1} \phi_{1,j} \mathbf{1}_{\{i^*_{m,j}(z,\eta)>0\}} + z^{\sigma-1} \phi_{2,j} \frac{i^*_{m,j}(z,\eta)^{\chi+1}}{\chi+1} \right) g_{m,j}(z,\eta) dz d\eta.$$

Combining equations (10)–(14) with prices $P_m = \left(\sum_j \gamma_j^\theta P_{m,j}^{1-\theta} \right)^{1/(1-\theta)}$ and $P_{m,r} = \frac{(P_m)^{1-\gamma_r} (S_m)^{\gamma_r}}{A_{m,r}}$, I can solve $\{\Pi_{m,n,j}, Y_{m,j}, W_m, S_m, P_{m,j}, P_m, P_{m,r}\}$.

4.5 Main Forces at Work

I now study a supply shock of educated labor in China. For analytical tractability, I focus on one region in China, $\#\mathcal{C} = 1$, and thus index this region by $\mathcal{C}$. 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.[14] 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.

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

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

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

Proof: See Appendix D.1. □

This proposition is intuitive: the skill premium (wages of educated labor relative to the less-educated) declines in response to an influx of educated labor. Although I imposed some regularities for tractability, this result holds in more general scenarios: a large empirical literature shows that an influx of college-educated workers leads to a lower skill premium (e.g., Katz and Murphy 1992, Card and Lemieux 2001). I also find that the skill premium experienced larger reductions in Chinese regions with greater exposure to the college expansion, as detailed in Section 6.

Denote $R_{\mathcal{C},j} = \sigma\pi_{\mathcal{C},\mathcal{C},j}$ and $R_{F,j} = \mathbf{1}_X \sigma\pi_{\mathcal{C},\mathcal{F},j}$ as domestic sales and exports by a Chinese firm in industry j. For ease, I omit the index for firm productivity. Let $SI_{\mathcal{C},j}$ be the share of educated labor's wages in total labor costs for 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.

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

(i) Proportional changes in domestic sales and exports (if the firm always exports) are:

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

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

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

(ii) If $\sigma > \theta \geq 1$ and $\Pi_{\mathcal{C},\mathcal{C},j}$ is similar across industries,[15] absent entry of new exporters, exports shift more to high skill-intensity industries than domestic sales when $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$.

(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 when $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$.

Proof: See Appendix D.2. □

Result (i) indicates how firm sales change in response to a lower skill premium, which reduces production costs by $SI_{\mathcal{C},j}\left(\hat{W}_{\mathcal{C}}-\hat{S}_{\mathcal{C}}\right)$ for industry j.[16] Firms' domestic sales change due to two reasons. First, the cheaper prices of more skill-intensive goods induce between-industry reallocation of demand, the strength of which is determined by between-industry elasticity of substitution θ and the share of expenses spent on domestic goods $\Pi_{\mathcal{C},\mathcal{C},j}$ (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 14 for an explanation), and thus exports are not affected by between-industry demand reallocation and the elasticity of substitution θ.

Result (ii) shows if $\sigma > \theta \geq 1$ and without entry of new exporters,[17] there is larger skill

[15] China's share of manufacturing expenses on domestic goods was 0.82 in 2005, and 70% of 2-digit industries had shares more than 0.8, according to China's Input-Output Tables.

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

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

upgrading of exports than domestic sales after an influx of educated labor, in line with evidence in Section 3.2. The intuition of $\sigma > \theta$ is that there is more substitution between varieties within an industry (e.g., Nike shoes vs. Adidas shoes) than between products in different industries (e.g., Nike shoes vs. iPhones), as empirically found in Broda and Weinstein (2006). In the next section, I will use reduced-form estimates to discipline the elasticities of substitution $\{\sigma, \theta\}$ and confirm $\sigma > \theta \geq 1$. Finally, Result (iii) shows that lower costs in more skill-intensive industries also encourage more export entry, which reinforces larger export expansion in more skill-intensive industries.

Finally, I look into innovation. With little abuse of notation, I interpret $R_{\mathcal{C},j}$ and $R_{F,j}$ as the amount of a firm's domestic sales and exports before any innovation. According to equation (9), an increase of educated labor alters innovation through two channels:

- Affect research costs $P_{\mathcal{C},r}$. This effect is uniform for all the firms.
- Affect innovation returns by changes in before-innovation profits $\frac{R_{\mathcal{C},j}}{\sigma} + \mathbf{1}_X(\frac{R_{\mathcal{F},j}}{\sigma} - f^X_{\mathcal{C},j})$, which vary across firms of different skill intensities and export exposure levels. The next proposition summarizes changes in innovation returns.

Proposition 3 (Interactions between Exports and Innovation).

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

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

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

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

Proof: See Appendix D.3. □

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 innovation activities (Schumpeter 1942, Acemoglu and Linn 2004). This interaction between exports and innovation increases aggregate R&D, as more skill-intensive industries are also more innovative in reality. It is also worth noting that in the model, export entry and innovation activities are jointly determined. Result (ii) shows that revenues from foreign markets induce export entrants to increase innovative activities. It is also possible that some firms perform innovation to be productive enough for export entry (see e.g., Lileeva and Trefler 2010).

5 Empirical Analysis

In this section, I exploit regional variation in the magnitude of the college expansion to empirically validate the model mechanisms shown in Section 4.5. The empirical results also discipline the structural demand elasticities $\{\theta, \sigma\}$ and will be used to validate the calibration results.

5.1 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 follow the labor literature to exploit regional variation to isolate the presumably exogenous supply changes of college-educated workers (e.g., Aghion et al. 2009).

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

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

Region-level changes in the relative supply of college-educated workers can also be endogenous, as productive regions (e.g., Beijing and Shanghai) may attract high-skill inmigrants. To disentangle labor supply from demand shocks, I follow the immigration literature (Card 2001, Burstein et al. 2017) to construct a Bartik-type instrument:

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

where $GRAD_{-m,2006-10}$ is the total amount of college graduates between 2006–2010, excluding those who graduated from colleges in region m. I use the share of region m's college enrollments in total enrollments in 1982,[18] $\frac{ENROLL_{m,1982}}{ENROLL_{1982}}$, to predict the number of college graduates in region m between 2006–2010. This instrument is motivated by that the college expansion was attained mainly by the scale-up of enrollments in previously existing colleges, as discussed in Section 2, and that migration barriers ("Hukou") restricted college graduates' movements. Overall, x_m^* predicts x_m well: across cities or provinces, the slope of x_m on x_m^* 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.3 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. Thus, 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 the shock. This pattern also supports that the college expansion did lead to reductions in college premium in China, which is essential for the model to generate differential sales growth and innovation responses, as previously discussed in Section 4.5.

Second, I will include region-specific fixed effects in all regressions, controlling region-specific characteristics correlated with initial shares of college endowments. There may still be the concern that the distribution of college resources in 1982 may be correlated with changes in labor demand of certain industries. I follow Goldsmith-Pinkham et al. (2020) to confirm that there are no pre-trends across industries, as shown below. 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.[19] Finally, in the calibration, I will use region-industry-specific productivity growth to match the observed output growth across regions and industries over time. As shown below, the model-generated data predicts quantitatively similar regression results as in the actual data. This indicates that the IV estimates are robust if the endogeneity concern is productivity growth,[20] and other factors not captured by the model may not substantially bias the IV regressions.

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

[19] The robustness checks of empirical results using additional instruments are available upon request.

[20] If changes in labor demand come from productivity growth and still bias the IV regressions, the IV coefficients tend to differ from the model-generated coefficients (Simonovska and Waugh 2014).

5.2 Empirical Results

5.2.1 Domestic Sales and Export Growth

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

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

For the dependent variable, I separately use log changes in domestic sales, ordinary exports, and production costs for firm ω between 2005–2010. In line with the theoretical results in Section 4.5, I measure exposure to the college expansion for firms in region m and industry j by $SI_{m,j}x_m$, where skill intensity $SI_{m,j}$ is measured by the share of college-educated workers in employment for region m and industry j from ASM 2004. I instrument $SI_{m,j}x_m$ with $SI_{m,j}x_m^*$. Controls $\mathbf{Z}_{m,j}$ include firm output, employment, capital and registration types in 2005, as well as input and output tariff reductions due to WTO. Finally, ι_m captures region-specific trends,[21] 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.

As production costs are unobserved, I use export prices as a proxy for production costs, because prices and production costs are perfectly aligned in the model. 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 they 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. This is motivated by that there is more variation in the city-level exposure to the college expansion, whereas I will use province-level shocks to discipline the model parameters, as my model will be calibrated to the provincial level due to data availability. 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 particular, ordi-

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

Table 1: College Expansion and Sales Growth, 2005–2010

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

Note: This table provides estimates from regressions in equation (17), separately treating regions as cities and provinces. "CE" is short for "college expansion". I control dummies for firm registration types (e.g., SOE), log employment, log fixed capital, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

nary exports responded more strongly to the college expansion than domestic sales. One standard-deviation increase in the exposure (0.04) between 2005–2010 would increase domestic sales and ordinary exports in 2010 by roughly 8% and 15%, while reducing export prices in 2010 by 2.5%. Guided by Result (i) in Proposition 2, I can use these estimates to discipline between-industry and within-industry elasticities of substitution (θ and σ):

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

By China's Input-Output Table in 2005, $\bar{\Pi}_{CC} \approx 0.8$ is the average share of China's expenses devoted to domestic goods across 2-digit manufacturing industries. The resulting θ and σ are 3.1 (3.5) and 6.9 (6.9) based on provincial (city-level) shocks.[22] As Proposition 2 was obtained using a simplified model, Appendix E.1 discusses the robustness of the mapping between reduced-form evidence and the structural elasticities of substitution in the quantitative model.

[22] My estimates are comparable to Broda and Weinstein (2006) who report that the average elasticity of substitution for varieties from different countries within 3-digit SITC industries was 6.8 between 1972–1988.

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

	Dependent Variable: Changes in R&D status					
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	export status in 2005		export status in 2005&2010		export-output share in 2005	
	nonexporter	ord. exporter	nonexporter	ord. exporter	all firms	export share<0.4
Exposure to CE	0.441***	0.513***	0.331***	0.529***	0.457***	0.418***
	(0.103)	(0.150)	(0.095)	(0.170)	(0.098)	(0.097)
Exposure to CE $\times$ export share					0.058	2.545**
					(0.416)	(1.205)
Obs	31,139	11,669	26,325	10,162	42,808	40,093
R-squared	0.016	0.038	0.012	0.041	0.022	0.022
First-stage F	428.58	413.47	456.99	410.38	224.76	224.28

Note: This table provides estimates from regressions in equation (17), treating regions as provinces. "CE" is short for "college expansion". I control dummies for firm registration types (e.g., SOE), log employment, log fixed capital, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. In Columns (5)–(6), the interaction term is instrumented by the interaction between $SI_{m,j}x_m^*$ and the export share, and I also control initial export shares. 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%.

5.2.2 Interaction between Innovation and Exports

I next investigate how the college expansion affects firms' innovation and the interaction between innovation and exports. I perform the same regression in equation (17), but use changes in R&D status (1 if R&D is positive and 0 otherwise) as the dependent variable.

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 in Proposition 3. One standard-deviation increase in the exposure (0.04) between 2005–2010 increased the share of R&D firms in 2010 among initial non-exporters and ordinary exporters by 1.8 and 2.1 percentage points, respectively. To avoid firm entry/exits associated with changes in innovation returns, Columns (3)–(4) restrict the sample to firms that did not switch export status between 2005–2010 and find similar results as in Columns (1)–(2).

In Column (5), I perform the regression for all firms, but add the interaction between exposure to the expansion and the firm's share of ordinary exports in total sales in 2005.

The effect of the college expansion on innovation did not appear to be significantly amplified by initial export shares. One reason is that very export-intensive Chinese firms tend to be small and unproductive (Lu 2010), thus unlikely to pay fixed costs to innovate.[23] I thus restrict the sample to firms with export shares lower than 0.4 (75% percentile of export-output shares among exporters) in Column (6), avoiding extremely export-intensive firms. The estimates show that firms with larger initial share of exports performed more innovation in response to the college expansion, consistent with Result (i) in Proposition 3. In the quantitative model, I will incorporate firm-level export demand shocks to allow for the existence of very export-intensive small firms.

5.2.3 Robustness Checks

In Appendix E.2, I perform several robustness checks. 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 E.2 shows that the prices of imported inputs or the number of imported inputs did not 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.

I perform pre-trend tests (Goldsmith-Pinkham et al. 2020) and find that within each province, 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 lessens the concern that the distribution of college resources in 1982 may be correlated with changes in labor demand of certain industries.

6 Model Estimation

In this section, I extend the analytical model to perform the quantitative analysis. I also discuss the calibration procedure and the estimation results.

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

6.1 Quantitative Model

I add some model features to replicate key aspects of China's exports and labor markets.[24]

Tariff Changes. I capture tariff changes due to China's WTO accession, by changing Chinese regions' export and import iceberg costs over time according to applied tariffs.

Processing Exports. I consider each manufacturing industry in a Chinese region also hosts processing exporters. Production- and trade-related variables and parameters are now qualified by $m(k)$ for a Chinese region m, with $k \in \{\mathcal{O}, \mathcal{P}\}$ indexing ordinary or processing regimes. The main differences between firms of two regimes are tariff treatments of imported inputs, domestic market access, and value added shares. I assume that processing exporters do not perform R&D. The details are provided in Appendix F.1.

Intermediate Inputs. I incorporate cross-industry production linkages $\{\gamma_{m(k),j}^{j'}, \gamma_{m(k),j}^{L}\}$, following Caliendo and Parro (2015). Parameter $\gamma_{m(k),j}^{j'}$ is the share of costs spent on raw materials from industry j' for firms in region m, industry j and regime k, and $\gamma_{m(k),j}^{L}$ is the share of costs spent on labor, with constant returns to scale, $\gamma_{m(k),j}^{L} + \sum_{j'} \gamma_{m(k),j}^{j'} = 1$.

R&D Tax Incentives. Firms pay the tax rate $\zeta(\cdot)$ on profits. Consistent with Chen et al. (2021), the tax rate $\zeta(\cdot)$ depends on the size of firm sales and R&D intensity (sales/R&D). This setting allows me to capture the policy change regarding R&D tax incentives.

Productivity Evolution and Export Demand Shocks. I assume that fruits of innovation are realized in the next year. To capture China's fast growth and firm-level productivity shocks (Hopenhayn 1992), I incorporate exogenous productivity growth $g_{m(k),j,t}$ (region-industry-regime-specific) and idiosyncratic productivity shocks $\xi \sim \mathcal{N}(0, \sigma_{\xi}^2)$. Finally, to capture export-intensive small firms, I introduce demand shifters ϵ into export demand $q = \epsilon p^{-\sigma} P_{\mathcal{F},j}^{\sigma} Q_{\mathcal{F},j}$. Export shocks evolve according to a log-normal AR(1) process, independently across firms, with autocorrelation parameter ρ_{ϵ} and standard deviation σ_{ϵ}.

Firm Entry and Exits. In period t, an *exogenous* measure $N_{m(k),j,t}^{e}$ of new firms enter in region m, industry j, and regime k. 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 $\delta_p >$

[24] Even though the model is enriched, I find that the key elements of the analytical model (skill intensity differences across sectors and the role of educated labor in innovation) account for more than 90% of the quantitative changes in the skill content of exports and innovation levels due to the college expansion.

0 capturing imperfect imitation. Upon entry, it draws research efficiency $\log \eta \sim \mathcal{N}(0, \sigma_\eta^2)$ and export demand shifter ϵ from the ergodic distribution. After firm entry occurs, all existing firms face an exogenous death rate δ. To incorporate endogenous exits, I assume that firms pay $f_{m(k),j}$ units of final goods per period to remain in business.

Workers' Age and Period-to-Period Migration. I explicitly model workers' age structure following Card and Lemieux (2001), as Figure 7b below reveals that China's college expansion had much stronger negative effects on the college premium of young workers than older ones.[25] Each worker lives for T periods. The amount of age a educated and less-educated workers in region m and period t is denoted as $H_{m,a,t}$ and $L_{m,a,t}$. The supply of labor services of educated (less-educated) labor in region m is a CES function of educated (less-educated) workers of different age groups,

$$H_{m,t} = \left(\sum_{a=1}^{T} \beta_a^H H_{m,a,t}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \quad L_{m,t} = \left(\sum_{a=1}^{T} \beta_a^L L_{m,a,t}^{\frac{\rho_a - 1}{\rho_a}} \right)^{\frac{\rho_a}{\rho_a - 1}}, \tag{18}$$

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

I follow Artuc et al. (2010) to model migration of Chinese workers between subnational regions within China, as my empirical analysis exploited regional variation, of which identification will be contaminated by regional spillovers via trade and migration (e.g., Mian and Sufi 2014). A worker has per-period log utility on the final good and discount the future utility by rate β. In each period, a worker draws location preferences $\{\varphi_n\}_{n \in \mathcal{C}}$ according to a Type-I Extreme Value distribution, i.i.d. over time and across locations, with ν being the scale parameter. If an educated (less-educated) worker moves from region m to n, she incurs migration costs $\tau_{m,n,a}^H$ ($\tau_{m,n,a}^L$).[26] These assumptions yield an analytical solution of migration probabilities $\Lambda_{m,n,a,t}^I$ $I \in \{H, L\}$ for age a workers from region m to n. The labor supply of Chinese region n in $t+1$ can be computed as $H_{n,a+1,t+1} = \sum_{m \in \mathcal{C}} \Lambda_{m,n,a,t}^H H_{m,a,t}$ and $L_{n,a+1,t+1} = \sum_{m \in \mathcal{C}} \Lambda_{m,n,a,t}^L L_{m,a,t}$.

Agriculture Wages. There are persistent wage differences between agriculture and non-

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

[26]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.

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 two sectors despite wage differences.[27] This assumption is important to match that half of Chinese workers were working in agriculture in the early 2000s.

6.2 Data

I calibrate the model to 33 industries (30 manufacturing industries, agriculture, mining, and services), 30 Chinese provinces, and a constructed Rest of World in 2000–2018. 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 particular, I adjust workers of education levels lower than high school to the equivalents of high-school graduates, using their relative wages in 2005. Because most data does not distinguish between college-educated workers with regular degrees and part-time degrees, I take into account college graduates with part-time degrees (adjusted to equivalents of college graduates with regular degrees using relative wages) to target the data moments.

6.3 Estimation 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.

6.3.1 Exogenously Calibrated Parameters

Table 3 presents the set of pre-determined parameters. A period in the model is one year. I set $T = 45$ years for the length of the working life (aged 20–64),[28] the discount rate $\beta = 0.95$, and migration elasticity $\nu = 2$ of annual frequency from Caliendo et al. (2019). I calibrate input-output linkages $\{\gamma^L_{m(k),j}, \gamma^{j'}_{m(k),j}\}$ using China's and the World Input-Output Tables in 2005. I obtain the amount of new college-educated and noncollege

[27] To rationalize wage differences between sectors, 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.

[28] 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) β	0.95	Discount rate	Common value
(3) ν	2	Migration elasticity	Caliendo et al. (2019)
(4) $\{\gamma^L_{m(k),j}, \gamma^{j'}_{m(k),j}\}_{m,k,j}$		Input-output parameters	Data
(5) $\{H_{m,0,t}, L_{m,0,t}\}_{m,t}$		Num of college and noncollege entrants	Data
(6) $\zeta_t(\cdot)$		R&D tax incentives	Chen et al. (2021)

workers across years $\{H_{m,0,t}, L_{m,0,t}\}$ from the data. The schedule of R&D tax incentives in each year $\zeta_t(\cdot)$ is drawn from Chen et al. (2021).[29]

6.3.2 Internally Calibrated Parameters

I now describe three steps to internally calibrate the remaining parameters using the 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 (j: industry; m: region; k: export regime; t: time) if the parameter is multi-valued along any dimension. The details on the moments are provided in Appendix F.4.

Step 1 of Calibration. As shown in Section 4.4, given labor and firm distributions,[30] the model is a static trade model. Thus, I exploit these distributions in 2005 and calibrate production-related parameters $\{\gamma_j, \gamma_r, \alpha_{j(k)}, c_{agr}, \beta^H_a, \beta^L_a, \frac{\sigma^2_\epsilon}{1-\rho^2_\epsilon}\}$, inter-provincial iceberg trade costs $\{d_{m(k),n(k'),j}\}$, and export costs $\{d_{m(k),F,j,2005}, d_{F,m(k),j,2005}, f^X_{k,j}\}$. To reduce the amount of parameters, I model inter-provincial trade costs from ordinary producers as a function of distance and contiguity, $\log d_{m,n,j} = \beta_{1,j} \log dist_{m,n} + \beta_{2,j} contig_{m,n},\ \forall m, n \in \mathcal{C}, m \neq n$ with $d_{m,m,j} = 1\ \forall\ m, j$. $dist_{m,n}$ is the distance between capitals of provinces m and n, and the dummy $contig_{m,n}$ captures the effect of contiguity between provinces m

[29] Before 2008, firms with R&D intensity larger than 5% are qualified to enjoy a reduction in profit tax rates from 33% to 15%. After 2008, firms are qualified to reduce profit tax rates from 25% to 15% with R&D intensity: (1) larger than 6% if their sales are smaller than 50 million RMB; (2) larger than 4% if their sales are between 50–200 million RMB; or (3) larger than 3% if their sales are larger than 200 million RMB.

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

and n.[31] The export and import costs are inter-provincial trade costs to the nearest port multiplied by industry-regime-specific costs of exports ($d^X_{k,j,t}$) and imports ($d^I_{k,j,t}$) from the port. Finally, I assume export marketing costs $f^X_{k,j}$ to be identical for Chinese firms in each industry j and regime k, whereas I abstract from marketing costs for foreign firms.

Table 4 presents the targeted moments. For instance, the effects of distance and contiguity on inter-provincial trade costs are informed by trade shares to non-self and contiguous provinces, respectively. International trade costs $\{d^X_{k,j,2005}, d^I_{k,j,2005}\}$ are disciplined by export and import shares in each Chinese industry and export regime in 2005, and I vary these costs across years to capture tariff changes. Export marketing costs $f^X_{k,j}$ are informed by the share of exporters in each industry. After the first step of calibration, I calibrate firms' operation costs $\{f_{m(k),j}\}$ to equal the lowest profits among operating firms for China's province-regime-industry or foreign industry.

Step 2 of Calibration. Given each year's observed firm distributions in the data, I simulate the model over time with workers' migration decisions to calibrate migration costs and labor elasticities. 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),

$$\tau^I_{m,n,a} = \gamma^I_{age} a + \gamma^I_{dist} \log dist_{m,n} + \gamma^I_{contig} contig_{m,n} + \mathbf{1}_{n \neq birthplace} \gamma^I_n, \; I \in \{H, L\}, \; m, n \in \mathcal{C}. \quad (19)$$

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.

I group workers based on education types, current locations of residence, and birthplaces.[32] I choose parameters in migration costs to target the effects of age, distance, and contiguity on migration rates, as well as the share of in-migrants in a destination's employment, from Population Census 2000. As the elasticities ρ_x and ρ_a determine relative

[31] As processing producers cannot sell domestically, I set their inter-provincial trade costs to be infinite.

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

wages across labor types and ages, I calibrate these two parameters to target the responses of provincial college premium to the expansion shock between 2003–2009 and the relative wages between young (less than 30 years old) and old (aged 30+) college workers in 2009.

Step 3 of Calibration. Finally, I calibrate the parameters regarding productivity evolution and firm entry/exits $\{g_{m(k),j,t}, N_{m(k),j,t}, \sigma_\epsilon, \delta, \delta_p, \rho_\epsilon\}$ and innovation $\{\chi, \sigma_\eta, \phi_{1,j}, \phi_{2,j}, A_{m,r,t}\}$. The productivity drift $\{g_{m(k),j,t}\}$ and the amount of new firms $\{N_{m(k),j,t}\}$ are informed by changes in output and the number of operating firms of each region, industry, and regime 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 assume aggregate research productivity to be region-specific with a common time trend $A_{m,r,t} = \bar{A}_{m,r} a_t$. $\bar{A}_{m,r}$ is informed by the share of R&D firms by province in 2005, and time-variant residual parameter a_t allows me to perfectly match aggregate manufacturing R&D intensity in 2000–2018, capturing unmodelled factors that affect innovation levels.

6.4 Estimation Results

Parameters. Table 4 reports the calibrated parameters, 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 1.6 and 3.8 respectively, similar to the typical values found in the macro literature (e.g., Katz and Murphy 1992, Card and Lemieux 2001).[33] 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).

Targeted Moments. Table 4 shows the model matches the targeted data moments well. The only moment with moderate deviation is the share of imports in domestic expenses for Chinese regions. This is because trade is balanced for each region in the model, whereas China ran trade surplus in reality with smaller imports than exports.

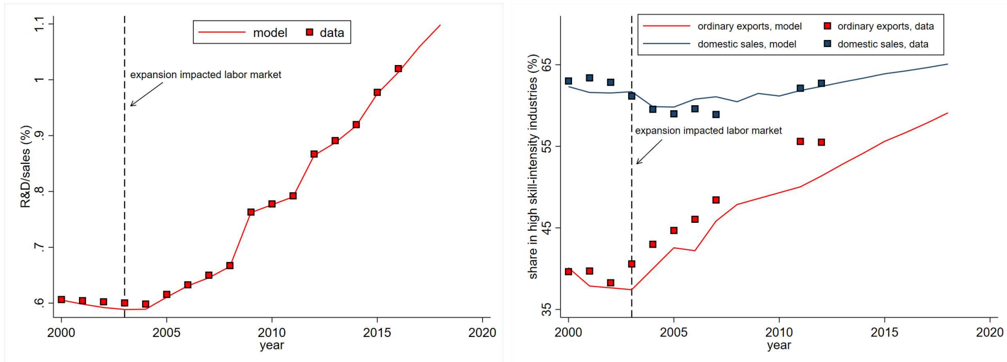
[33]For instance, Katz and Murphy (1992) find the elasticity of substitution between college-educated and high-school workers to be 1.4, whereas Card and Lemieux (2001) find that to be 2.5. Card and Lemieux (2001) find the elasticity across age groups to be 5.

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	0.51	Cost share of college labor in R&D	Share of full-time R&D workers	0.65%	0.65%
(3) $\{\beta_a^H, \beta_a^L\}_a$	0.07 (0.02)	Age-specific productivity	Wages rel. to youngest workers	1.22 (0.14)	1.22 (0.14)
(4) $\{\alpha_{j(k)}\}_{j,k}$	0.70 (0.09)	Skill intensities	$\{$ College employment shares Aggregate college premium	0.11 (0.07) 0.67	0.14 (0.09) 0.67
(5) $\frac{\sigma_\epsilon^2}{1-\rho_\epsilon^2}$	0.32	Variance of export demand	Std of export-output ratios	0.30	0.29
(6) c_{agr}	0.25	Wages in agri rel. to nonagriculture	Share of agricultural employment	0.48	0.48
(7.1) $\{\beta_{1,j}\}_j$	0.11 (0.05)	Trade costs w.r.t. distance	Sum of trade shares to nonself provinces	18.82 (5.84)	19.24 (5.60)
(7.2) $\{\beta_{2,j}\}_j$	-0.07 (0.08)	Trade costs w.r.t. contiguity	Sum of trade shares to nearby provinces	4.40 (1.46)	4.19 (1.51)
(8.1) $\{d_{k,j,2005}\}_{k,j}$	2.09 (1.85)	Export costs (from port)	Share of foreign expenses on China's exports	0.02 (0.03)	0.02 (0.03)
(8.2) $\{d_{k,j,2005}\}_{k,j}$	2.67 (2.33)	Import costs (from port)	Share of Chinese expenses on imports	0.40 (0.35)	0.36 (0.37)
(9) $\{f_{k,j}^X\}_{k,j}$	$4e{-}4(3e{-}3)$	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) $\gamma_{age}^H, \gamma_{age}^L$	0.01, 0.05	Age effects on migration costs	Corr btw migration rates and age	-0.11, -0.13	-0.09, -0.14
(2) $\gamma_{dist}^H, \gamma_{dist}^L$	2.01, 2.42	Distance effects on migration costs	Corr btw migration rates and distance	-0.12, -0.12	-0.10, -0.11
(3) $\gamma_{contig}^H, \gamma_{contig}^L$	-0.45, 0.45	Contiguity effects on migration costs	Corr btw migration rates and contiguity	0.09, 0.12	0.09, 0.12
(4.1) $\{\gamma_m^H\}_m$	5.54 (3.71)	Destination mig. costs, college labor	Share of annual in-migrants in college labor	0.008 (0.007)	0.008 (0.007)
(4.2) $\{\gamma_m^L\}_m$	5.17 (5.05)	Destination mig. costs, noncollege	Share of annual in-migrants in noncollege labor	0.008 (0.010)	0.008 (0.011)
(5) ρ_x	1.6	Elast. btw college/noncollege labor	Slope of provincial skill premium to shocks	0.33	0.33
(6) ρ_a	3.8	Elast. across age groups	Wage difference btw young/old college labor	-0.44	-0.45
			Panel C: Step 3 of Calibration		
(1) $\{g_{m(k),j,t}\}_{m,k,j,t}$	0.01 (1.06)	Exg. productivity growth	$\{$ Output growth rel. to services (before 2011) China's GDP growth rel. to foreign (after 2011)	0.08 (0.56) 0.08 (0.05)	0.08 (0.56) 0.09 (0.06)
(2) $\{N_{m(k),j,t}^e\}_{m,k,j,t}$	1,532 (14,810)	Num of new firm entrants	Changes in num of firms	310 (3,205)	321 (3,232)
(3) σ_ϵ	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	0.6	Autocorrelation of export demand	Autocorrelation of log ord. exports	0.81	0.75
(7) σ_η	1.6	Std of research intensity	Std of research intensity among R&D firms	0.024	0.022
(8) χ	0.76	Convexity of innovation costs	Slope of sales growth to R&D intensity	2	2
(9.1) $\{\phi_{1,j}\}_j$	$4e{-}5(3e{-}5)$	Fixed costs of innovation	Share of R&D firms, by industry	0.10 (0.08)	0.10 (0.08)
(9.2) $\{\phi_{2,j}\}_j$	193.69 (747.37)	Variable costs of innovation	R&D intensity, by industry	0.005 (0.005)	0.005 (0.005)
(10.1) $\{\bar{A}_{m,r}\}_m$	1.38 (0.49)	Research productivity by province	Share of R&D firms, by province	0.11 (0.04)	0.11 (0.04)
(10.2) $\{a_t\}_t$	2.06 (1.31)	Time trend of research productivity	Each year's manufacturing R&D intensity	0.008 (0.002)	0.008 (0.002)

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.

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



(a) R&D sales/sales

(b) Export Skill Upgrading

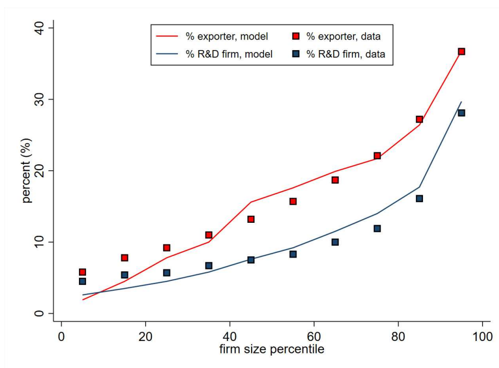
Figure 5 shows that the model can replicate the documented pattern of China's innovation surge and export skill upgrading. Panel (a) presents yearly manufacturing R&D intensity. As I targeted the overall trend of manufacturing R&D intensity using changes in aggregate research productivity, the model replicates the data well. Panel (b) reports the time-series pattern of the share of sales in high skill-intensity industries for domestic sales and ordinary exports. 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.5 shows that the model can also replicate changes in the share of processing exports.

Untargeted Moments. Figure 6 presents the untargeted 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 pretty well.

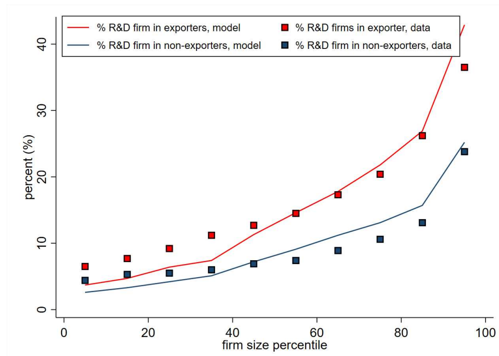
Figure 7a shows that the model can match the observed changes in employment by provinces and education levels between 2000–2010. Figure 7b shows that in the 2000s, the model and the data both predict a decline of college premium for young workers, and an increase of college premium for old workers (see Appendix G for the estimation method). In the model, the former pattern is due to a large inflow of young college graduates, and the latter pattern is driven by fast growth of manufacturing firms' sales.

Finally, Table 5 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 (17) and the instruments constructed in Section 5. I find that the model-generated responses are quite close to the observed responses.

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

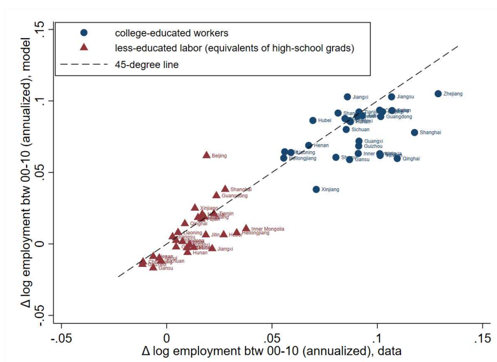


(a) Share of R&D Firms and Exporters

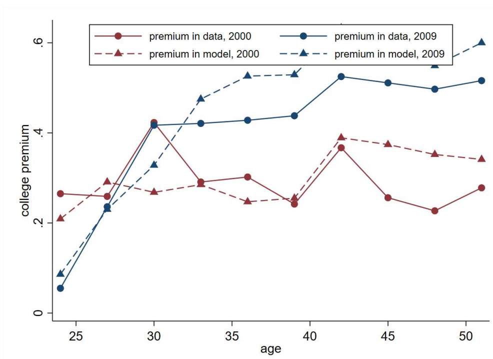


(b) Innovative Activities by Export Status

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



(a) Changes in Employment between 2000–10



(b) College Wage Premium by Age

Note: The data on employment by education levels and provinces are from Population Census 2000 and 2010. The estimation method for college premium by age is presented in Appendix G, and the data comes from the Urban Household Survey.

Table 5: Dep Var: Annualized Province-industry-level Changes between 2005–2010

Dep var:					Δshare of R&D firms			
	Δlog(domestic sales)		Δlog(ordinary exports)		non-exporter		ordinary exporter	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	data	model	data	model	data	model	data	model
Exposure to CE	0.385*	0.334***	0.785***	0.678***	0.084***	0.063***	0.101***	0.109***
	(0.197)	(0.133)	(0.162)	(0.153)	(0.023)	(0.028)	(0.039)	(0.029)
Obs	745	785	587	600	783	787	586	599
R-squared	0.541	0.485	0.353	0.322	0.447	0.549	0.566	0.650
First-stage F	432.96	435.49	138.45	140.31	518.47	519.21	232.86	233.75

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 5. 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. I control the share of SOEs, log employment, log capital, and log output in 2005, province fixed effects, as well as input and output tariff reductions. In Columns (1)–(4), regressions are weighted by the amount of domestic sales and ordinary exports within each province-industry pair in 2005. In Columns (5)–(8), regressions are weighted by the number of firms 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%.

7 Quantitative Analysis

I now 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.

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 be 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 each Chinese province and Foreign.[34]

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. To explore the outcomes of innovation, Figure 8b further reports the contributions of the college expansion to manufacturing output growth through changes in innovation and composition of college-educated/noncollege labor.[35] 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), it appears that college expansion has become an important engine of China's manufacturing development in recent years.

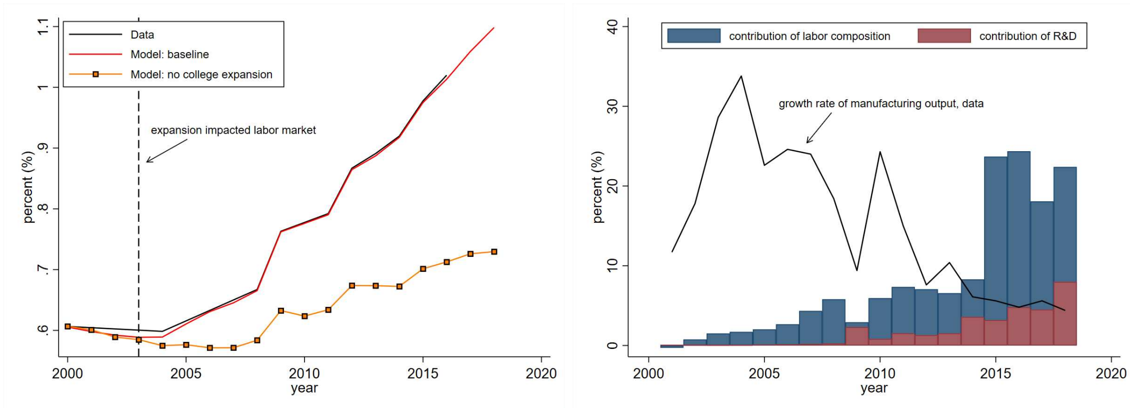
It is worth comparing the differential effects of China's college expansion through labor composition and innovation. Although the college expansion produces positive output effects through increases in high-skill workers, the rapid accumulation of college-educated workers faces declining marginal returns. In fact, the marginal products of new college-educated workers were 20% higher than high-school graduates of the same age in 2018, declining from 84% 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).[36] On the other hand, the increasing stock of college-educated workers raises R&D intensity, speeding up annual productivity growth persistently. Figure 8b shows that higher innovation due to the college expansion accounted for 8% of manufacturing output growth in 2018, and this contribution will become more considerable with China's rapid increases in innovation levels (Wei et al. 2017).

[34] To isolate the effects of the expansion of regular college education, I keep each year's enrollments in part-time colleges unchanged in all simulations. This restriction will be discussed in Appendix Section H. I normalize the GDP-weighted average price of final goods across Chinese regions to be 1. I also experimented with foreign GDP as the numeraire except for autarky, and the results are similar.

[35] I isolate the effects of innovation by simulating the calibrated equilibrium using firms' research intensity from the scenario of "no college expansion", while keeping all other components of productivity evolution as unchanged. I isolate the effects of labor composition by recomputing the calibrated equilibrium with the same firm productivity distributions but labor composition from the "no college expansion" scenario.

[36] 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 7b), it is possible that skill-biased technology became important in the 2010s, for which period I do not have

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



(a) Manu R&D/sales

(b) Decomposition of Effects

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

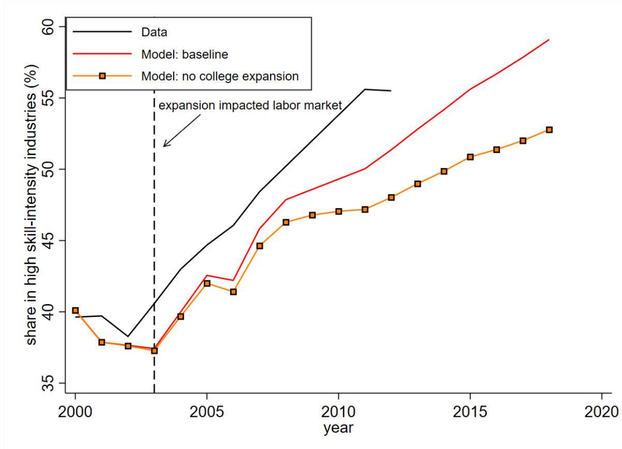
7.2 Export Skill Upgrading

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-intensity industries increased by 21.7 percentage points, from 37.4% in 2003 to 59.1% in 2018. This increase dropped to 15.5 percentage points in the absence of the college expansion; therefore, the contribution of the college expansion to skill upgrading of ordinary exports was $\frac{21.7-15.5}{21.7} = 29\%$. According to Figure 9, the college expansion has fueled China's export skill upgrading 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.5 shows that China's college expansion explained 11% of the decline in the share of processing exports between 2003–2018, thus also contributing to export skill upgrading by shifting the composition between processing and ordinary exports.[37]

available data on the college premium.

[37]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-intensity industries within ordinary exports were stronger than from processing to ordinary exports.

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



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 better 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.[38] Table 6 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 9.64%, 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. The amplification effects of trade openness on GDP and manufacturing output in 2018 were 10–13%, as trade shifted industry composition and reduced

[38] 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 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 relative productivity of college-educated workers relative to the less-educated workers such that the aggregate college premium is the same as the baseline model. I keep all other parameters at their baseline levels.

Table 6: 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	9.64%	10.93%	0.36 p.p.	-0.60
Autarky	8.75%	9.69%	0.31 p.p.	-0.62
Amplification effect of trade (% from autarky to baseline)	10.2%	12.8%	16.1%	-3.4%

Note: The college premium is the average wage of college-educated workers relative to the average wage of high-school graduates.

the diminishing returns of additional college-educated workers. Thus, trade openness also tamed the negative impact of the college expansion on the college premium by 3%. More interestingly, the amplification effects of trade on innovation were even larger (16%), as exporters were intensively engaged in innovative activities.

7.4 Costs and Benefits of China's College Expansion

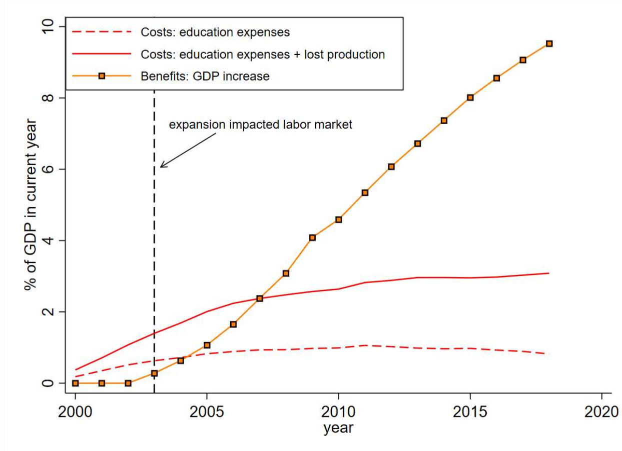
China's college expansion did not come at no economic costs. First, the expansion of college education led to higher education investments, which can otherwise be used as consumption or other types of investments. Moreover, new college graduates could have entered the labor market earlier if they had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

I compute increases in education expenses in each year by multiplying additional enrollments[39] with average education expenses (including tuition and government subsidies) per college enrollment from China's Education Statistical Yearbooks. I compute implicit costs by multiplying additional enrollments with average marginal products of high-school graduates (aged less than 23) in the baseline equilibrium.

Figure 10 compares the costs of college expansion against the increase in GDP thanks to the college expansion. The additional education expenses represented roughly 1% of GDP in the 2010s, which were relatively small compared with the loss of production (2% of GDP in the 2010s). The increase in yearly GDP driven by the college expansion started to exceed 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.

[39] 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: Costs and Benefits of China's College Expansion



7.5 Robustness Checks

Appendix Section H shows that the quantitative results are robust to: (1) including endogenous entry of firms; (2) misreporting of R&D; (3) incorporating part-time college education; and (4) modelling changes in migration costs over time. I also show that abstracting from China's intranational regions will exaggerate the impact of college expansion on exports and innovation. This last result indicates that the geographic distribution of new college graduates was unfavorable for aggregate productivity, confirming the mismatch between between regional development levels and the distribution of college resources discussed in Section 2.

8 Conclusion

Combining a quantitative model with empirical evidence, this paper sheds light on the contribution of China's massive college expansion to China's recent increases 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.

This paper focuses on the role of the increasing supply of talents. 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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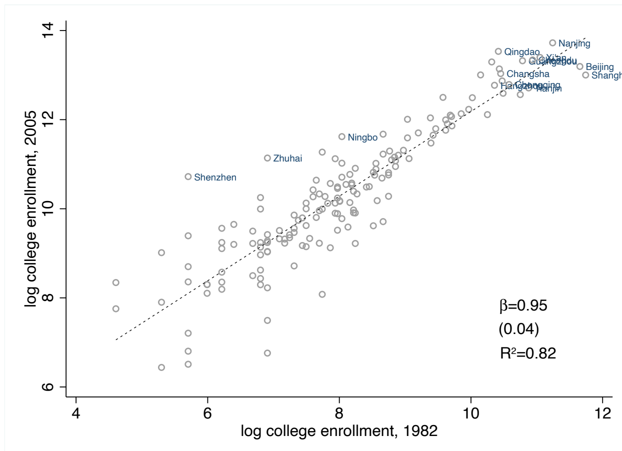
Appendix for Online Publication

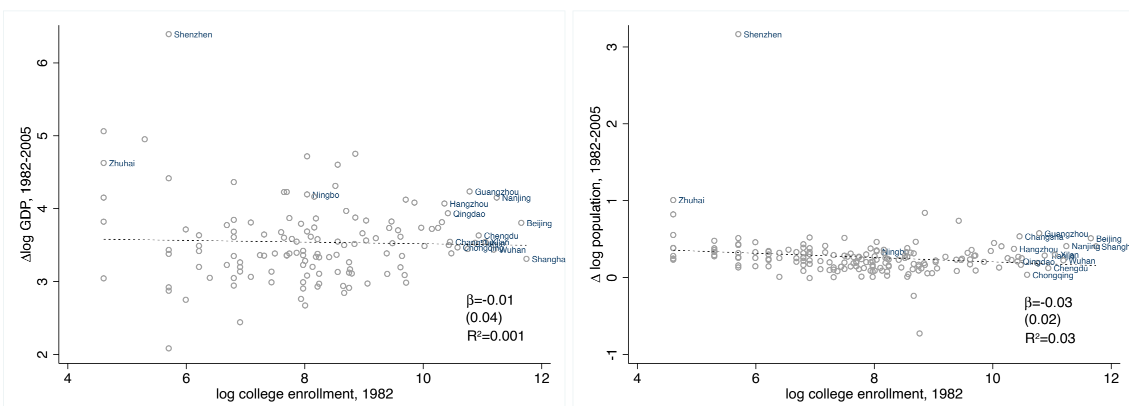
A Additional Graphs

Figure A.1: College Enrollments across Cities



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

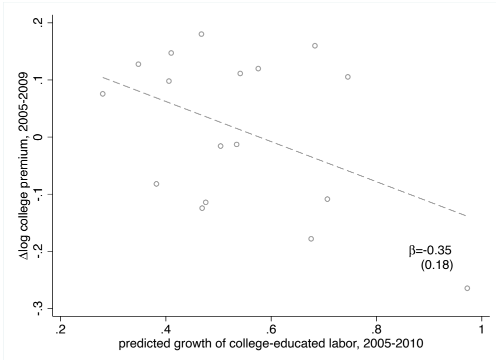
Figure A.2: College Enrollments and Changes in GDP and Population



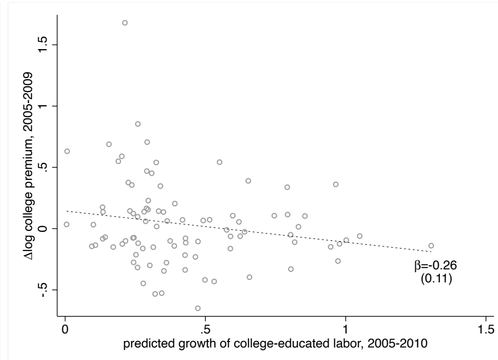
(a) GDP (b) Population

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

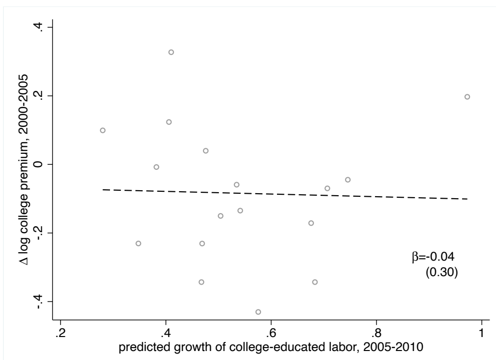
Figure A.3: IV and Changes in Young Workers' College Premium



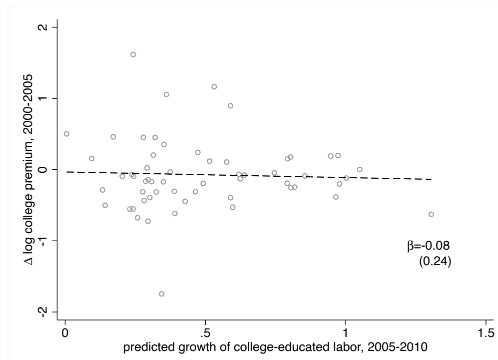
(a) Provincial, 2005–2009



(b) City level, 2005–2009



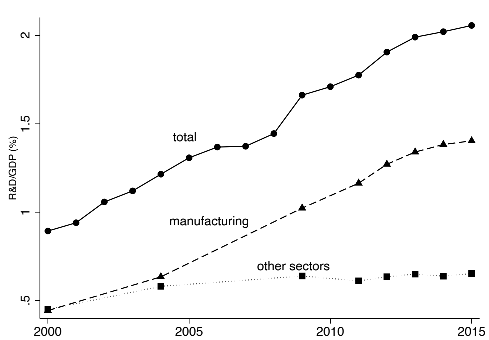
(c) Provincial, 2000–2005



(d) City level, 2000–2005

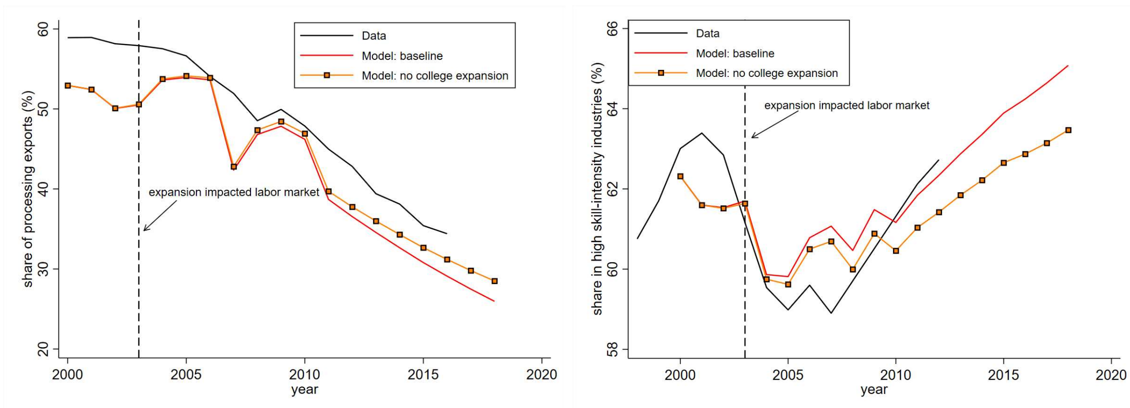
Note: I use the Urban Household Survey and measure young workers' college premium by using the average wage of college-educated workers (aged less than 28) relative to the average wage of all workers with high-school education. For older college-educated workers, the instrumented shock was uncorrelated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

Figure A.4: China's R&D Expenses by Sectors



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

Figure A.5: Effects of the College Expansion on Processing Exports and Domestic Sales



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

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 a 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,[40] 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 domestic college graduates from regular college education in the meantime (67.2 million).

C Robustness Checks of Section 3

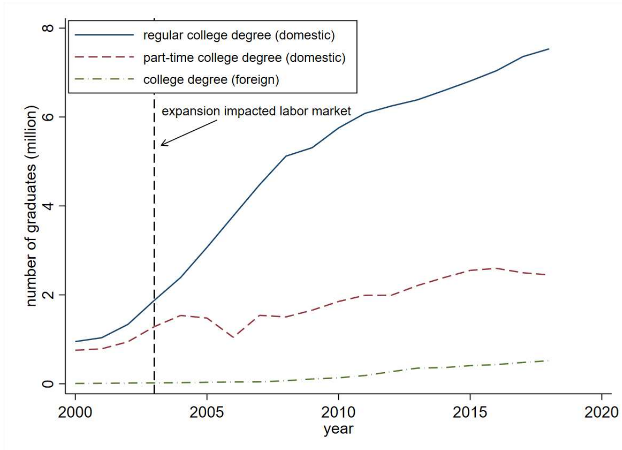
C.1 Robustness Checks of Section 3.2

C.1.1 Alternative Measure of Skill Intensities

I test the robustness of my results using an alternative measure of skill intensities—the ratio of nonproduction workers to employment. I compute the ratio of nonproduction workers to employment for 4-digit SIC industries (459 manufacturing industries) in the

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

Figure B.1: Number of College graduates (Annual)



U.S. in 1990, according to the NBER Manufacturing Database. I define an industry to be a high-intensity industry if its ratio is larger than the average ratio across industries.

I convert domestic sales in ASM from China's Industry Classification (CIC) to SIC industries using the CIC-ISIC concordance from Dean and Lovely (2010) and the ISIC-SIC concordance.[41] I convert my customs data to 4-digit SIC industries using the HS-SIC concordances from the World Integrated Trade Solution (WITS). Compared to the linked ASM-Customs data used in the main text, using SIC industries provides two advantages. First, as the customs database contains all China's exports by HS products, I can thus apply the direct conversion from HS products to SIC industries for China's total exports. In other words, there is a full coverage of this skill-intensity measure on exports. Second, I have access to exports by HS products in the period 1997–2016. This allows me to extend the time series of exports to the period 1997–2016 and have longer pre-shock years.

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

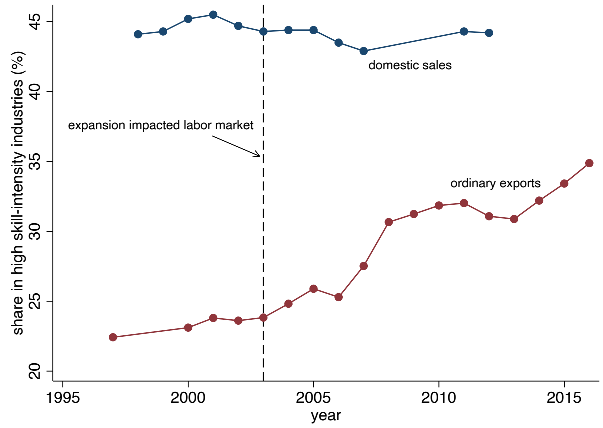
I show that my results in Figure 3 were not driven by the specific cutoff of high skill-intensity industries I chose. I run a regression on the 4-digit industry level as follows:

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

where $s_{j,t}$ is total domestic sales (ordinary exports) of industry j in year t. α_t is the common growth rate across industries. SI_j is the skill-intensity measure of industry j. β_t is the coefficient of interest. $\beta_t > 0$ implies that more skill-intensive industries exhibit higher

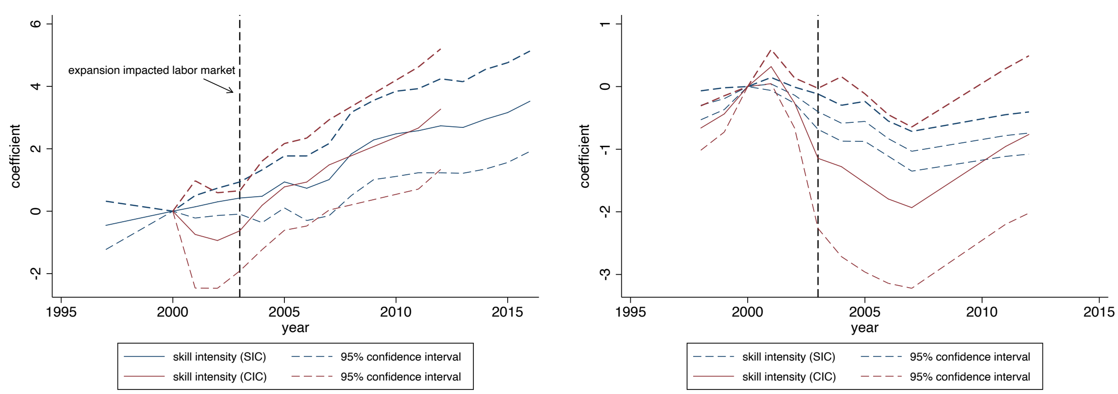
[41] The ISIC-SIC concordance is drawn from Peter Schott's website on international trade data.

Figure C.1: Share of Sales in High Skill-intensity Industries (Based on SIC Industries)



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.

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



(a) Ordinary Exports

(b) Domestic Sales

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 U.S. 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 Robustness of Section 3.3

C.2.1 Construction of Balanced Panels

I construct the balanced firm panels in the following steps. First, I clean the ASM and the SAT data by dropping firms with missing or nonpositive sales and value added, as well as firms with missing or negative exports. Second, I clean and standardize firm names in the ASM, the SAT, and the customs data, following the steps in He et al. (2018). Third, I merge the different sets of data using firm names. Finally, firm-level exports reported in the ASM and the SAT may be different from the exports reported in the customs data due to imperfect match or misreporting. To ensure that the measurement of exports and domestic sales is consistent, I adjust the exports reported in the customs data proportionally (by each firm) to match firms' reported exports in the ASM or the SAT.[42] I also exclude purely processing exporters (firms that only export processing products) in the data. Table C.1 summarizes the sample statistics.

C.2.2 Robustness Checks of Figure 4

Controlling Industry Composition. To control the industry composition, I first compute the changes in innovation 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 innovation 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.

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

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

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 high-tech industries may increase their innovative activities due to R&D tax incentives.[43] Row (4) in Table C.2 replicates the results excluding electoral machinery, electronics, medicine, and transportation industries, which tend to be high-tech. I find very similar findings.

Using Patent Data. I also provide a measure of innovation output, using records of firms' invention patent applications in 1998–2009 from He et al. (2018). As my patent data end 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

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

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

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.2.3 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.

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.

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: 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%.

D Proofs

D.1 Proof of Proposition 1

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

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

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

$$\hat{H}_{\mathcal{C},j} - \hat{L}_{\mathcal{C},j} = -\rho_x(\hat{S}_{\mathcal{C}} - \hat{W}_{\mathcal{C}}) \tag{D.1}$$

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

$$\hat{E}_{\mathcal{C}} + (\theta-1)(\hat{P}_{\mathcal{C}} - \hat{P}_{\mathcal{C},j}) = (1-SI_{\mathcal{C},j})(\hat{W}_{\mathcal{C}} + \hat{L}_{\mathcal{C},j}) + SI_{\mathcal{C},j}(\hat{S}_{\mathcal{C}} + \hat{H}_{\mathcal{C},j}) \tag{D.2}$$

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

$$P_{\mathcal{C},j}^{1-\sigma} = N_{\mathcal{C},j}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_{\mathcal{C}}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_{\mathcal{C}}^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}} \int\int z^{\sigma-1} g_{\mathcal{C},j}(z,\eta)dzd\eta. \tag{D.3}$$

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

$$\hat{P}_{\mathcal{C},j} = (1 - SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}} + SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}} \tag{D.4}$$

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

Combining equation (D.1), (D.2) and (D.4), I obtain:

$$\theta\hat{W}_{\mathcal{C}} = (\rho_x - \theta)SI_{\mathcal{C},j}(\hat{S}_{\mathcal{C}} - \hat{W}_{\mathcal{C}}) - \hat{L}_{\mathcal{C},j} + \hat{E}_{\mathcal{C}} + (\theta-1)\hat{P}_{\mathcal{C}} \tag{D.5}$$

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

Note that I do not consider innovation here, and therefore all the labor is used in production. I then have $\hat{L}_{\mathcal{C}} = \sum_j \Lambda_{\mathcal{C},j}^L \hat{L}_{\mathcal{C},j}$ and $\hat{H}_{\mathcal{C}} = \sum_j \Lambda_{\mathcal{C},j}^H \hat{H}_{\mathcal{C},j}$, where $\Lambda_{\mathcal{C},j}^H$ ($\Lambda_{\mathcal{C},j}^L$) is the amount of college (noncollege) labor in industry j as the share of the amount of regional college (noncollege) workers. Combining this with equation (D.5) and (D.6), I obtain:

$$\hat{S}_{\mathcal{C}} - \hat{W}_{\mathcal{C}} = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{\mathcal{C},j}(\Lambda_{\mathcal{C},j}^H - \Lambda_{\mathcal{C},j}^L))}(\hat{L}_{\mathcal{C}} - \hat{H}_{\mathcal{C}}). \tag{D.7}$$

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

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

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

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

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

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

$$\Phi_{\mathcal{C}} = \frac{1}{\theta + (\rho_x - \theta)(1 - \sum_j SI_{\mathcal{C},j}(\Lambda_{\mathcal{C},j}^H - \Lambda_{\mathcal{C},j}^L))}. \tag{D.8}$$

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

D.2 Proof of Proposition 2

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

$$R_{\mathcal{C},j} = \frac{p_{\mathcal{C},\mathcal{C},j}(z)^{1-\sigma}}{P^{1-\sigma}_{\mathcal{C},\mathcal{C},j} + P^{1-\sigma}_{F,\mathcal{C},j}} \gamma_j^\theta \left(\frac{P_{\mathcal{C},j}}{P_\mathcal{C}}\right)^{1-\theta} E_\mathcal{C}, \tag{D.9}$$

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

$$P^{1-\sigma}_{\mathcal{C},\mathcal{C},j} = N_{\mathcal{C},j}\left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_\mathcal{C}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_\mathcal{C}^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}} \int\int z^{\sigma-1} g_{\mathcal{C},j}(z,\eta) dz d\eta. \tag{D.10}$$

where $N_{\mathcal{C},j}$ is the number of firms that are located in region $\mathcal{C}$. The aggregate price indices can be obtained as:

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

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

Log differentiating equation (D.9) and noting that $\hat{P}_{\mathcal{C},\mathcal{C},j} = \hat{p}_{\mathcal{C},\mathcal{C},j}(z)$ as I abstract from the extensive margin of selling to domestic markets, I obtain

$$\hat{R}_{\mathcal{C},j} = (1-\sigma)(1-\Pi_{\mathcal{C},\mathcal{C},j})\hat{P}_{\mathcal{C},\mathcal{C},j} + (1-\theta)\Pi_{\mathcal{C},\mathcal{C},j}\hat{P}_{\mathcal{C},\mathcal{C},j} + (\theta-1)\hat{P}_\mathcal{C} + \hat{E}_\mathcal{C} \tag{D.11}$$

Log differentiating equation (D.10) gives me proportional changes in domestic price indices:

$$\hat{P}_{\mathcal{C},\mathcal{C},j} = (1 - SI_{\mathcal{C},j})\hat{W}_\mathcal{C} + SI_{\mathcal{C},j}\hat{S}_\mathcal{C}. \tag{D.12}$$

Combining equations (D.11) and (D.12) leads to proportional changes in domestic sales.

Now consider exports for a firm that exports before and after the shock. First note that exports can be written as:

$$R_{F,j} = \left(\frac{p_{\mathcal{C},F,j}(z)}{P_{F,j}}\right)^{1-\sigma} \gamma_j^\theta \left(\frac{P_{F,j}}{P_F}\right)^{1-\theta} E_F, \tag{D.13}$$

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

$$p_{\mathcal{C},F,j}(z)^{1-\sigma} = \left(\frac{\sigma}{(\sigma-1)z}\right)^{1-\sigma}\left[\frac{\alpha_j^{\rho_x}}{W_\mathcal{C}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_\mathcal{C}^{\rho_x-1}}\right]^{\frac{1-\sigma}{1-\rho_x}}. \tag{D.14}$$

I assumed in Section 4.5 that Chinese regional economies will not affect equilibrium outcomes in foreign regions, which indicates that $P_{F,j}$ and P_F remain constant. Therefore, log differentiating equation (D.13), I can derive:

$$\hat{R}_{F,j} = (1-\sigma)\hat{p}_{\mathcal{C},F,j}, \tag{D.15}$$

where $\hat{p}_{\mathcal{C},F,j}$ can be derived by log differentiating equation (D.14),

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

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

Result (ii). Finally, consider that there is no new export entry. If $\sigma > \theta$ and self-import ratios $\Pi_{\mathcal{C},\mathcal{C},j} > 0$ are similar across industries, for two industries with skill intensities $SI_{\mathcal{C},j} > SI_{\mathcal{C},j'}$, from Result (i), I have:

$$\underbrace{(\sigma-1)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'})}_{\text{relative growth in exports}} > \underbrace{(\sigma-1)(SI_{\mathcal{C},j} - SI_{\mathcal{C},j'}) + (\theta-\sigma)\left(\Pi_{\mathcal{C},\mathcal{C},j}SI_{\mathcal{C},j} - \Pi_{\mathcal{C},\mathcal{C},j'}SI_{\mathcal{C},j'}\right)}_{\text{relative growth in domestic sales}}. \tag{D.17}$$

where the left-hand side is the relative growth of exports across two industries, and the right-hand side is the relative growth of domestic sales. Therefore, the difference in growth rates between more and less skill-intensive industries is larger for exports than for domestic sales. Thus, the skill structure of exports shifts more toward high skill-intensity industries than domestic sales. The results are analogous when there is new export entry and the productivity distribution is Pareto, which implies that the extensive margin of exports is identical across industries. This completes the proof.

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

$$\frac{R_{F,j}}{\sigma} - f_{\mathcal{C},F,j}P_{\mathcal{C}} = 0 \;\Rightarrow\; z_j^* = \left(\frac{\sigma f_{\mathcal{C},F,j}P_{\mathcal{C}}}{E_F P_F^{\theta-1} P_{F,j}^{\sigma-\theta}\gamma_j^{\theta}}\right)^{\frac{1}{\sigma-1}} \frac{\sigma}{(\sigma-1)}\left[\frac{\alpha_j^{\rho_x}}{W_{\mathcal{C}}^{\rho_x-1}} + \frac{(1-\alpha_j)^{\rho_x}}{S_{\mathcal{C}}^{\rho_x-1}}\right]^{\frac{1}{1-\rho_x}} \tag{D.18}$$

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

$$\hat{z}_j^* = (1 - SI_{\mathcal{C},j})\hat{W}_{\mathcal{C}} + SI_{\mathcal{C},j}\hat{S}_{\mathcal{C}} \tag{D.19}$$

Therefore, the threshold z_j^* declines more in the more skill-intensive industry when $\hat{W}_{\mathcal{C}} - \hat{S}_{\mathcal{C}} > 0$. If the density of firms around the export threshold is identical in two industries, there would be more export entry in the more skill-intensive industry. ***Q.E.D.***

D.3 Proof of Proposition 3

Result (i) combines proportional growth of domestic sales and exports from Result (i) of Proposition 2. Result (ii) arises from the observation that starting to export improves revenues, thus increasing returns to innovation. ***Q.E.D.***

E Robustness of Empirical Analysis

E.1 Mapping from Reduced-form Estimate to Structural Parameters

In Proposition 2, I abstract from input-output linkages, innovation, firm entry, operation costs, and demand and productivity shocks. I discuss how these abstractions affect the mapping between the reduced-form estimates and the structural parameters.

First, incorporating input-output linkages does not affect the transmission of production costs to exports and domestic sales. Therefore, the mapping remains the same.

Second, introducing innovation makes the transmission of the college expansion to changes in production costs firm-specific, because different firms have different innovation levels. However, it does not affect the transmission of changes in production costs to changes in exports and domestic sales. As long as I use the same set of firms to estimate the responses to the college expansion, modelling innovation does not affect the mapping between the reduced-form estimates and the structural parameters.

Third, modelling 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 E.1, I regress changes in the number of new entrants between 2005–2011,[44] where entrants are identified by firms' birthyear, on the exposure to the college expansion. I find that larger exposure to the college expansion triggered more firm entry. In Column (2) of Table E.1, for each province-industry pair, I regress the sales share in 2011 of firms that entered between 2005–2011, on the exposure to the college expansion. The result shows that the college expansion did not significantly affect sales across industries in 2011 through firm entry between 2005–2011, as new firms tended to be small.

Finally, modelling operation costs and idiosyncratic shocks could also bias the mapping, as firms that operated in 2005 might exit in later years, and firms that remained operating in 2010 could be selective. Because more productive firms were less likely to suffer from selection effects, I experimented with restricting the sample to initially large firms (in terms of employment, output value, or export value), which leads to quantitatively similar regression results as in Table 1.

As another check, I look into how exiting firms affected industry sales. In Column (3) of Table E.1, for each province-industry pair, I regress the number of firms that exited between 2005–2011,[45] normalized by the number of firms in 2005, on the exposure to the

[44] I use ASM 2005 and 2011 for regressions because ASM provides a full coverage of firms above certain sales thresholds, while SAT is only a sample of firms.

[45] The exiting firm is defined as a firm that showed up in ASM 2005 but disappeared in ASM 2011.

Table E.1: Dependent Variable: Province-industry-level Variables in 2005–2011

Dep var:	Δlog(num of entrants)	% entrants' sales	% exiters	% exiters' sales
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
Exposure to CE	2.411**	-0.152	-0.471***	0.112
	(1.180)	(0.245)	(0.110)	(0.448)
Obs	585	789	798	798
R-squared	0.474	0.388	0.483	0.465
First-stage F	425.10	481.99	402.56	414.61

Note: This table provides estimates from regressions, treating regions as provinces, using the same constructed shocks and instruments as in Section 5. I also exclude purely processing exporters to be consistent with Section 5. I control the share of SOE firms, log employment, log fixed capital, and log production value for each province-industry-pair in 2005, as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Regressions in Columns (1) and (3) are weighted by the number of entrants and the total number of firms in each province-industry pair in 2005, respectively. Regressions in Columns (2) and (4) are weighted by the total sales of firms in each province-industry pair in the corresponding year. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

college expansion. I find that larger exposure to the college expansion led to fewer firm exits. In Column (4), for each province-industry pair, I regress the sales share in 2005 of firms that exited between 2005–2011, on the exposure to the college expansion. The result shows that exiting firms between 2005–2011 due to the college expansion were small and did not significantly affect sales across industries in 2005.

E.2 Robustness Checks of Empirical Results

E.2.1 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 they 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).[46]

[46] 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 E.2: Dependent Variable: Firm-level Changes between 2005–2010

Dep var:	Δlog(imported input prices)		Δlog(num of imported inputs)	
	all goods	high-tech capital goods	all goods	high-tech capital goods
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
Exposure to CE	-0.728	-0.722	0.183	0.042
	(0.467)	(1.144)	(0.459)	(0.584)
Obs	2,877	1,607	3,872	2,183
R-squared	0.024	0.036	0.012	0.022
First-stage F	688.08	717.04	573.41	654.14

Note: This table provides estimates from regressions in equation (17). I control dummies for firm registration types (e.g., SOE), log employment, log fixed capital, and log production value in 2005 as well as region-specific trends. I also control input and output tariff reductions for each industry due to China's WTO accession. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

Columns (1)–(2) of Table E.2 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.

E.3 Pre-trend Tests

As suggested by Goldsmith-Pinkham et al. (2020), I perform pre-trend tests to support the validity of my instrument. I regress province-industry-level trends of sales and innovation before and after 2005 on the exposure to the college expansion between 2005–2010, using the same constructed shock and instrument as in Section 5. Table E.3 shows that the college expansion between 2005–2010 had no positive effects on industry-level changes in domestic sales, exports, and innovation between 2001–2005 (when the college expansion had small effects on labor markets). The effects on the changes after 2005 were sizable.

F Calibration

F.1 Incorporating Processing Producers into the Model

I assume each Chinese region and manufacturing industry to host a number of processing firms. Production in Chinese region $m \in \mathcal{C}$ is now specific to export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$. Parameters of processing firms differ from ordinary firms in the following aspects.

Table E.3: Dependent Variable: Province-industry-level Annualized Changes

Dep var:					Δshare of R&D firms			
	Δlog(domestic sales)		Δlog(ordinary exports)		nonexporter		ordinary exporter	
Period	01–05	05–11	01–05	05–11	01–05	05–10	01–05	05–10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Exposure to CE	-0.913***	0.385*	0.511	0.785***	0.027	0.084***	0.042	0.101**
	(0.203)	(0.202)	(0.466)	(0.162)	(0.027)	(0.024)	(0.042)	(0.040)
Obs	786	745	600	587	785	783	600	586
R-squared	0.400	0.541	0.225	0.353	0.194	0.447	0.175	0.566
First-stage F	502.38	432.96	147.09	138.45	635.23	518.47	302.85	232.86

Note: This table provides regressions of province-industry-level changes on the exposure to the college expansion, with the same constructed shocks and instruments in Section 5. 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. I control the share of SOEs, log employment, log capital, and log output in 2005, province fixed effects, as well as input and output tariff reductions. In Columns (1)–(4), regressions are weighted by the amount of domestic sales and ordinary exports within each province-industry pair in 2005. In Columns (5)–(8), regressions are weighted by the number of firms in 2005. Standard errors are clustered on the province-industry level. I also report Kleibergen-Paap F statistic for the test of weak instruments, from the first-stage regression. Significance levels: * 10%, ** 5%, *** 1%.

- Processing exporters are duty-free and intensively use imports. Therefore, I let variable import trade costs $d_{F,m(k),j}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$ and be disciplined by shares of imports in total expenditures for each industry and regime.
- Processing exporters have lower valued added shares than ordinary exporters (Kee and Tang 2016). I thus let parameters in firm production $\{\gamma^L_{m(k),j}, \gamma^{j'}_{m(k),j}\}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$.
- Processing exporters have lower skill intensities than ordinary exporters, and thus I let skill intensities in firm production $\alpha_{j(k)}$ differ by export regimes $k \in \{\mathcal{O}, \mathcal{P}\}$.
- Processing exporters cannot sell to domestic markets, and thus trade costs for processing producers in domestic markets are $d_{n(\mathcal{P}),m(k),j} \to \infty \; \forall n, m \in \mathcal{C}, k \in \{\mathcal{O}, \mathcal{P}\}$.
- Processing exporters barely innovate. Therefore, I do not consider processing exporters' innovation decisions.

I assume that workers are perfectly mobile between processing and ordinary firms in each province, and thus adding processing firms does not change workers' problem. Foreign producers now source varieties from both China's processing and ordinary firms.

F.2 Provinces and Industries

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

F.3 Description of Data Sources

Output and Exports. I obtain China's manufacturing output by industry and province between 2000–2012 from ASM. I obtain processing and ordinary exports by province and industry from the matched ASM-Customs Database.[47] For each province-industry, the difference between total output and processing exports is the output of ordinary production. I draw provincial production in agriculture, mining, and services by province between 2000–2012 from input-output tables.[48]

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 foreign industrial output to my 33 industries using concordances in Dean and Lovely (2010).

As my data does not have information on China's and foreign industry-level output after 2012, I will calibrate productivity growth to match GDP growth rates of China relative to Foreign after 2012. The GDP growth rates between 2012–2018 are available from Penn Table 9.1. Between 2018–2030, I assume that China's GDP grows at an annualized rate of 2% relative to Foreign, according to the World Economic Outlook Reports.

Input-Output Tables. I obtain China's input-output parameters from China's input-output tables in 2005, and rescale value added shares separately for processing and ordinary firms to match the ones computed from the ASM-Customs matched data. I allow for input-output parameters in Foreign to differ from China, using the World Input-Output Database to compute input-output parameters for Foreign.

Imports by Industry and Regime. I obtain imports by export regime and province from China's Customs Transactions Database. The original data is based on 8-digit HS products. I aggregate these data into my 33 industries using the concordances between HS products and ISIC in WITS and between ISIC and CIC in Dean and Lovely (2010).

Export and Import Tariffs by Industry and Regime. I obtain tariff data for 4-digit HS products between 2000–2012 from UNCTAD TRAINS Database and compute weighted-average tariffs for China's exports and imports by 33 industries, using the concordances between HS products and ISIC in WITS and between ISIC and CIC in Dean and Lovely (2010). I assume that China's export and import tariffs remain unchanged after 2012.

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

[48] I obtain provincial production in agriculture, mining and services in 2002, 2007, and 2012 from input-output tables and interpolate the values in missing years using the linear trend interpolation.

Inter-provincial Trade by Industry and Regime. I obtain China's inter-provincial bilateral trade flows using China's regional input-output table for 42 CIC industries in 2007. I deflate these trade flows to the year 2005 using growth rates of China's industrial output between 2005–2007 and aggregate them into 33 industries, and I construct trade flows between province-regime-industry pairs following Liu and Ma (2018).

Firm Distribution. I obtain the number of firms by province and industry from Firm Census 2004, 2008, and 2013, and divide the number of firms in each province-industry into two export regimes (ordinary or processing) using the relative number of two types of firms in the matched ASM-Customs Database 2000–2012. I interpolate and extrapolate the data for the missing years between 2000–2030 using the linear trend. Due to the lack of firm data in Foreign, I assume that in 2005, for each industry, the ratio of firm numbers in Foreign to China's firm numbers is equal to the relative output ratio. I then use employment growth to obtain firm numbers in Foreign for all other years.

Labor Market Data. I obtain employment by age, province, and education level in 2000 from 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.[49] 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 use inter-provincial migration flows in Population Census 2000 to inform migration costs.

I obtain the number of college graduates by province between 2000–2014 from City Statistical Yearbooks and extrapolate these data until 2018 using the distribution of graduates in 2014 and changes in the total amount of college graduates. When I simulate the model until 2030, I set the number of college graduates between 2019–2030 by province to be identical as in 2018. I infer the amount of new noncollege labor between 2000–2018 from changes in China's labor force and the number of college graduates. I set the growth rate of the labor force between 2019–2030 to be -0.3%, according to the predicted pattern of the World Population Prospects on those aged 20–65 in China. Due to the lack of data, I set the distribution of new noncollege labor across provinces to be the same as that in the 2000 Population Census. I also set the distribution of birthplace provinces for new college-educated and noncollege workers according to the 2000 Population Census.

I obtain foreign college-educated and noncollege employment by age between 2000–2018 from Barro and Lee (2013) and adjust each year's employment proportionally to match the total amount of employment from the World Bank. I adjust noncollege workers to the equivalents of high-school graduates (12 years of schooling) by assuming that the returns to one year of schooling are 10%. I further extrapolate these data until 2030 using the linear trend of the labor force before 2018 (1.5% annual growth rate).

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

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 ratio of full-time R&D workers to manufacturing employment in China. (3) The share of college-educated workers in employment by industry and export regime (relative to services), and aggregate college premium in China.[50] (4) The relative wages of workers across age groups in China. (5) The standard deviation of export-output ratios among exporters. (6) China's agricultural employment share. (7) For each industry, the sum of trade shares to nonself and contiguous provinces.[51] (8) For each industry and export regime, the share of foreign expenses sourced from China, and the share of each China's expenses sourced from Foreign. (9) For each industry and export regime, the share of exporting firms in China.[52] 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. 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) For each worker type, the correlation between migration rates and workers' age. (2) For each worker type, the correlation between migration rates and bilateral distance. (3) For each worker type, the correlation between migration rates and the contiguity between origin and destinations. (4) For each province and worker type, the share of in-migrants in total employment.[53] (5) Across provinces, the slope of changes in the college premium on the strength of the college expansion, between 2003–2009. (6) Average differences in the college premium between young (aged 20–28)

[50] I use relative shares because the overall share of college-educated workers in employment is already given by the data and thus does not inform the parameters. These shares are computed from ASM 2004 for manufacturing industries and export regimes, and from Population Census 2005 for other nonmanufacturing industries. The aggregate college premium is computed as the average wage of college-educated workers relative to aged 20–22 high-school graduates, from Population Census 2005.

[51] The sum of trade shares to nonself provinces is computed as $\sum_{m\in\mathcal{C}}\sum_{n\in\mathcal{C},n\neq m}\sum_{k\in\{\mathcal{O},\mathcal{P}\}}\Pi_{m(\mathcal{O}),n(k),j}$, where $\Pi_{m(\mathcal{O}),n(k),j}$ is the share of expenses in province-regime $n(k)$ on imports from ordinary producers in province m. The sum of trade shares to contiguous provinces is similarly computed.

[52] Because all processing firms export, I set firms' marketing costs to be zero for processing exporters.

[53] The correlation between migration rates and age is $corr(\Lambda^I_{m,n,a}, a)$ for $m \neq n$. The correlations between migration rates and distance (contiguity) are analogously obtained. The share of in-migrants in employment for province n is $\sum_{m\neq n}\sum_a H_{m,a}\Lambda^H_{m,n,a}/(\sum_m\sum_a H_{m,a}\Lambda^H_{m,n,a})$ for college-educated labor and $\sum_{m\neq n}\sum_a L_{m,a}\Lambda^L_{m,n,a}/(\sum_m\sum_a L_{m,a}\Lambda^L_{m,n,a})$ for noncollege labor.

and old workers (aged 29+) in 2009. I compute migration rates based on workers' current province and province of residence 5 years ago, drawn from Population Census 2000 and adjusted to an annual frequency. I compute the college premium in 2003 and 2009 using the average log wage of college-educated workers relative to high-school graduates, from the Urban Household Survey. I use the instrument x^*_m introduced in Section 5.1 to proxy for the strength of college expansion.

Although I focus on the 2000–2018 period, I simulate the model until 2030 as workers are forward-looking when making migration decisions (see Appendix F.3 for how I extrapolate the data to 2030). I still require firms' productivity to solve the model. Before 2011, for each region-industry-regime pair, I choose the average productivity level of firms to match the output level (the firm-level productivity is still Pareto-distributed with the same shape parameter as in Step 1). After 2012, when detailed data on industry-level output is not available, I assume that the average productivity of Chinese firms in each province-industry-regime grows at a common yearly rate starting from 2012 (relative to foreign firms) to match the growth of China's GDP relative to Foreign GDP in each year.

Step 3. I target the following moments. (1) Before 2011, the output in each Chinese province-industry-regime or foreign industry (relative to output of foreign services). After 2012, I assume that China's firm productivity grows at a commonly yearly rate relative to foreign firms to match the relative GDP growth. (2) Changes in the number of firms in each China's province-industry-regime or foreign industry between 2000–2018. (3) The standard deviation of annual sales growth for upper 10% firms (in terms of each year's sales) in 2000–2007. (4) The annual exit rate for upper 10% firms (in terms of each year's sales) in 2000–2007. (5) The sales of new entrants (identified by firms' birthyear) relative to incumbents in 2000–2007. (6) The autocorrelation parameter of a firm's ordinary exports in adjacent years, in 2000–2007. (7) The slope of a firm's sales growth on its R&D intensity in the previous year, in 2001–2007.[54] (8) The standard deviation of R&D intensity among R&D firms in 2005. (9) The share of R&D firms and the average R&D intensity in 2005 for each industry. (10) The share of R&D firms in each province in 2005, and aggregate manufacturing R&D intensity in 2000–2018. I use ASM 2000–2007 to compute moments (2)–(9), and other moments come from aggregate data. As I focus on Chinese manufacturing firms' innovation, moments (7)–(10) are computed based on China's manufacturing industries. I set other industries' R&D expenses as given by the data.

I simplify the next-period's firm value as $V'(\mathbf{s}_{c(m),j}) = C_s \left(\sum_n \pi^{+'}_{m,n,j} - f_{m,j} P'_m \right)$ for computational tractability, with the discount rate $C_s = \sum_{t=0}^{\infty} \frac{(1-\text{average profit tax})(1-\delta)^t}{(1+r)^t}$ reflecting profit taxes, death rates and interest rates. 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., Chen et al. 2021, Desmet et al. 2018).

[54] 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.

G Estimating Age-specific College Premium

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

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

$\log w_{im}$ is log yearly wage for worker i in province m. X ={23–25,26–28,...} is the set of three-year age bins. $\mathbf{1}_{col}$ is a dummy variable indicating college-educated workers. I interpret $\phi_{x,2}$ as the college premium for workers in age group $x \in X$, relative to average wages of noncollege workers in the same age group. Control variable agr_{im} is a dummy variable indicating whether the worker is in agriculture, because workers' wages are much lower in agriculture than in other industries. ι_m is a set of province fixed effects.

I use workers' yearly wage data in the Urban Household Survey in 2000–2009 to estimate the observed college premium.[55] I restrict the sample to workers with high-school education or above, and therefore the baseline group in the regression is workers with high-school education. In the calibrated model, I perform the same regression with noncollege labor (high-school graduates) and educated labor (college-educated workers).

H Model Extensions and Additional Quantitative Results

H.1 Adding Firm Entry

China has experienced massive entry of new firms (Brandt et al. 2012), and reduced R&D costs may play a role in it, as creation of new firms is typically assumed to require R&D (e.g., Atkeson and Burstein 2010, Grossman and Helpman 2014). I thus consider endogenous firm entry. Following the typical assumption in the literature (e.g., Atkeson and Burstein 2010, Grossman and Helpman 2014), I assume that an entrant needs to pay $f^e_{m(k),j}$ units of research goods to enter export regime k in region m and industry j. Let $V^e_{m(k),j}$ be the value of a new entrant. Thus, in the equilibrium, the number of potential entrants is thus *endogenously* decided by the free-entry condition:

$$f^e_{m(k),j} P_{m,r} = V^e_{m(k),j}. \tag{H.1}$$

There are two quantitative challenges. First, China has experienced very fast growth in the number of manufacturing firms. If I directly apply equation (H.1) to compute entry costs, a large portion of Chinese college-educated workers needed to be used in producing research goods for entry of manufacturing firms in 2018, which was unrealistic. Second, as shown by Kucheryavyy et al. (2017), free entry of new firms implies large

[55] I use the college premium by ages in Population Census 2005 to calibrate the relative productivities of workers across skills and ages. I find that the college premium by ages is quantitatively similar in Population Census 2005 and Urban Household Survey 2005. The wage information is not available in other years' Population Censuses except for the 2005 version.

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

	Contribution of College Expansion to Changes during 2003–2018	
	share of high-skill ordinary exports	manu R&D/sales
(1) Baseline model	29%	72%
(2) Adding endogenous firm entry	59%	50%
(3) With R&D misreporting	26%	64%
(4) With expansion of part-time edu	30%	66%
(5) Without intranational regions	33%	80%
(6) Changes in migration costs	30%	74%

Note: The contributions are computed in the same way as in Section 7. For the model with R&D misreporting, R&D intensity is the ratio of reported R&D to sales.

economies of scale and may lead to corner solutions. Therefore, I modify equation (H.1) for a Chinese province-industry-regime $u \in \tilde{\mathcal{C}}$ as:

$$f^e_{m(k),j} P_{m,r} N^{\nu_F}_{m(k),j} = \rho V^e_{m(k),j}.$$

The parameter $\nu_F > 0$ captures the inverse elasticity of the number of entrants with regard to the value of entrants, which helps avoids corner solutions. Using the responses of the number and the sales of entrants to the college expansion, I find $\nu_F = 0.25$.[56] I also introduce the parameter $0 < \rho < 1$ to capture that it is difficult to capitalize future profits to finance entry costs in China (Song et al. 2011). I choose $\rho = 0.15$ so that entry costs are around one-year expected profits of an entrant. I then use this modified equation to calibrate entry costs $\{f^e_{m(k),j,t}\}$ that generate the same amount of entrants as $\{N_{m(k),j,t}\}$.

Quantitatively, as shown in Table H.1, allowing for endogenous firm entry reduced the contribution of the college expansion to manufacturing innovation to 50% between 2003–2018. Specifically, 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 firm entry in highly skill-intensive industries, the contribution of China's college expansion to export skill upgrading was reinforced.

H.2 Incorporating R&D Misreporting

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

[56] I regress log changes in the number of entrants and average sales of entrants between 2005–2010 on the exposure to the college expansion, with same controls as in Table E.1. I find that the response of the number of entrants to the college expansion is about 4 times as large as the response of average sales of entrants. If average sales of entrants can represent their value, the data estimates imply $\nu_F = 0.25$.

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:

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

$y(\omega)$ is the ratio of non-R&D admin expenses to R&D expenses required to attain the tax incentive (see footnote 29). The dummy variable D equals 1 if the firm satisfies the threshold of R&D. The parameter β_1 captures the drop in non-R&D admin expenses at the threshold, and the parameter β_2 shows how the drop relies on the firm's affiliated-industry skill intensity. I control a cubic function of differences between firms' R&D intensities $Z(\omega)$ and the threshold c, as well as industry-level skill intensities SI_j to allow non-R&D expenses to differ across industries. I use SAT 2009–2011 for estimation and still measure skill intensity SI_j from ASM 2004. I focus on 2-digit manufacturing industries.

Column (1) of Table H.2 shows that firms at the threshold on average misreported 27.5% of the required R&D expenses from non-R&D admin costs.[57] Column (2) of Table H.2 finds that the drop in non-R&D admin costs at the threshold increased with industry-level skill intensities. To test the robustness of my model, I interpret this result as reflecting that larger wage bills to college-educated workers can facilitate R&D misreporting.

In the model, I assume that Chinese firms can reclassify non-R&D costs as up to a portion $(k_1 + k_2 SI_{u,j,t})$ of required R&D expenses to attain the tax incentive, where $SI_{u,j,t}$ is the share of payments to college-educated labor in total labor bills for each region and industry. I also assume that firms above the threshold do not misreport R&D, because misreporting only brings risks of being caught for them. I calibrate 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 H.2. I find that with $k_1 = 0.18$ and $k_2 = 0.43$, the model-generated data matches the pattern of reclassification of non-R&D costs across industries, as shown in Column (3) of Table H.2.

Figure H.1 presents the impact of China's college expansion on R&D, in the model with R&D misreporting. I highlight three findings. First, according to the estimate, only 79% of reported manufacturing R&D was actually spent in 2018. Second, the college expansion still accounted for $\frac{0.32 \text{ p.p.}}{0.50 \text{ p.p.}} = 64\%$ of increases in China's manufacturing reported R&D/sales between 2003–2018. Third, the college expansion also induced more R&D misreporting. Only 81% of the increase in China's manufacturing reported R&D intensity between 2003–2018 was driven by actual increases.

[57] 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 H.2: 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)	(0.018)
Obs	22,608	22,608	30
R-squared	0.028	0.028	0.960
Avg % R&D misreported (firms at the threshold)	27.5%	27.5%	27.9%

Note: Columns (1)–(2) present the results from regression (H.2). I restrict the sample to firms within 2 percentage points of the required R&D 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%.

H.3 Incorporating 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 H.1.[58]

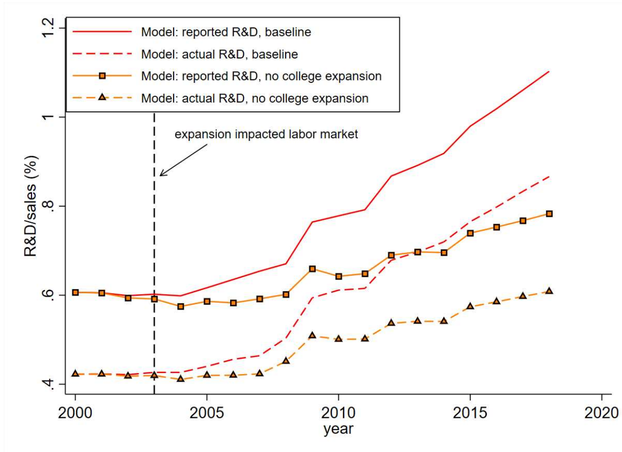
H.4 Abstracting from Intranational Regions

I considered multiple Chinese regions with trade and migration networks to be consistent with cross-regional empirical evidence. I now recalibrate the model following the same steps in Section 6, except for no intranational regions within China.[59] In Table H.1, I find that compared with the baseline model, abstracting from China's intranational regions slightly increased the overall impact of the college expansion on innovation and export skill upgrading. This indicates that the geographic distribution of new college graduates was unfavorable for aggregate productivity, confirming the mismatch between college

[58] 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.

[59] I still apply the same between-industry and within-industry elasticities of substitution as in the baseline model.

Figure H.1: Effects of the College Expansion on Manufacturing R&D (with Misreporting)



enrollments and regional development levels discussed in Section 2.

H.5 Reductions in Migration Costs

I calibrated the destination-specific term in migration costs to match the share of in-migrants across provinces in 2000 and remain constant over time, whereas in reality, internal migration costs kept declining after 2000 (Tombe and Zhu 2019, Hao et al. 2020). Thus, I consider the destination-specific term to experience proportional changes annually after 2000. For each destination province, I calibrate annual changes of migration costs in the 2000–2005, 2006–2010, and 2011–2015 periods to match changes in the share of in-migrant population in the same periods. I set migration costs to remain unchanged after 2015. I find that the average reduction in the destination-specific term of migration costs was 63% between 2000–2015 (weighted by migrant population in 2000), consistent with the findings in Hao et al. (2020).[60]

Table H.1 shows that compared with the baseline results, with the reductions in migration costs, the impact of the college expansion on innovation and the skill content of exports became slightly larger, as new college graduates can more easily relocate toward more productive regions. This echoes the recent findings on the possible interaction between migration costs and other policies (e.g., Caliendo et al. 2021).

[60] I compute the share of in-migrants population based on people's current province and province of residence 5 years ago, obtained from Population Censuses 2000, 2005, 2010, and 2015. Due to data limits, I consider changes in migration costs to be identical for both college-educated and noncollege workers at each destination province. Hao et al. (2020) find the average reduction in between-province migration costs to be 60% in 2000–2015.