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Skill-Biased Imports, Human Capital Accumulation, and the Allocation of Talent

Lei Li*

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*Department of Economics, University of Mannheim, L7, 3-5, 68161, Mannheim, Germany. E-mail: lei.li@unimannheim.de

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Abstract

This paper proposes that imported capital goods, which embody skill-complementary technologies, can lead to an increase in the supply of skill in developing countries like China. By exploiting the cross-prefecture variation in imported capital goods, I show that the surge in imported capital goods encourages human capital accumulation and migration in China. To tackle causality, I instrument a prefecture's import growth of capital goods with that in other regions. There are three main findings. Firstly, the regional difference in imported capital goods can explain 27 percent of the regional difference in college share between 2000 and 2010. A prefecture with a $100 increase in imported capital goods per capita had a 1.4 percentage points increase in college share. Secondly, this paper quantifies the importance of the three channels, namely skill acquisition of local stayers, immigration of skilled workers, and emigration of skilled workers, through which imported capital goods increase college share. I find that the first channel is the most important. Thirdly, I trace out the responses of skill supply to the demand shift. I find that imported capital goods increase college wage premium and the effect attenuates over time with the increase in skill supply.

JEL Classifications: F14, F16, F66, J24, J61

Keywords: Imported Capital Goods, Demand for Skill, Supply of Skill, Human Capital Accumulation, Migration

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†Department of Economics, University of Mannheim, L7, 3-5, 68161, Mannheim, Germany. E-mail: lei.li@uni-mannheim.de.

1 Introduction

Human capital is important for the long-run economic growth, and the impact of international trade on human capital has been an essential topic for policymakers and academics. Many developing countries import a large share of capital goods, such as modern production machinery and computers, yet their impacts on human capital formation and geographic distribution have been rarely explored in the literature.

In this paper, I propose that imported capital goods encourage human capital accumulation and migration in developing countries like China. The logic goes as follows: for developing countries, technological advances mainly come from the adoption of foreign technologies that are usually embodied in capital goods, rather than domestic innovation.[1] Because of capital-skill complementarity (e.g., Krusell et al. 2000), imported capital goods drive up the demand for skill, which, consequently, drives up the skill premium (e.g., Burstein, Cravino and Vogel 2013; Parro 2013; Raveh and Reshef 2016; Fan 2019; Koren and Csillag 2019).[2] This paper goes one step further and quantifies the responses of skill supply to the demand shift. The supply of skill responds through three channels. The first is skill acquisition, the second is more immigration of skilled workers, and the third is less emigration of skilled workers.

This paper is the first to empirically investigate the impact of imported capital goods on human capital accumulation and migration. To be more specific, I seek to address three questions. First, how important are imported capital goods in explaining the rise in college share? Second, how important are the three channels, namely skill acquisition, immigration, and emigration, through which importing capital goods increases college share? Third, what are the short-run and long-run effects of importing capital goods on wage structure?

China provides a perfect setting to answer the above questions. After several rounds of radical tariff reductions since 1992, China experienced a surge in capital goods imports. From 1992 to 2010, China's imported capital goods increased rapidly from 27 billion U.S. dollars to 551 billion U.S. dollars, with an average annual growth rate of 20 percent (Figure 1). Accompanied by the rapid growth of imported capital goods were the increases in college wage premium and share of college graduates. The college wage premium for college-educated workers rose from 14.3 percent

[1] Because technology advances are highly concentrated in several developed economies (Eaton and Kortum, 2001), international technology diffusion plays a major role in shaping domestic technology advancement in most countries (Grossman and Helpman, 1991; Coe and Helpman, 1995; Acemoglu and Zilibotti, 2001; Burstein, Cravino and Vogel, 2013). For most countries, about 90 percent of domestic productivity growth may be attributed to international technology diffusion (Keller, 2004).

[2] In developing countries such as the U.S., skill-biased technological change is one of the most important driving forces for the rising skill premium (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman, Bound and Griliches, 1994; Goldin and Katz, 1998; Katz and Autor, 1999; Krusell et al., 2000; Acemoglu and Autor, 2011, 2012).

in 1992 to 44.4 percent in 2009, as shown in Figure 2. Meanwhile, the share of college workers in China quadrupled from 1.9 percent in 1990 to 8.2 percent in 2009. These facts are consistent with my story. Besides, the import exposure differs significantly across Chinese prefectures, providing ample variation to identify the labor market consequences of imported capital goods. Moreover, the granularity of the micro data allows me to have a better understanding of the composition of the rising college share by migration status and allows me to trace out the short-run and long-run effects of imported capital goods on wage structure.

[INSERT Figure 1 & 2]

Drawing on a rich data set I assembled on China's regional economy and exploiting regional variations in imported capital goods across the universe of Chinese prefectures, I find that the spatial distribution of the growth in imported capital goods coincides with the spatial distribution of the increase in college share. To tackle causality, I adopt an instrumental-variable strategy to alleviate the interference of confounding factors. I construct a shift-share instrument (Bartik, 1991) by combining each prefecture's initial mix of imported capital goods with the national import growth. The instrument captures the exogenous component of the import growth in a prefecture by characterizing this prefecture's exposure to national import growth of capital goods.

There are three main findings. Firstly, I find that imported capital goods are indeed a key driving force for the regional difference in human capital stock in China. Between 2000 and 2010, a region with an increase in imported capital goods per capita by 100 U.S. dollars had a higher college share by 1.4 percentage points. The regional difference in imported capital goods can explain 27 percent of the regional difference in college share. Rather than solely relying on the cross-section variation, I also exploit the differential responses across cohorts within the same prefecture. The by-cohort analysis shows that the impact of imported capital goods was the strongest for young people and decreases with age. This is intuitive as it is less costly for young people to respond to trade shocks. Moreover, the analysis for the older cohorts also serves as a falsification exercise, suggesting that the estimated effect is unlikely driven by unobserved confounding factors.

Secondly, the granularity of my data allows me to understand the underlying mechanisms for the regional difference in college share. An increase in the college share in a region can be attributed to the human capital accumulation of local people, more immigrants, and fewer emigrants. Based on people's migration history, I decompose the regional difference in college share into the three components mentioned above. The decomposition results show that imported capital goods have a substantial impact on local people's human capital accumulation but only a modest impact on the relocation of skilled laborers. The by-cohort analysis shows that for younger generations, the regional difference in the growth of college share can mainly be attributed to the human capital accumulation of local stayers, i.e., local high school graduates attend college. Take people born between 1986 and 1989 as an example. A \$100 rise in imported capital goods per capita increases the college share by 15 percentage points, and 88% of the increase can be attributed to human capital accumulation. For older generations, the impacts are smaller. Take people born between 1974 and 1977 as an example. A \$100 rise in imported capital goods per capita increases the college share by 3 percentage points. These results are intuitive, as it is more costly for the older generation to go to college and/or migrate.

I address several issues that may contaminate the results. Firstly, one may be concerned that China's college expansion triggers an increase in skill supply. To address this concern, I capture the exogenous component of changes in college supply at prefecture-level by utilizing a quasi-experiment of college reallocation in the early 1950s. Secondly, one may be concerned that the rising demand for skill is triggered by other trade shocks. I address this concern by including the initial industry structure and incorporating the exogenous component of export growth into the regression. I show that the estimates are unlikely to be affected by omitted variable bias. Thirdly, I deal with the measurement error problem by conducting robustness checks and controlling for prefectures that are likely to be subject to over-report issue. Fourthly, I address the concern of the spillover effect, which is expected to reduce a region's share of people with college education because regions are competing for talents. I measure the spillover effect as the weighted average of import growth in other neighboring regions. The results suggest that the import growth in other regions indeed exerts an opposite effect, but the magnitude of the negative effect is small. The impact of imported capital goods is not affected by the cross-region spillover effect.

Thirdly, I trace out how the supply of skill responds to the shift in the demand for skill by exploring the impact of imported capital goods on regional wage structure and firm performances. I find that the wage growth is more prominent for skilled workers in regions with faster growth of imported capital goods. An increase in the annual growth of imported capital goods per capita by 10 percent would increase the skill premium by 2 percent. The positive effect of imported capital goods on skill premium, however, attenuates overtime time, as the supply of skill gradually increase. For the firm-level analysis, I find that firms that import more capital goods hire more skilled workers, pay higher wages, have higher labor productivity, and use computers more intensively. The additional regional and firm-level evidence is consistent with the story that imported capital goods drive up demand for skill.

The contribution of this paper to the literature is twofold. First, this paper is the first to study the impact of imported capital goods on human capital accumulation. By exploring a novel channel, I show that imported capital goods increase the demand for skill and encourage human capital accumulation. Second, this paper is also the first to empirically quantify the impact of imported capital goods on migration. The detailed information in the data allows me to decompose changes in the college share by migration status and study how the skilled migrants can account for regional differences in human capital stock. In the presence of high migration costs, I find that the regional differences in the share of people with some college education can mainly be attributed to the skill acquisition of local stayers rather than migration.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the background, describes the data, and highlights the key features in the data. Section 4 illustrates the empirical approach used in the analysis. Section 5 and 6 present the empirical findings of the impact of imported capital goods on college share and wage structure, respectively. Section 7 supplements the above analysis by providing further discussions. Section 8 concludes.

2 Literature Review

This paper contributes to the literature on the labor market consequences of skill-biased technological change. Though the literature has identified skill-biased technological change as one of the major driving forces for the rising demand for skill (Katz and Murphy, 1992; Berman, Bound and Griliches, 1994; Autor, Katz and Krueger, 1998; Bekman, Bound and Machin, 1998; Goldin and Katz, 1998; Katz and Autor, 1999; Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011), less is known about its impact on the supply of skill. This paper contributes to the literature by showing that in developing countries imported capital goods which embodies skill-biased technology can not only increase the demand for skill but also the supply of skill.

This paper also contributes to the literature on the distributional effect of international trade in developing countries (Goldberg and Pavcnik, 2007; Pavcnik, 2017). To understand the labor market consequences of trade, several explanations are proposed (Feenstra and Hanson, 1996, 1999; Yeaple, 2005; Bernard, Jensen and Redding, 2007; Verhoogen, 2008; Bustos, 2011*b*).[3] This paper is mostly related to the strand of literature on imported capital goods. Burstein, Cravino and Vogel (2013), Parro (2013), and Fan (2019) incorporate capital-skill complementarity to study the impact of trade

[3] Along the literature on trade and demand for skill in developing countries, one explanation is offshoring (Feenstra and Hanson, 1996, 1999; Sheng and Yang, 2017). This literature incorporates intermediate inputs into the production function and relaxes the assumption that only final goods can be traded. Because the offshored tasks are more skill-intensive for the developing countries, offshoring increases the demand for skill in recipient developing countries. Another well-studied channel is trade-induced technology upgrading. Exporting to larger markets (Bustos, 2011*b*) or exporting to richer countries makes technological adoption more profitable due to product quality considerations (Verhoogen, 2008). Because the adoption and operation of new technology requires skill (Bustos, 2011*a*), exporting may increase demand for skill.

on the skill premium. Raveh and Reshef (2016), Li, Li and Ma (2018), Koren and Csillag (2019) use detailed country, city, and plant-level data to provide empirical support for the hypothesis that imported capital goods can induce skill-biased technological change. Compared to the literature, this paper relaxes the assumption that skill supply is exogenously given and is the first paper to study how skill supply endogenously responds to the surge in imported capital goods.

The decomposition analysis in this paper improves our understanding of the impact of trade on human capital accumulation. Findlay and Kierzkowski (1983) endogenize human capital formation in the Heckscher-Ohlin model and show that trade could widen the economic gap across countries via its impact on educational attainment. Several empirical papers that examine the impact of trade on human capital accumulation in developing countries provide supports for this argument (Atkin, 2016; Blanchard and Olney, 2017; Li, 2018).[4] In this paper, I quantify the impact of a new channel, namely importing capital goods, on human capital accumulation. I show that imported capital goods are skill-complementary and can encourage skill acquisition.

The decomposition analysis in this paper also contributes to a small but growing body of literature on the impact of trade on migration. While the impacts of adverse trade shocks on internal migration are limited (Topalova, 2010; Kovak, 2013) as summarized by Pavcnik (2017), there is a small but growing body of literature showing that there have been significant spatial labor adjustments in response to positive trade shocks in China. The reduced trade uncertainty (Potlogea and Cheng, 2017; Facchini et al., 2018) and reduced tariffs (Zi, 2017) both contribute to greater internal migration and regional population growth. Relative to the literature, this paper focuses on the impact of imported capital goods on migration, and this channel has been rarely discussed. Furthermore, the granularity of the microdata not only allows me to quantify the impacts of imported capital goods on population inflows but population outflows as well. In comparison, data limitation prevents most of the previous literature from studying the brain drain effect. Besides, I am also able to studies the differential responses by cohort thanks to the detailed information in the data.

[4] Atkin (2016) finds that export expansion in Mexico increased the demand for low skilled export-manufacturing jobs and thus reduced school attainment. In that case, the effect of rising opportunity costs of schooling dominated the income effect. Blanchard and Olney (2017) further decompose exports and provide cross-country evidence showing that low skill-intensive exports depressed educational attainment and skill-intensive exports increased schooling. Li (2018) also reports similar findings in China that low-skill exports reduced high school and college enrollment, and high-skill exports increased both. The net impact of exports is negative. Apart from exports, Topalova (2010) finds that intensified import competition reduced job opportunities and increased the poverty rate. As a result, there was a decrease in children's schooling in India (Edmonds, Topalova and Pavcnik, 2009; Edmonds, Pavcnik and Topalova, 2010), which is likely due to the negative income effect and the deteriorating economic opportunities of children.

3 China's Trade Liberalization and Human Capital Accumulation

In this section, I document the history of China's trade liberalization and higher education reform, describe the data, and present the key empirical patterns about the surge in imported capital goods, the rapid human capital accumulation, and the widening wage gap between skilled workers and unskilled workers in China.

3.1 Empirical context

China's surge of imported capital goods

One remarkable feature of China's trade liberalization is the surge of imported capital goods (Figure 1).[5] As technology advances are highly concentrated in a handful of developed economies (Eaton and Kortum, 2001), international technology diffusion has been an important channel of knowledge transfer among most countries (Keller, 2004). China had been isolated from the rest of the world since 1949, and its technology level was far from the world frontier. Given the strong demand for advanced technology, China set "bring in advanced foreign technology" as one of its main objectives of the "reform and opening" in 1978. Among other forms of international technology transfer, importing capital equipment has been particularly popular for its convenience and transparency. To facilitate the import of capital goods, the Chinese government engaged in substantial reforms, including voluntary tariff cuts, reducing or eliminating special import arrangements and trade licenses. As shown in Figure 1, China's imports in capital goods increased rapidly, with an average annual growth rate of 20 percent after China entered the World Trade Organization (WTO). The import growth of capital goods was slower in the 1990s. These imports rose from 27 billion U.S. dollars in 1992, the earliest year when the trade data is available, to 89 billion U.S. dollars in 2000, corresponding to an annual growth rate of 16 percent. In 2010, China's import of capital goods was as much as 551 billion U.S. dollars.

Higher education in China

The overall education level in China was low before the "reform and opening" in 1978. According to the World Bank, China's college enrollment was as low as 0.1 percent in 1970, while the world's average college enrollment rate was 10.1 percent. Despite the low level of education, China's higher education system experienced several structural changes. One important reform was the college

[5]Capital goods are defined as based on ISIC Rev. 3 and Broad Economic Classification (BEC), including goods that fall into the categories of ISIC Rev. 3 codes 29-33, excluding those that are not belong to BEC industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry).

reallocation reform. Under the influence of the Soviet Union, the Chinese government launched an education reform to establish a highly specialized higher education system in the 1950s (Glaeser and Lu, 2018). During the reform, comprehensive universities were replaced by discipline colleges of science or liberal arts or multi-disciplinary universities of science and technology. Of the 502 departments that were moved out of colleges, 282 departments were moved to other prefectures. Of the 623 departments that were moved in, 333 came from other prefectures. In the upcoming empirical analysis, I will use this quasi-natural experiment to check whether the exogenous change in college supply has affected the impact of imported capital goods on human capital.

China saw a modest increase in the number of college students between 1978 and 1999. The number of college admissions rose from 0.4 million in 1978 to 1 million in 1998, with an annual growth rate of 5.1 percent. Since 1999, the increase in college enrollment has accelerated. The number of college admissions rose from 1 million in 1998 to 7 million in 2017, with an annual growth rate of 11 percent. The growth of the share of people with a college degree was also slower in the 1990s than in the 2000s (2.7 percent vs. 3.6 percent). Though the college enrollment quota has increased dramatically, students still face fierce competition in the college entrance exam.

3.2 Data

Trade data

The trade data are from the UN Comtrade database and China's Customs Bureau. The latter provides detailed data on import and export activities by HS 6-digit product and customs-district (which is roughly half as large as a prefecture on average) in the years 1997, 2000, 2005, and 2010. I focus on the period between 2000 and 2010, during which China has experienced rapid import growth. Prefecture-level trade data are available as of 1997, and I use that year to construct the shift-share instrument.

There are substantial variations in the imports of capital goods across regions, which provides the identifying variations for the empirical analysis in later sections. I start by comparing the imports of capital goods in coastal and inland China. As suggested in Panel A of Figure 3, coastal regions experienced a faster import growth of capital goods. Moreover, coastal regions' import share, measured as imported capital goods over total imports, increased between 1997 and 2009, while inland regions experienced a decline in the import share of capital goods (Figure 3 Panel B). At the prefecture-level, there was also a large regional disparity in the import growth of capital goods per capita between 2000 and 2010 (Figure 4). Table 1 further presents the summary statistics at the prefecture-level. The average import growth of capital goods per capita across prefectures was 0.7 (measured in units of 100 U.S. dollars, and thus corresponding to $70 per capita), with an inter-quartile range of 0 to 0.3, implying substantial skewness.

[INSERT Figure 3, Figure 4 and Table 1]

Population survey data

To study the regional difference in human capital, I use the data from China's National Population Census in the year 2000 and 2010 and the 1% China's National Population Sample Survey in the year 2005. The census data covered all the Chinese citizens, and the 1% National Population Sample Survey, also known as the Mini-Census, covered 1% of the population in China. The data were collected by the National Bureau of Statistics of China (NBSC), and they are the most representative data available. The three waves of population surveys allow me to study the impact of imported capital goods with the economy-wide data.[6] The sample available to me covers 0.1 percent, 0.2 percent, and 0.3 percent of the Chinese population in the three years, respectively. To test the representativeness of the microdata, I compare various prefecture-level economic indicators calculated from the micro-samples and compare them with the tabulated data from the full-sample of the national population census reported by the NBSC. The results suggest that samples are representative of national data. I take prefectures as the unit of analysis. On average, a prefecture is twice as large as a communing zone in the United States. In the subsample of the 2010 census, seven cities that are severely under-sampled.[7] To alleviate the concern that data for these cities are not representative, I drop the 7 cities and use data for the remaining 330 cities in the analysis.

There has been a widening regional disparity. As shown in Appendix Figure A1, college enrollment rates differed across regions and were higher for coastal regions compared with inland regions.[8] Interestingly, the spatial difference in the share of people with some college education has co-occurred with the increasing regional difference in capital goods import growth. Between 2000 and 2010, the difference in the share of people with some college education between the coastal regions and the inland regions increased from 1.3 to 3.0 percentage points.

Wage data

[6] China's National Bureau of Statistics conducted population surveys for the entire population in 2000 and 2010, and a survey of 20 percent of the population in 2005. Compared to the alternative of using manufacturing firm data, this approach alleviates the concern of sample representativeness and selection problems as well-educated people may be more likely to be employed in formal manufacturing firms in developing countries (Goldberg and Pavcnik, 2003; McCaig and Pavcnik, 2015).

[7] The seven cities include Cangzhou, Hengshui, Heze, Langfang, Liangshan, Zhoukou and Zhumadian.

[8] A few exceptions are the regions with high minority shares, such as Tibet and Xinjiang. To reduce the regional inequality in human capital stock, more favorable policies were given to these regions.

I calculate the national skill premium (1992-2009) and the regional skill premium (2000, 2005 and 2009) using the Urban Household Survey (UHS, 1992-2009), which is also collected by the National Bureau of Statistics of China (NBSC). The national survey offers the most-comprehensive household survey in China. It provides a detailed record of demographic, employment, and income information of urban residents, and it forms the basis for the reported wage and consumption information in the national statistical yearbooks. The first advantage of the UHS data is representativeness. When selecting households, the NBSC has adopted a probabilistic and stratified multistage sampling method. Another advantage of the UHS data is comparability. Because the NBSC uses similar sampling methods and questionnaires in each survey, the data are comparable over time and across regions. By having a long time span, the UHS data allows me to study the labor market dynamics of China. The data cover 31 provinces in China; I have access to data covering 18 provinces, which are representative regarding the geographic location and economic development.[9] Because this paper focuses on education attainment and migration, I focus on people aged between 16 and 60 and exclude kids who are too young to go to college and senior people who are not mobile. To calculate the prefecture-level skill premium, I separately estimate a Mincerian wage regression (Mincer, 1974) for each prefecture in each year.

Over the past several years, China has experienced a fast rise in the skill premium (Li et al., 2012). As shown in Figure 2, the skill premium, or the wage gap between workers with a college degree and those without widened between 1992 and 2009. In 1992, skilled workers earned 14 percent more than unskilled workers. The wage gap has widened since China entered the WTO in 2001, rising to 44 percent in 2009.

Meanwhile, the regional difference in the skill premium has also widened, as shown in Figure 5. The difference in the skill premium between the coastal regions and the inland regions increased from 5.7 percentage points in 2000 to 11.6 percentage points in 2010. Accompanying the widening regional inequality in the skill premium was the widening regional disparity in the college share, which increased from 1.3 percentage points in 2000 to 3.0 percentage points in 2010.

[INSERT Figure 5]

Supplementary data

To provide additional evidence for capital-skill complementarity, I use the Annual Survey of Industrial Production (ASIP) data, which is also collected by the National Bureau of Statistics of China (NBSC). All state-owned enterprises (SOEs) and all non-state firms with annual sales above

[9] The 18 provinces include coastal provinces (Beijing, Guangdong, Jiangsu, Liaoning, Shandong, Shanghai, and Zhejiang), and inland provinces (Anhui, Chongqing, Gansu, Heilongjiang, Henan, Hubei, Jiangxi, Sichuan, Shaanxi, Shanxi, and Yunnan).

5 million RMB in the mining, manufacturing, and public utility sectors are included in the survey. This firm-level data contains balance sheet information and production information.[10] In addition, information on employment by workers' education and the number of computers used by each firm is available, as 2004 was the industrial census year. Data on college enrollment come from the China Education Statistical Yearbooks. Other socioeconomic variables at the prefecture-level come from various statistical yearbooks and population censuses. The distance between any two prefectures is calculated using information from China Data Online.[11]

4 Empirical Approach

This section describes the variable construction and empirical approach. I adopt the local-labor-market approach following Topalova (2010), Autor, Dorn and Hanson (2013), and Kovak (2013) and study the impact of the changes in imported capital goods on the changes in the share of people with some college education in China. After listing the potential threats for identification, I describe how I deal with the endogeneity problems.

4.1 Defining local labor markets

In the analysis, I use prefectures as the unit of analysis, which is a common practice in the literature (e.g., Zi, 2017; Autor et al., 2018; Li, 2018;). A prefecture in China is an administrative unit smaller than a province and bigger than a county. To account for the changes in prefecture boundaries, I construct time-consistent county groups and match prefectures across census years based on China's administration division in 2000.[12] According to China's Ministry of Civil Affairs, there were 337 prefecture-level administrative units in the 31 provinces of mainland China in 2000, including 4 municipalities under the direct administration of the central government, and 333 prefecture-level regions which are usually referred to as cities.[13] Prefectures in China are, on average, twice the size of commuting zones in the United States. I define local labor markets by prefectures for the following three reasons. First, there are strong commuting ties within prefectures and weak commuting ties across prefectures, as people's activities are usually confined within prefecture boundaries. Second,

[10] As documented in Brandt et al. (2012), firms in the ASIP data set account for 90 percent, 91 percent, 97 percent, and 70 percent of the gross assets, sales, exports, and employment respectively in the manufacturing sector.

[11] http://chinadataonline.org/

[12] The construction of the county-level crosswalk is based on information on the administrative division changes published by the Ministry of Civil Affairs (www.mca.gov.cn/article/sj/xzqh//1980/). The Appendix provides additional details on this process.

[13] The province-controlling counties (accounting for 1 percent of China's population in 2000) in which the provincial government could by-pass the prefecture government to gain direct control, are merged into prefectures that used to govern the counties.

counties within the same prefectures are more economically integrated, as many government policies — e.g., *the hukou* policy, land policies, and investment policies — are conducted at the prefecture-level. Third, the county or township level data for most of the variables of interest are not available or of poor quality.

4.2 Econometric specification

I evaluate the impacts of imported capital goods by estimating the following equation:

$$\Delta Y_{it} = \beta_1 \Delta KIP_{it} + \alpha_{pt} + X_{it}^{'} \delta + \epsilon_{it}, \tag{1}$$

where ΔY_{it} is the change in regional outcome variables such as the change in the share of people with some college education in prefecture i between $t-1$ and t, and ΔKIP_{it} is the growth of imported capital goods per capita in prefecture i between $t-1$ and t. When estimating equation (1) for the long interval between 2000 and 2010, I stack the 5-year equivalent first differences for two periods, 2000 to 2005, and 2005 to 2010. The stacked first difference regression, which removes the time-invariant prefecture-specific determinants of outcome variables, is similar to a three-year fixed-effect model. To account for the time-variant shocks in each province where prefecture i is located, I include province $\times$ year dummies (α_{pt}). Additionally, I also include a rich set of start-of-period controls ($X_{it}^{'}$) that may exert independent impacts on educational outcomes. In all regressions, each observation is weighted by the start-of-period population share, and standard errors are clustered at the province level to account for possible spatial correlations across prefectures within the same province.[14]

4.3 Changes in college attainment

I construct various indicators for prefecture-level educational attainment by using the education information and other demographic information in the population survey data. The census defines educational attainment as the highest level of schooling that a person has ever attended. For example, the education level of a freshman is classified as college rather than senior high school. This census definition is broader than the definition in which educational attainment is measured by the highest diploma that a person has received.[15] Under the above definition, I construct the key

[14]For regressions run for each age/cohort group separately, the weights used are the start-of-period population shares by age/cohort group.

[15]Following the definition in the population survey, the definition implies that people who were in college during the survey are also considered skilled laborers in the analysis, which allows me to study the regional difference in college attainment.

outcome variable as follows:

$$\Delta Y_{it}^{g} = \frac{Skill_{it}^{g}}{P_{it}^{g}} - \frac{Skill_{it-1}^{g}}{P_{it-1}^{g}} \tag{2}$$

where ΔY_{it}^{g} is the change in the share of people with some college education or above of group g (certain birth cohort) in prefecture i between 2000 and 2005 or between 2005 and 2010, $Skill$ is the number of people with some college education or above living in prefecture i in year t, and P_{it}^{g} is the residence-based population of group g in prefecture i in year t.[16] For people who have not reached college age in $t-1$, ΔY_{it}^{g} captures the skill acquisition effect. For older cohorts, ΔY_{it}^{g} captures the relocation effect.

4.4 Import demand shocks

The baseline measure of import exposure in Equation (1) is the growth of imported capital goods per capita in a region:

$$\Delta KIP_{it} = \frac{M_{it} - M_{it-1}}{P_{it-1}} = \frac{\Delta M_{it}}{P_{it-1}}, \tag{3}$$

where ΔM_{it} is the change in imported capital goods in region i between 2000 and 2005 or between 2005 and 2010, and P_{it-1} is the residence-based population in region i in year $t-1$.[17] The above definition makes clear that the variations in imported capital goods growth per capita across regions arise from two sources: differential growth of imported capital goods and different population sizes. The latter is not the primary source of variation, as the growth of imported capital goods and the population in China between 2000 and 2010 were 520 percent and 5.8 percent, respectively.

4.5 Threats to identification and instrumentation strategy

In this section, I address three threats to the identification: omitted variables, reverse causality, and measurement error. Omitted variables will bias the estimation if a third factor affects both a prefecture's share of people with college education and its imports of capital goods. I address the time-invariant factors in three ways. First, the first-difference approach sweeps out time-invariant prefecture features. Second, the province-period dummies control for omitted variables that change

[16] Compared with *hukou*-based population data, which is available for each year, residence-based prefecture-level population data are only available in the census year such as 1990, 2000, and 2010. Each prefecture's population in 2005 is estimated as the geometric mean of population in 2000 and 2010.

[17] Scaling import growth by the size of the local economy is a more appropriate approach than using the change in log imports given that some regions began with relatively low levels of imported capital goods. In this paper, a local economy is a prefecture, and I will introduce the related background information later. Using prefecture-level population aggregated from county-level data to scale import growth is a better way compared to using output data because not all counties report output data and some of the available data are subject to measurement error problems, as explained in Autor et al., 2018.

over time within the 31 provinces. For instance, the college enrollment quota. Third, a set of prefecture-level start-of-period controls address for the local demand or supply shocks that change over time within a prefecture. Among the time-variant prefecture-level confounding factors, two obvious omitted variables may affect schooling. First, a prefecture may have more colleges, which can increase local college enrollment. To address this concern, I capture the exogenous component of changes in college supply at the prefecture-level by utilizing a quasi-experiment of college reallocation in the early 1950s. Second, regions that import more capital goods may also experience positive export demand shocks, which affects local demand for skill. I address this concern by incorporating the exogenous component of export growth into the regression. I find that the effect of imported capital goods remains stable.

The establishment of the causal link may also be hampered by other unobserved confounding factors, as well as the reverse causality problem. To account for the above concerns, I employ an instrumental-variable strategy by adopting the shift-share approach (Bartik, 1991).

$$\Delta KIP_{it}^{Bartik} = \left[\sum_j \frac{M_{ijt_0}}{M_{it_0}} \left(\frac{M_{jt}^{-i} - M_{jt-1}^{-i}}{M_{jt-1}^{-i}} \right) \right] \frac{M_{it_0}}{P_{it_0}}, \tag{4}$$

where M_{jt}^{-i} is China's imports of capital goods in product j and year t by excluding the province where region i locates, M_{ijt_0}/M_{it_0} is the year 1997's share of product j in region i's imports which captures a region's reliance on a certain type of capital equipment, and $M_{ijt_0}/P_{it_0}$is imported capital goods per capita of region i in the year 1997. To avoid introducing a common source of measurement error on both sides of the equation, I measure the weight M_{ijt_0}/M_{it_0} and the scaling variable M_{it_0}/P_{it_0}, using values in 1997, the pre-sample year. I choose 1997 instead of 1995 as the pre-sample year for the period between 2000 and 2010 because 1997 is the earliest year for which prefecture-level trade data is available. Because residence-based prefecture-level population data is only available in the census years such as 1990, 2000, and 2010, I estimate the 1997 population data based on data in 1990 and 2000 and assume that population growth is constant over time. In Equation (4), product j is defined at the HS 2-digit product level. The approach in Equation (4) predicts a region's import growth of capital goods by combining each region's initial import structure with the product-level national import growth. It captures the exogenous component of the regional import growth by characterizing the initial exposure of a prefecture to national import growth, which exposes the prefecture to national-level shocks more in some types of capital goods than in others.

I show that this exclusion restriction is plausibly satisfied. As shown in Borusyak, Hull and Jaravel (2018), one critical condition for the exclusion restriction to be satisfied is the exogeneity of the national import growth. To satisfy this condition, I use the leave-one-out strategy to calculate the national import growth, which excludes the interference of local demand for machinery and equipment. To alleviate the concern for the endogeneity of the import structure (Goldsmith-Pinkham, Sorkin and Swift, 2018), I use the pre-sample year's import data to construct the import share for each prefecture. In addition, I test the exogeneity of the shift-share instruments by including initial industry structures (Goldsmith-Pinkham, Sorkin and Swift, 2018), and the results remain robust. Furthermore, the by-cohort analysis, which finds that middle-aged people and old people do not respond to import shocks, provides supportive evidence. If the exclusion restriction is not satisfied and there is a spurious relationship, imported capital goods would increase the share of middle-aged and old people with some college education.

I also show that the requirement for relevance and monotonicity of the instrument are satisfied. I plot the instrument variable in Equation (4) against imported capital goods growth per capita in Equation (3). The figure reveals a substantial predictive power of the Bartik instrument for the changes in imported capital goods per capita. Moreover, the relationship between the two variables is linear.

Another threat to the identification is measurement error. The first type of measurement error is the classical measurement error. For instance, the report of regional import flows might be subject to random errors. Such measurement error attenuates β_1 and could bias the estimation towards zero. The shift-share instrument can mitigate this concern since import growth at the national level is much more reliable. The second type is the non-classical measurement error due to transit trade or wholesale. The transit trade problem, also known as the Rotterdam effect, refers to the measurement error that the imported goods by inland regions are recorded as imports by the entrepots. The wholesale problem refers to the fact that some firms, especially those located in the coastal regions, may resale some imported goods to other firms. It will be problematic if the transaction happens between firms located in different regions. Transit trade and wholesales across regions both raise the problem that the imports used by some regions, mainly coastal regions, are less than what is reported by the Customs. To examine how severe this measurement error problem is, I merge the firm-level trade data with the firm-level production data. I construct an index, namely the total imports as a share of total inputs, which tells whether a firm imports more than its actual need. I find that only 1 percent of the firms imported more products than the inputs used in production. Furthermore, most of these firms are located in coastal regions.[18] To address the measurement error problem, I check the data and find that seven cities have exceptionally high levels of exposure

[18] Most of the firms with high import to input ratio are located in Dongguan, Guangzhou, Qingdao, Shanghai, Shenzhen, and Suzhou.

to capital imports growth, indicating that they imported more capital goods than they could use in production. These cities are Dongguan, Guangzhou, Haikou, Shenzhen, Suzhou, Xiamen, and Zhuhai. Four of the cities, which lie close to Hong Kong or Macao, are in the Guangdong province; Haikou is on the northern coast of the Hainan province and by the mouth of the Nandu river; Suzhou is a prefecture that borders Shanghai, and Xiamen is a prefecture beside the Taiwan Strait. Hence, the outliers in terms of imported capital goods growth are cities that have access to major international ports and that were among the earliest prefectures with special economic zones (Alder, Shao and Zilibotti, 2016). In the next section, I will address this concern by controlling for the dummies for major ports and their interactions with time.

Finally, I cluster the standard errors at the prefecture-level to prevent the misleading inference due to the serial correlation in the error term across periods within a prefecture (Bertrand, Duflo and Mullainathan, 2004). The number of prefectures is 330, which is large enough to mitigate the spurious correlation concern.

5 Imported Capital Goods and College Share

This section examines the response of the share of people with some college education to imported capital goods over the 2000—2010 period. To identify the exogenous component of imported capital goods, I construct the shift-share instrument, which captures the demand-driven component of imported capital goods.

5.1 First stage results

The instrumental variable strategy, as outlined above, isolates the national demand for imported capital goods from other factors that may also be associated with the import growth of capital goods. The predicted imported capital goods growth per capita is allocated to various regions based on their initial import structure. The logic behind the expression in Equation (4) as a determinant of imported capital goods growth is that the initial import pattern in a prefecture exposes the prefecture to national-level shocks more in some industries than in others.

To give an overview of the data, Figures 6 plots the instrument variable in Equation (4) against imported capital goods growth per capita in Equation (3). It reveals the substantial predictive power of the Bartik instrument on the changes in imported capital goods per capita. A $100 predicted increase in imported capital goods per capita corresponds to a $156 increase in actual import exposure, and the R-square is as large as 0.59. Column (1) of Table 2 Panel B shows the result of the linear regression by including a period dummy. In column (2) and (3) of Table 2, I further control for province fixed effects and province-year dummies, respectively. The coefficients increase modestly and range from 1.60 to 1.84. That the estimated coefficients are similar in magnitude in all the models underscores the stability of the statistical relationships. A threat to the identification is the measurement error due to transit trade or wholesale, which are discussed in the previous section. I address these problems by controlling for the dummies for major ports and their interactions with time dummy.[19] As shown in column (4), the correlation between predicted and observed imported capital goods growth drops to 1.25 but remains strongly positive. Meanwhile, the explanatory power increases, with the R-square rising to 0.95. I further examine the relationship between the two periods separately in Appendix Figure A2. The positive correlations are robust across different periods.

[INSERT Figure 6 & Table 2]

5.2 Baseline results

Table 2 Panel A presents the initial estimates of the relationship between changes in imported capital goods and educational attainment based on the econometric specification in Equation (1). All regressions are weighted by the residence-based population in 2000. Standard errors are clustered at the province level to account for the potential covariance between the error terms across prefectures within the same province. Column (1) provides stacked first differences estimates of Equation 1. There is a positive correlation between the two variables in the OLS estimation. Figure 7 plots the bivariate reduced form regression. The positive correlation between the change in the share of people with college education and the change in imported capital goods per capita is 0.32.

[INSERT Figure 7]

In column (2)-(7), I present the 2SLS estimation results for the period of 2000—2010. Column (7) displays the preferred specification, and the coefficient of 1.39 suggests that a $100 rise in a prefecture's imported capital goods per capita increased its share of people with college education among for working-age population by 1.4 percentage points.

Comparing the OLS estimation in column (1) with the IV estimation in column (2), I find that the coefficient of the IV estimation is slightly larger than that in the OLS estimation. This downward bias suggests that the share of people with college education grows faster in cities that have faster growth of imported capital goods due to national trends, but less so in cities that have

[19] A prefecture is defined as a major port of importing capital goods if its realized imported capital goods are more than its predicted imports. Based on this standard, Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, Xiamen and, Zhuhai are defined as major ports of imported capital goods.

greater growth of imported capital goods due to prefecture-specific shocks. A possible explanation is that prefecture-specific shocks are short-term fluctuations that have less impact on education and mobility choices. For example, unobserved local government industrial policies that encourage imported capital goods have more modest impacts on human capital accumulation than national trends. Another possible explanation is the classical measurement error problem, which drives the coefficient towards zero.

From Column (3) to (7), I augment the first-difference model with a set of measures that test the robustness and eliminate the potential confounding factors. Column (3) augments the regression model by controlling for province-year fixed effects that absorb region-year-specific trends in the share of people with some college education. These dummies modestly reduce the estimated effect of imported capital goods. In column (4), I address the non-classical measurement error problem due to transit trade or wholesale discussed before. This measurement error causes a downward bias in the OLS estimation. Indeed, the impact of imported capital goods increased after I control for the dummies of major ports and their interactions with the year dummy. These prefectures are the major ports that imported capital goods and then resold some to other inland prefectures.

In column (5), I add the number of people in each cohort as a share of the total population at the start-of-period to absorb prefecture-cohort-specific trends. I also add the share of minorities at the start-of-period to absorb the changes in the share of people with some college education that are related to minority share.[20] Minority share is included because the government may provide more favorable education policies to regions with higher minority shares. The specification finds a smaller effect of import exposure on the share of people with some college education, but the relationship remains economically large and statistically significant.

There are some additional threats to the identification. The first one is China's education policy. A prefecture's initial import structure may be correlated with the education policy, which affects skill supply.[21] This concern can be addressed by controlling for the province-year fixed effects. In China, the college enrollment quota is assigned at the province level, not at the prefecture level. Students in each prefecture are competing for the college enrollment quotas with students in other prefectures within the same province, not with students from other provinces. This suggests that within the same province the number of students that can go to college in each prefecture is mainly

[20] People who are classified as being in the same cohort are those who were born in the same decade.

[21] The existing evidence suggests that China's college expansion is the consequence of the rising demand for skill (Li et al., 2017). Firstly, the return to college education in China has continued to increase rapidly despite the unprecedented increase in college enrollment (Figure 2), implying a strong demand-side force. Moreover, international evidence shows that the demand-side force also plays an essential role in other newly industrialized economies. Li, Liang and Wu (2016) show that college enrollment also increased quickly during the economic take-offs of other fast-growing economies, which do not have a centrally-planned allocation system. The above evidence suggests that China's college expansion is an endogenous response to the rising demand for skill.

driven by the market forces instead of government intervention. Because this paper's analysis unit is the prefecture, education policies, such as quota allocation policy, should not affect skill supply once I control for the province-year fixed effects (column 3).

To further alleviate the concern that the estimated effect of imported capital goods may capture the impact of prefecture-specific education policies, I conduct an additional robustness check to control for one source of the skill supply. In column (6), I capture the exogenous components of changes in college supply at the prefecture-level by utilizing a novel dataset released by Glaeser and Lu (2018). As described in the background section, there was a radical college reallocation in China in the early 1950s. By utilizing this quasi-experiment, I study the impact of department reallocation policy in the 1950s on the changes in skill supply between 2000 and 2010 in column (6). I find that regions with more departments moving in had faster growth of college share. Meanwhile, the impact of imported capital goods remains robust.[22] This result is further supported by the spatial distribution of imported capital goods growth in Figure 4 and college admission in Figure A1 in the appendix. By comparing the two figures, I find that regions that had more college admissions were not always regions with higher import growth.

The second potential threat to identification is that a prefecture's initial import structure may correlate with the local unobserved time-varying demand-side forces (Goldsmith-Pinkham, Sorkin and Swift, 2018). To address this concern, I augment the model by including the start-of-period manufacturing employment share, export share of textile, and export share of electronics and machinery into the regression in Table 2 column (7). As the manufacturing sector has a huge demand for machines, the inclusion of manufacturing employment share absorbs the changes in skill share that are related to the manufacturing sector. The textile sector and electronics and machinery sector are China's major exporting sectors. Controlling for the start-of-period export structures addresses the concern that the import exposure may, in part, capture the impact of exports on changes in skill share. These controls leave the main results unaffected. [23]The results indicate that a prefecture with a $100 rise in imported capital goods per capita at the start of the period had an increase of 1.4 percentage points in the share of people with some college education in the subsequent period. Note that the start-of-period population-weighted imported capital goods growth in the time interval 2000 through 2010 was approximately $70 per capita. The point estimate suggests that the

[22]It is possible that using the department reallocation policy to control for skill supply is not sufficient. In light of this, I also examine the relationship between the reallocation policy and imported capital goods. I find that the reallocation policy doesn't affect capital imports at the prefecture level. This falsification exercise suggests that education supply drives capital imports and not vice versa.

[23]To address the concern that the estimated impacts of imported capital goods do not pick up the effects of other trade flows, I examine the impact of non-capital goods imports and export on the share of people with college education in the appendix Table A4. The effect of imported capital goods remains to be robust. Since export and import are high correlated, the positive impact of imported capital goods is noisily estimated.

share of people with college education on average increased by one percentage point in response to the imported capital goods growth between 2000 and 2010. This indicates that 27% of the growth in share of people with some college education can be attributed to importing capital goods.[24] In addition, I also construct the trade policy uncertainty index at the prefecture-level following Pierce and Schott (2015); Handley and Limão (2017); Autor et al. (2018), which captures the exogenous component of regional export growth. I find that the effect of imported capital goods remains robust after the inclusion of the trade policy uncertainty index, as shown in Table 4 Column (4). [25]

5.3 Analysis by cohort

This section examines the heterogeneous impacts of imported capital goods across different cohorts. To be consistent with the decomposition analysis in the later section, I change the dependent variable from the changes in college share to the changes in the number of skilled people as a share of the total population at the start of the period. As shown in Figure 8, the impacts of imported capital goods are mainly concentrated among young people. This result is quite intuitive, as young people have much lower migration costs, and it is also easier for them to acquire higher education compared with older cohorts. Moreover, the analysis for the older cohorts also serves as a falsification exercise, suggesting that the estimated effect is unlikely driven by unobserved confounding factors.

In Table 3, I show the by-cohort analysis using the same econometric specification as that in Table 2 column (7) and Figure 8. Consistent with Figure 8, the impact of imported capital goods are concentrated among younger cohorts and decays for older cohorts. For people born between 1986 and 1989, the point estimate indicates that a $100 rise in imported capital goods exposure per

[24]In the Appendix Table A1, I also show the results by directly including export growth per capita. Panel A displays the correlations between capital goods import growth per capita and export growth per capita. The two variables are highly correlated with a correlation of 0.84. Panel B displays the corresponding second-stage results where both capital goods import growth per capita and export growth per capita are instrumented with their corresponding shift-share instruments. The results suggest that export reduces skill share during the sample period. This results is consistent with the previous findings (Atkin, 2016; Blanchard and Olney, 2017; Li, 2018) that labor-intensive export demand shocks raise the opportunity cost of schooling and thus reduce school attainment. Because of multi-collinearity, the coefficients are larger in magnitude and are noisily estimated.

[25]There is also a concern that the imported capital goods may partly capture the impacts of other imported products. To verify that the impact of imported capital goods is not driven by the imports of other products, I further examine the impact of non-capital goods imports on skill share in the appendix Table A1. Panel A displays the correlations between imported capital goods and other trade flows. Panel B displays the corresponding second-stage results. In column (1), the specification finds a larger effect of changes in imported capital goods per capita when including non-capital goods imports; this could result from the multi-collinearity problem given that the correlation between imported capital goods and non-capital goods imports is quite high as shown in Panel A. Furthermore, I also break down the non-capital goods imports into consumption goods imports and input and raw material imports. If imported intermediate inputs are more sophisticated to work with, factories may need skilled workers to work with them; therefore, imported intermediate goods may have a positive effect on the demand for skill. The results suggest that the various kinds of non-capital goods imports, including imported intermediate inputs, have either no effect or a negative effect on skill shares. The negative impacts of non-capital goods imports and exports are also negative in the by-cohort analysis.

capita increased the college share by about 18.6 percentage points. Note that the interquartile range in prefecture-level imported capital goods exposurefrom 2000 to 2010 was approximately $30 per capita. This suggests that the college share of a prefecture at the 75th percentile of import exposure increased by 5.6 percentage points more than in a prefecture at the 25th percentile between 2000 and 2010. As a comparison, Li (2018) finds that an interquartile range increase in high-skill (low-skill) export raises (reduces) the college share of people aged 19-22 by 1.1 (2.1) percentage points between 1990 and 2005. The effects of imported capital goods decay for older cohorts. For people born between 1950 and 1959, the effect of imported capital goods on them is about 6% as that of the 1986-1989 cohort. This result is quite intuitive, as it is more costly for older cohorts to respond to the trade shocks by obtaining more education or migrating to more trade-exposed regions. In addition, the by-cohort analysis suggests that the identification strategy is reliable. Because not all cohorts are responsive to the import shocks, the estimated effect is unlikely driven by reverse causality and some omitted confounding factors.

[INSERT Figure 8 & Table 3]

In Table 4, I further conduct several robustness checks. Column (1) repeats the result for the cohort 1986-1989 in Table 3 column (1). I try two alternative measurements for skill supply by putting the start-of-period prefecture-level average years of schooling (column 2), or urban share (column 3) into the regression. Regions with higher initial educational attainment and higher urbanization rate indeed have faster growth of college share, yet these controls leave the main results unaffected. Column (4) captures the exogenous component of export growth by using the measurement of trade policy uncertainty following Pierce and Schott (2015); Handley and Limão (2017); Autor et al. (2018). Again, the regression result remains stable. Column (5) augments the regression model with the employment share of state-owned enterprises (SOE) and foreign-owned enterprises (FOE). Foreign-owned enterprises mainly involve labor-intensive productions, and regions with higher FOE share have lower demand for skill. Column (6) includes all the controls in previous columns, and the estimates are insensitive to these controls. The robustness checks for other cohorts have similar patterns.

[INSERT Table 4]

5.4 Decomposition: education vs. migration

In this section, I quantify how migration can account for the regional difference in skill composition, based on the information on people's places of residence five years prior. Taking advantage of this information, I can categorize people based on migration status. To more specific, I can identify local residents, i.e., people who were living in the same prefecture i during the survey as well as five years prior, and immigrants, i.e., people who were living in current prefecture i during the survey but were living in a different prefecture j five years ago. Moreover, I can identify emigrants who lived in prefecture i five years ago but had moved to another prefecture j by the survey year. Instead of using the changes in college share in Equation (2) as the outcome variable, I use the change in the number of skilled laborers as a share of the start-of-period total population because the latter is more suitable for decomposition. As shown below, the latter can be decomposed into the following three components:

$$\begin{aligned}\Delta Y'^{g}_{it} &= \frac{Skill^{g}_{it} - Skill^{g}_{it-1}}{P^{g}_{it-1}} \\ &= \frac{Skill\,(Unskill_{it-1})^{g}_{it} - Skill\,(Dead)^{g}_{it}}{P^{g}_{it-1}} + \frac{Skill\,(IM)^{g}_{it}}{P^{g}_{it-1}} - \frac{Skill\,(EM)^{g}_{it}}{P^{g}_{it-1}}\end{aligned} \tag{5}$$

where $\Delta Y'^{g}_{it}$ is the changes in the number of people with some college education or above of group g (certain birth cohort) as a share of the total population of group g living in prefecture i between 2000 and 2005 or between 2005 and 2010, $Skill^{g}_{it}$ and P^{g}_{it} are as defined in Equation (2), $Skill\,(Unskill_{it-1})^{g}_{it}$ is the number of people of group g living in prefecture i who did not attended college in year $t-1$ but have received some college education or above in year t, $Skill\,(Dead)^{g}_{it}$ is the number of people of group g who received some college education or above in prefecture i in year $t-1$ and are dead or have missing information in year t, $Skill\,(IM)^{g}_{it}$ is the number of people of group g who received some college education or above and live in other prefectures in year $t-1$ and immigrate to prefecture i in year t, $Skill\,(EM)^{g}_{it}$ is the number of people of group g who received some college education or above and lived in prefecture i in year $t-1$ and emigrate to other prefectures in year t. The identification of people's prefecture residence 5 years ago is based on two pieces of information, namely the current resident prefecture, migration status, *hukou*-registered prefecture, and residence province 5 years prior. The first component, $\frac{Skill(Unskill_{it-1})^{g}_{it} - Skill(Dead)^{g}_{it}}{P^{g}_{it-1}}$, is the combined effect of the skill acquisition of local unskilled workers and the death of local skilled workers. Due to data limitations, I can not further decompose it. For people who did not reach college age in $t-1$ and reach the normal age for college in t, the college share is the college enrollment rate. The above breakdown tells us how much the rise in skill acquisition can be attributed to the skill acquisition of local stayers, how much to the immigrants, and how much to the emigrants. For skilled immigrants and skill emigrants, I am unable to tell whether they have attended college before the trade shocks, and thus I do not know whether the effect is due to skill acquisition or migration. For older cohorts, the college share mainly reflects the migration of incumbent skilled laborers across regions. The above breakdown tells about how much the rise in the share of people with college education can be attributed to local stayers, how much to the immigration of skilled laborers, and how much to the emigration of local skilled laborers.

Regions with faster growth of imported capital goods enjoy faster growth of the share of people with some college education, as shown in Figure 9. For young people, the effects mainly come from the skill acquisition of local stayers. As shown in Panel A in Table 5, a prefecture with a hundred dollar higher imported capital goods growth per capita at the start of the period had an increase of 13.8 percentage points in college share for people born between 1986 and 1989 in the subsequent period. The decomposition analysis shows that most of the increase in the share of people with some college education is due to the skill acquisition of local stayers. As for older cohorts, imported capital goods have weaker effects, and they mainly affect the share of people with some college education through migration.

[INSERT Figure 9 & Table 5]

5.5 Spatial spillover effects

The identification strategy relies on the assumption that prefecture i 's share of people with some college education is not affected by the labor market conditions in other prefectures. Nevertheless, the import of capital goods elsewhere can also affect people's education decisions and migration decisions. To quantify the spillover effects and estimate the "total" impacts of imported capital goods, I need to use a different source of variation. As with most of the spatial problems, the share of people with college education in prefecture i could be a function of the imported capital goods of all the other prefectures. Because it is difficult to estimate the functions precisely, I adopt three approaches to examine the impact of imported capital goods in other regions.

First, I construct the employment share weighted imported capital goods growth per capita of the neighboring prefectures which share borders with prefecture i (Li, 2018).

$$\Delta KIP^{S1}_{it} = \sum_j \frac{Employment_j}{\sum_{j \in neighbor_i} Employment_j} \Delta KIP_{jt} \tag{6}$$

where $Employment_j$ is the employment of prefecture j, ΔKIP_{jt} is the imported capital goods growth per capita in prefecture j between $t-1$ and t, and $\Delta KIP^{S1}_{it}$is my first measurement for the imported capital goods in other regions.

Second, I estimate the spatial distance between prefecture i and other prefectures, normalize the sum of the inverse distance to 1, use the normalized inverse distance to weight prefecture j's imported capital goods growth per capita and then sum across prefectures.

$$\Delta KIP_{it}^{S2} = \sum_{j} \frac{\frac{1}{D_{ij}}}{\sum_{j \neq i} \frac{1}{D_{ij}}} \Delta KIP_{jt} \tag{7}$$

where D_{ij} is the spatial distance between prefecture i and prefecture j, ΔKIP_{jt} is the imported capital goods growth per capita in prefecture j between $t-1$ and t, and $\Delta KIP_{it}^{S2}$is my second measurement for the imported capital goods in other regions.

Third, I construct prefecture i 's share of neighboring prefectures with more substantial imported capital goods growth per capita than prefecture i following Muralidharan, Niehaus and Sukhtankar (2018). Here neighboring prefectures refer to prefectures lying with the chosen radii. In the analysis, the radii is set as 200 km.[26] To test the sensitivity of the results to the definition of neighborhoods, I also try various radii, and the results are robust.

Table 6 presents the results incorporating the spillover effects of imported capital goods using the first approach. The capital goods import growth in neighboring prefectures indeed exerts a negative effect on the local skill share, and it mainly works through the channel of migration. The results confirm that regions are competing for talents. However, the negative effect is very small in magnitude. Furthermore, the impact of local imported capital goods growth, which is the variable of interest, on the local skill share is independent of the inclusion of the spillover effect. I then test the robustness of the results by using the two alternative measures, and the results are shown in the appendix. Adopting the two sets of spillover indicators yields similar results.

[INSERT Table 6]

6 Imported Capital Goods and Wage Structure

6.1 Region-level evidence

Section 5 estimates the effect of capital imports on the college share on the idea that embodied technology found in capital goods boosts demand for skilled labor. Presumably, the change in supply is a response to the change in demand. To show the demand channel, I explore the impact of imported capital goods on the average wage, the wage of skilled workers, the wage of low skilled

[26] The radii is set based on the average size of provinces and prefectures in China. China covers roughly 9,600,000 km^2. There are 31 provinces and the average radii is about 314 km ((9600000/31/3.14)^(0.5)). There are 337 prefectures and the average radii is about 95 km ((9600000/337/3.14)^(0.5)).

workers, and the skill premium. I find that imported capital goods increase the college premium, and the positive effect attenuates over time.

Following the specification in Table 2 column (7), I present the benchmark results of the 2SLS regressions in Table 7. In column (1), I regress the log change in average wage on the log change in imported capital goods per capita, the province-year fixed effect, and a set of start-of-period controls. I find that imported capital goods do not have a significant impact on the average wage.

In column (2) and (3), I examine the impacts of imported capital goods on the wages by different skill levels. In regions with faster growth of imported capital goods, skilled workers experienced faster wage growth, while the wage growth of unskilled workers is not affected much. When taking the one-year first difference (Panel A), I find that a 10 percent increase in imported capital goods per capita increases the average wage of skilled workers by 0.6 percent. The significant positive effects, however, attenuates over time. When taking the seven-year first difference (Panel C), I find that the impact of imported capital goods is no longer significant anymore.[27]

Similarly, I find that the impact of imported capital goods on skill premium is positive, and it attenuates over time. I calculate the skill premium using two methods. The first method is to calculate the wage difference between skill workers and unskilled workers as a percentage of the wage of unskilled workers (column 4). The second method is to estimate the Mincer-style OLS regression after I control for gender, working experience, and its square term, employer ownership type, and industry dummies (column 5). When taking the one-year first difference, I find that a 10 percent increase in imported capital goods growth per capita increases the average wage growth of skilled workers by 2 percent. The effects become slightly larger when I take the three-year difference, as firms have more time to adjust the wage. The positive effects, however, decline when I take the seven-year difference. The equalization of skill premium across regions is likely due to the faster increase in skill supply in more trade-exposed regions. Combined with the findings in the previous section, I show that imported capital goods are indeed a key driver for the rising demand for skill.

[INSERT Table 7]

6.2 Firm-level evidence

I supplement the above analysis by providing direct evidence on how firms adjust production and how imported capital goods affects a firm's demand for skill. I utilize the Annual Survey of Industrial Firms (ASIF), a national representative firm survey. The ASIP data covers a long time span and

[27] In the UHS data, the number of cities surveyed after 2002 is twice as many as the that before 2002. To guarantee that the sample size is not too small, I cannot use data before 2002 when making the long-run analysis.

allows me to control for time-invariant firm fixed effects.[28] The specification has the following form:

$$y_{it} = \beta_1 K_{it} + X_{it}\delta + \mu_i + \gamma_t + \varepsilon_{it} \tag{8}$$

where y_{it} includes a set of dependent variables for firm i in year t, K_{it} is the ratio of imported capital goods over its total imports, X_{it} is a set of firm-level controls, μ_i and γ_t are firm fixed effects and year fixed effects respectively. For regressions in which the dependent variables are only available in 2004, the census year, I control for prefecture-industry fixed effects instead (Table 8 columns 3-6).

Column (1) of Table 8 shows that capital goods importers pay higher wages. From 2000 to 2007, a one percentage point increase in capital goods import intensity, on average, is associated with an increase of wage by 2.5 percent. Because the national firm survey does not have wage data by education, I am unable to examine the relationship between imported capital goods and skill premium.

To provide supporting evidence, I examine the impact of imported capital goods on labor productivity, employment structure, computer usage, and profit rate. As shown in column (2), capital goods importers have higher labor productivity. In column (3), I further explore the employment structure using the 2004 census data. Because I can not control for firm fixed effects, I control for the city- and industry-specific factors, total employment, firm ownership dummies instead. Firms with more imported capital goods have higher shares of skilled laborers (as measured by the share of workers with a college degree or above). This is consistent with the findings by Bernard and Jensen (1997), who show that more capital-intensive plants hire a higher proportion of skilled workers and offer higher wages. Both the export share of total revenue and imported input share of total inputs are positively associated with labor productivity after controlling for firm fixed effects. The above findings are consistent with the findings by Dai, Maitra and Yu (2016). Column (4) shows that capital goods importers use more computers, which are generally considered to be embedded with skill-biased technology. A large body of literature has used the computerization of US firms as reflecting skill-biased technology change (Berman, Bound and Griliches, 1994; Autor, Levy and Murnane, 2003). The firm census in 2004 provides valuable information on computer usage. As shown in column (4), increasing capital import intensity by 10 percentage points is associated with an increase of 0.6 computers per hundred workers. In column (5) and (6), I use two different ways to measure the profit rate and get consistent results that capital goods importers have higher profit rates. Although I cannot rule out the possibility of endogeneity in the OLS regressions, the results

[28] Most of the variables are reported by firms annually except for employment structure and computer usage, which are only reported in the census year (2004).

indicate that imported capital goods are skilled-biased and thus increase the demand for skill.

[INSERT Table 8]

7 Discussions

Can imported capital goods also encourage human capital accumulation and migration in other developing countries? It is challenging to quantify the importance of imported capital goods for all the developing countries. I try to explore this topic by providing some descriptive evidence. In Figure 10, I show the import shares of capital goods of China, seven developed countries, newly industrialized countries with high manufacturing shares, and newly industrialized countries with low manufacturing shares. China's import share of capital goods rose from 39 percentage points in 1998 to 47 percentage points in 2006 and dropped back to 41 percentage points due to the global financial crisis. However, capital goods import share was much lower for the newly industrialized countries with low manufacturing shares and the G7 countries.[29] For the G7, the import share of capital goods was 29 percentage points in 1998, which was 10 percentage points smaller than China. Since then, it has kept declining. In 2009, the import share of capital goods of the seven developed countries was only 22 percentage points, 22 percentage points smaller than China. The international comparison reveals that newly industrialized countries that have a comparative advantage in manufacturing also tend to have a higher share of imported capital goods during the economic take-off. Despite the above descriptive analysis, there is limited direct international evidence on the impact of imported capital goods on human capital accumulation and migration in the literature (Acemoglu and Zilibotti, 2001). A related empirical paper is Raveh and Reshef (2016), who provide international evidence on the positive impact of imported capital goods on skill premium.

[INSERT Figure 10]

Another related question is whether China can continuously rely on the capital goods import channel to acquire advanced technology and increase demand for skill. The answer is likely to be no. As shown in Figure 1, the growth of imported capital goods in China slowed down in recent years. On the one hand, the gains from adopting advanced technologies from other countries have become smaller as China moves closer to the international technology frontier. On the other hand, the restrictions on international technology transfer have also risen, as Chinese firms have become more competitive. In the future, China will rely more on domestic innovation, and the growth of TFP will slow down as innovation needs more time than technology transfer.

[29] The seven developed countries include Canada, France, Germany, Japan, Italy, the United Kingdom, and the United States.

8 Conclusion

Human capital is an important determinant of the long-run economic growth, so it is crucial to understand how trade affects human capital accumulation as countries are becoming more globalized. This paper shows that imported capital goods can increase college share. Imported capital goods, which embodied skill-biased technology, boost the demand for skill. The demand shift leads to an outward supply movement of skilled workers through either skill acquisition or migration. By drawing on several rich data sets and taking the regional economy as the unit of analysis, this paper addresses three issues: quantifying the impact of imported capital goods on the share of college workers, quantifying how skill acquisition and migration can explain the regional differences in the share of college workers, and exploring the mechanism by quantifying the impact of imported capital goods on college wage premium. To tackle causality, I construct a shift-share instrument for the changes in imported capital goods per capita by using each prefecture's initial import shares to characterize the exposure of a prefecture to national import growth. I find that prefectures with a \$100 increase in imported capital goods growth per capita experienced faster increases in the share of college workers by 1.4 percentage points. The effects are mainly concentrated among young people, who have lower migration costs and can more easily attain higher education. By decomposing changes in the share of college workers, I show that skill acquisition rather than migration is the major cause of the regional difference in college share. Despite identifying the direct positive impact of imported capital goods, I also quantify the spillover effects, which is negative and small in magnitude. The imported capital goods in other regions mitigate the impact of local imported capital goods via the migration channel. To explore the mechanism, I provide regional evidence to show that imported capital goods encourage skill acquisition and migration by increasing the college wage premium. The additional firm-level analysis further provides supportive evidence.

The findings have several implications on the labor market consequences of imported capital goods. First, because of technology-skill complementarity, encouraging capital goods imports can increase demand for skill and thus incentivize people to acquire more education. The impact of imported technical change can be larger than innovation, as it is less costly and more efficient to adopt the existing mature technology than conducting R&D. Second, regional differences in imported capital goods widen regional inequality in human capital. Because human capital is a key driver for the long-run economic growth, the widening regional inequality in human capital can have profound impacts on the regional inequality in economic development in the long run. Third, migration aggravates the regional inequality in human capital by enticing skilled laborers to immigrate to more-exposed regions and intensifying the brain drain in regions with lower demand for skill.

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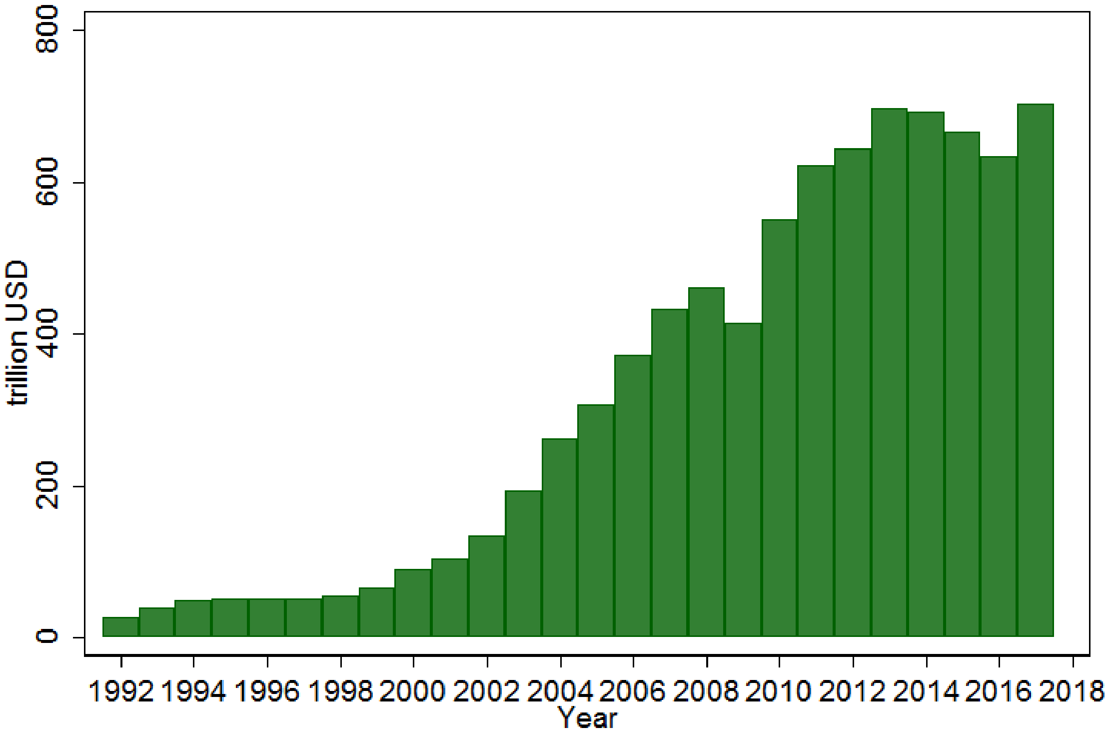
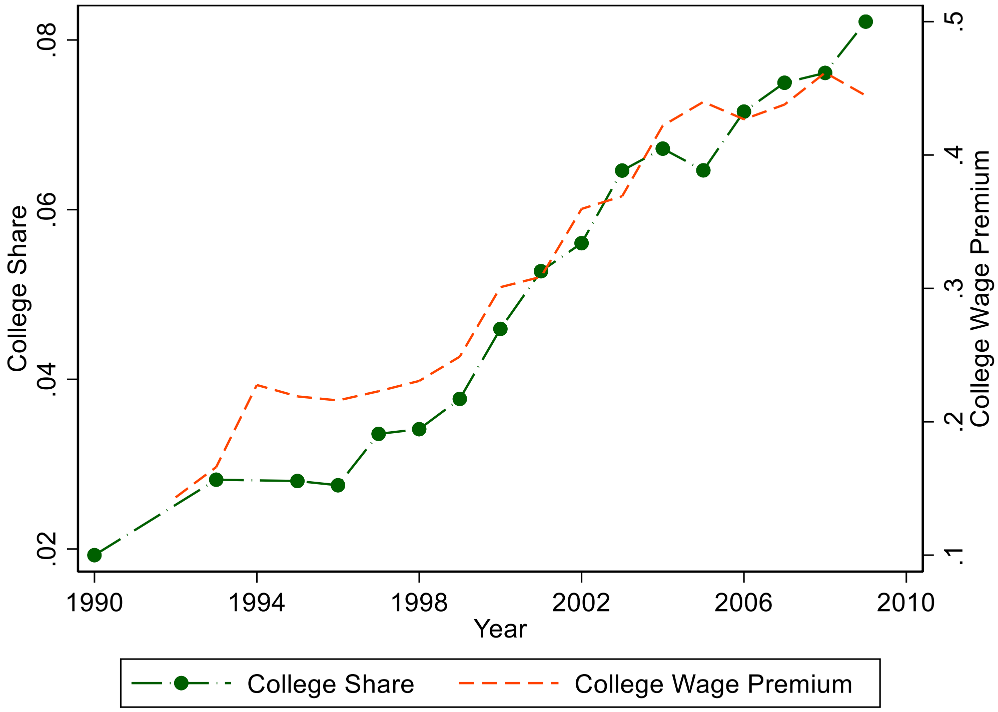
Figure 1 Capital Goods Imports



Data: UN Comtrade Database, 1992-2017

Note: These figures show the pattern of Chinese total imported capital goods (unit: 1 billion US$). I define capital goods to be the sum of ISIC Rev. 3 codes 29-33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry).

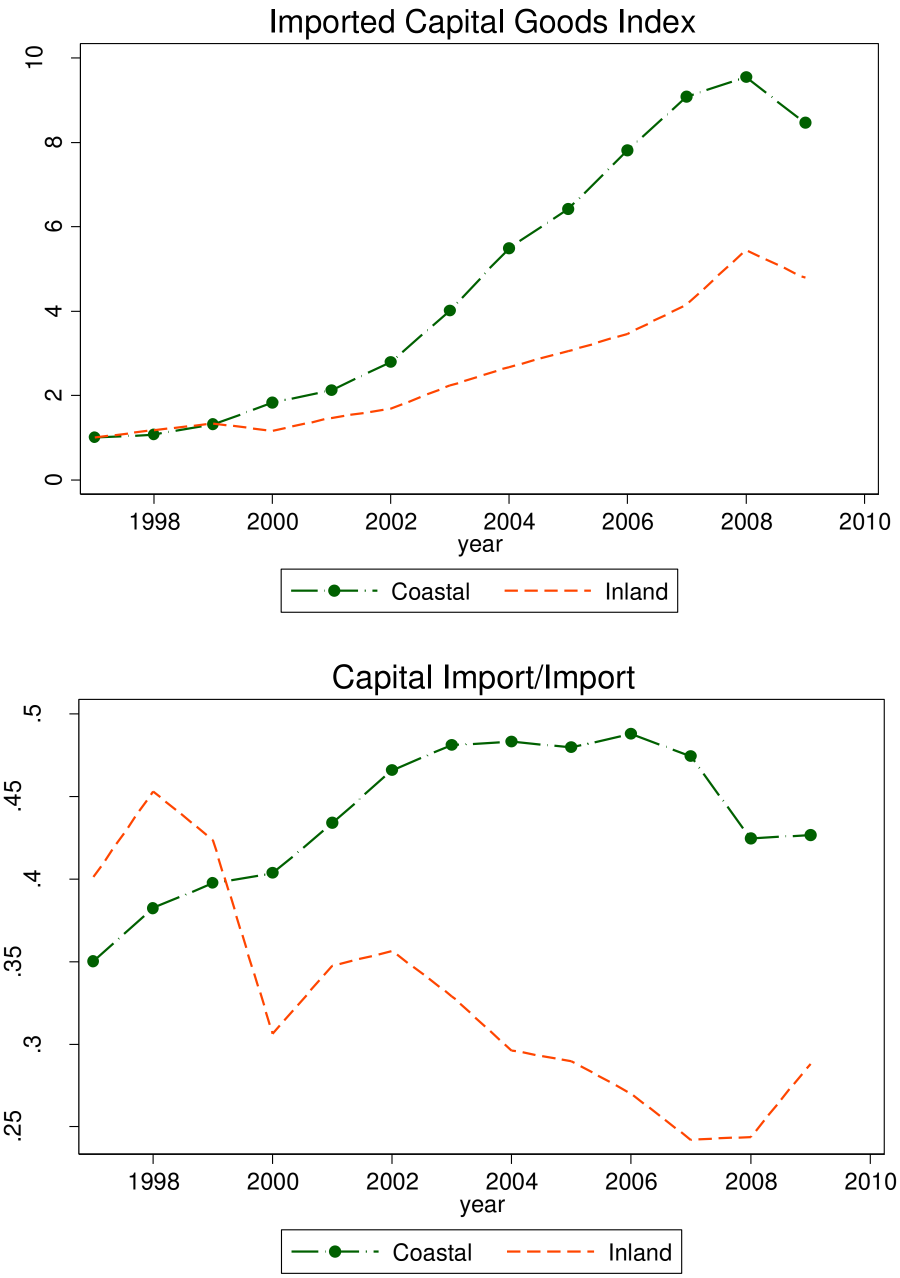
Figure 2 China's Rising College Share and College Wage Premium



Data: China Statistical Year Books (1990-2010) and Household Survey (1992-2009)

Note: The college share is defined as the number of people with at least some college education or above as a share of people aged above 15 years old. The skill premium is the wage gap between people with at least some college education and those without. It is estimated based on the Mincer-style OLS regression after I control for gender, working experience and its square term, employer ownership type, and industry dummies. Due to data limitation, I am unable to calculate the skill premium before 1992 or after 2009. In later sections, I will use the terms skill premium and college premium interchangeably.

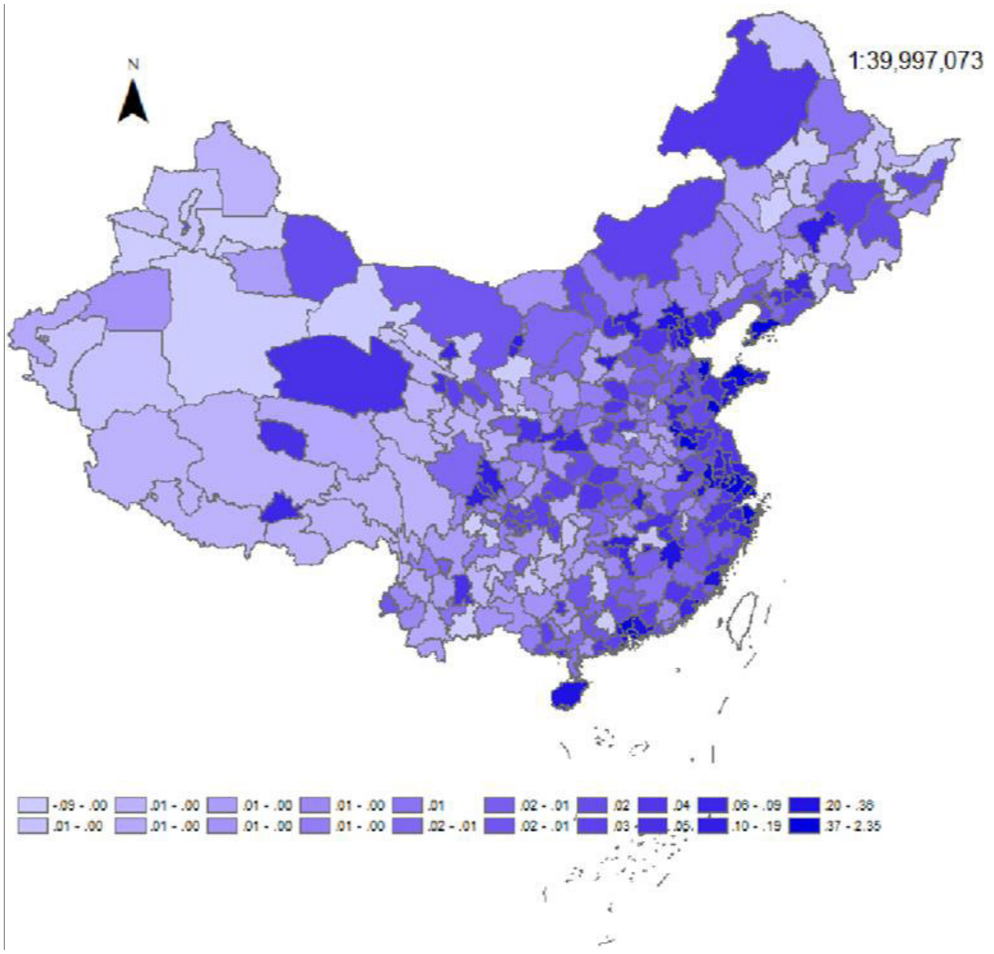
Figure 3 Capital Goods Imports and Import Share of Capital Goods by Region



Data: China General Administration of Customs, 1997-2009

Note: I define capital goods to be the sum of ISIC Rev. 3 codes 29-33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry).

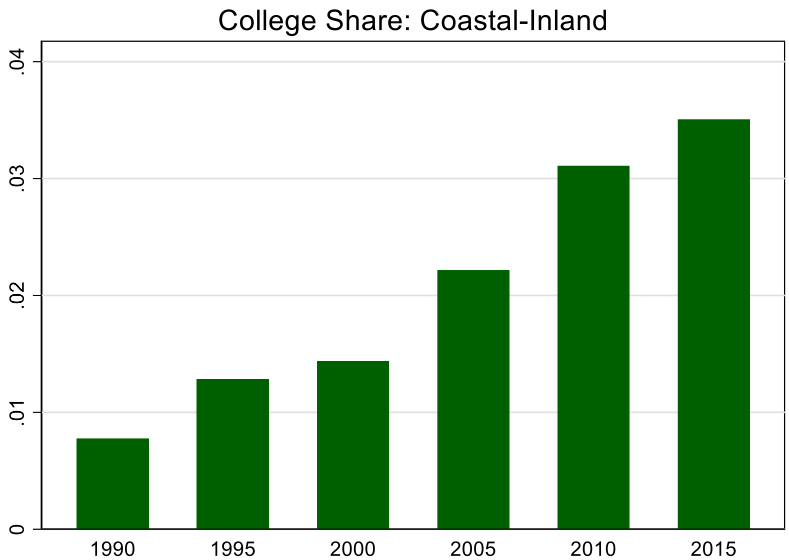
Figure 4 Spatial Distribution of Changes in Capital Goods Import per Capita between 2000 and 2010

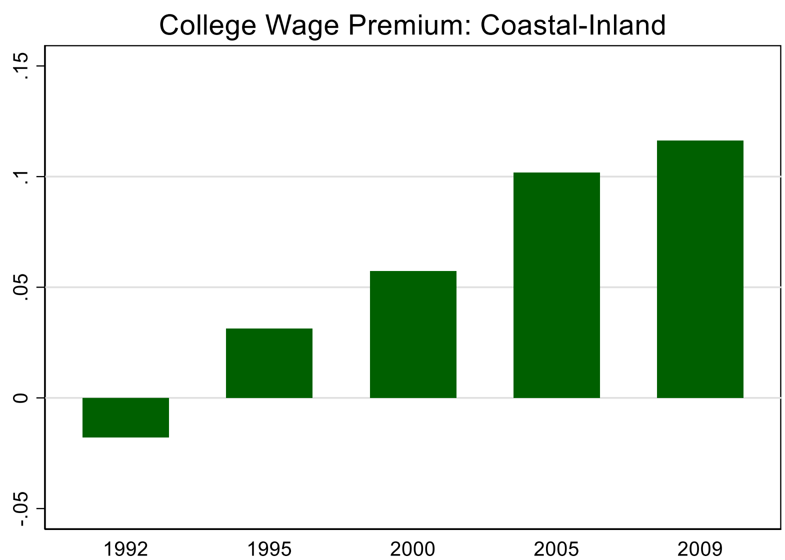


Data: China General Administration of Customs, 2000 and 2010

Note: I define capital goods to be the sum of ISIC Rev. 3 codes 29-33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry). Growth in capital goods imports per capita is measured in 1,000 U.S. dollars.

Figure 5 The Widening Regional Differences in College Share and College Wage Premium

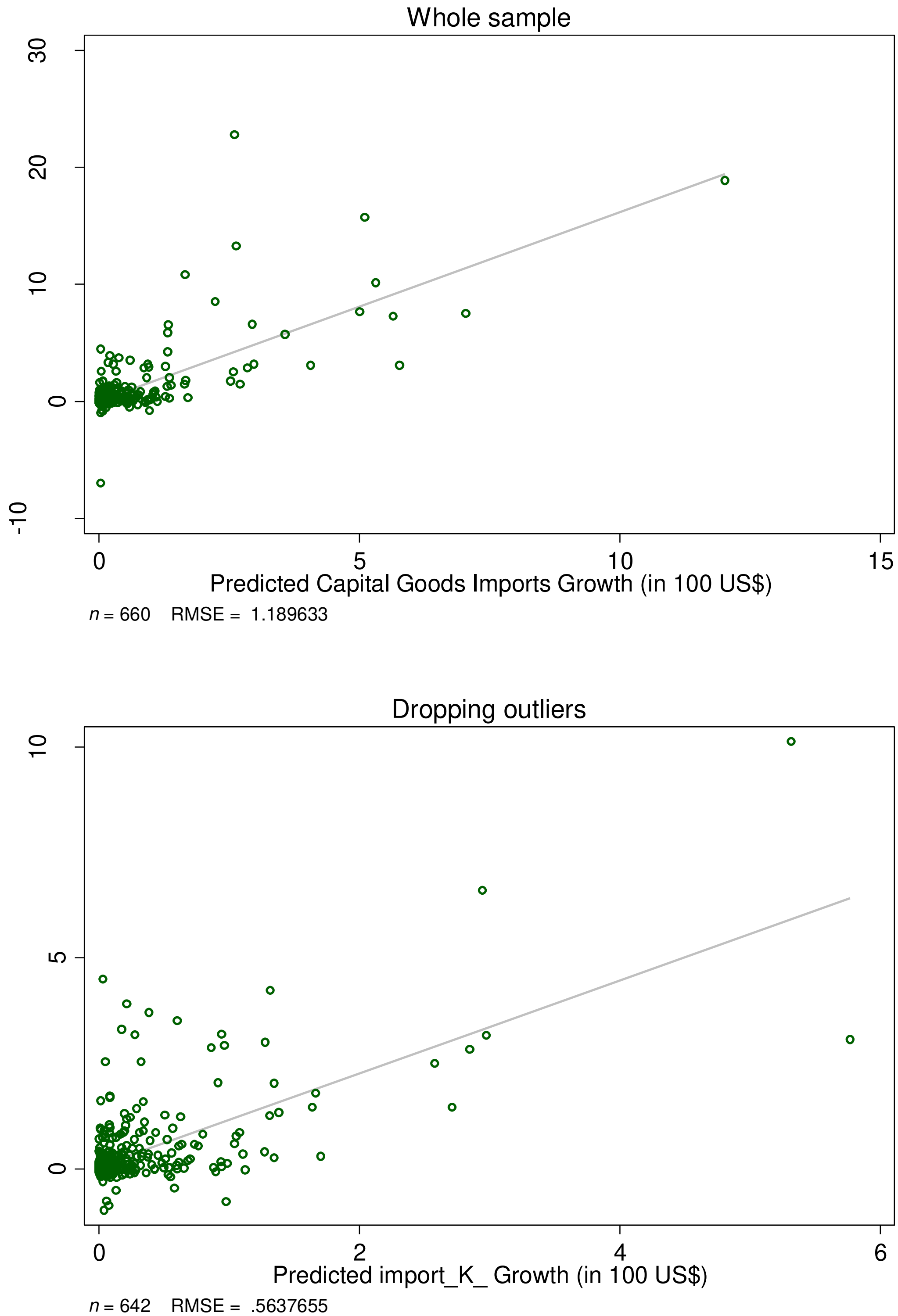




Data: China Statistical Year Books (1990-2010) and Household Survey (1992-2009).

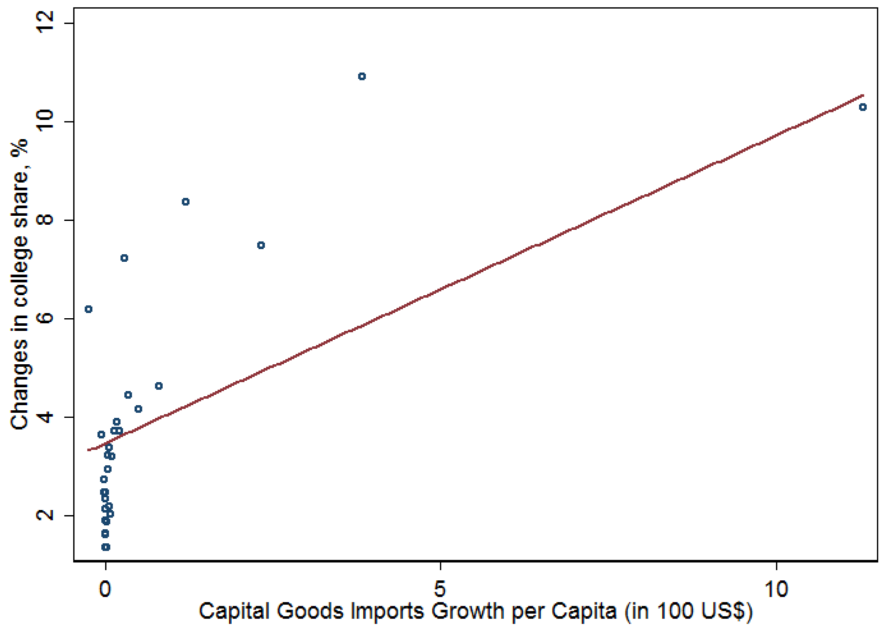
Note: The share of skilled workers is defined as the number of people with some college education or above as a share of the total population. Skill premium is estimated based on Mincer-style OLS regression after I control for gender, working experience and its square term, employer ownership type, and industry dummies. The Household Survey data covers 18 provinces in China. Following the regional classification by China's National Bureau of Statistics, coastal regions include Beijing, Guangdong, Jiangsu, Liaoning, Shandong, Shanghai, and Zhejiang, and inland regions include central China (Anhui, Heilongjiang, Henan, Hubei, Jiangxi, and Shanxi) and western China (Chongqing, Gansu, Sichuan, Yunnan, and Shaanxi).

Figure 6 First Stage



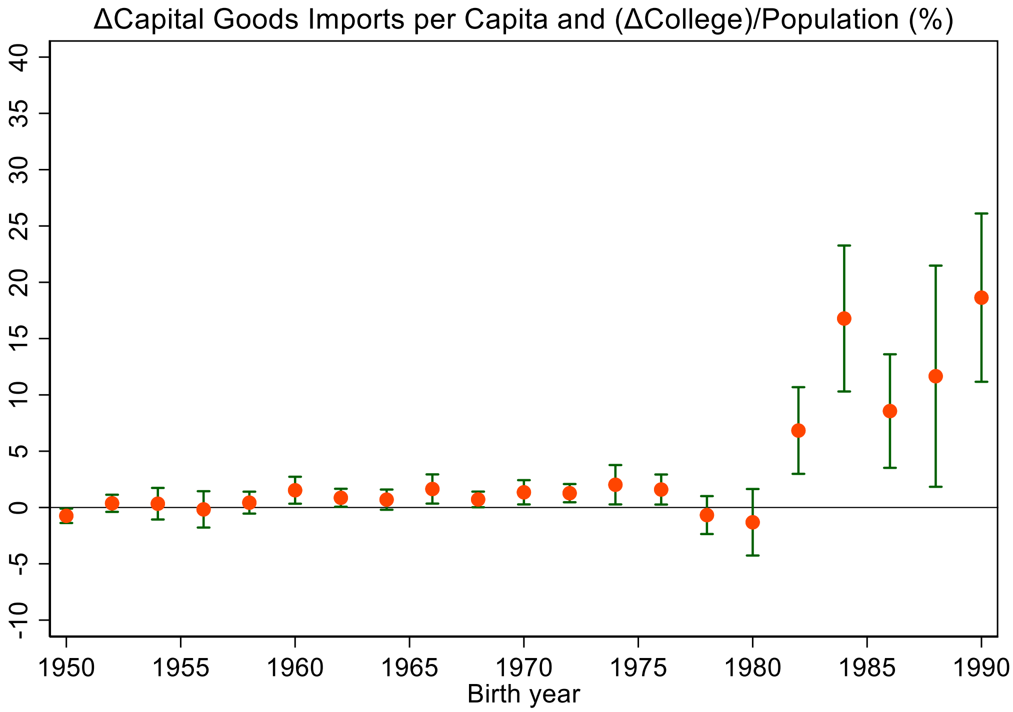
Note: The scatter plots display the relationships between the predicted capital goods imports growth per capita (the instrument) and capital goods imports growth per capita.

Figure 7 Second Stage: the Change in Capital Goods Imports per Capita and the Change in College Share



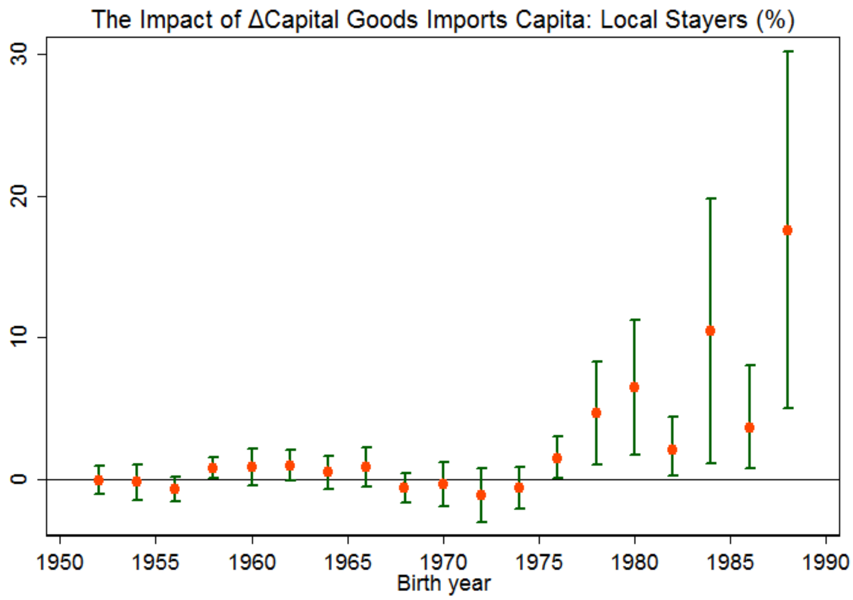
Note: The binned scatter plots display the relationships between the capital goods imports growth per capita and changes in skillshare.

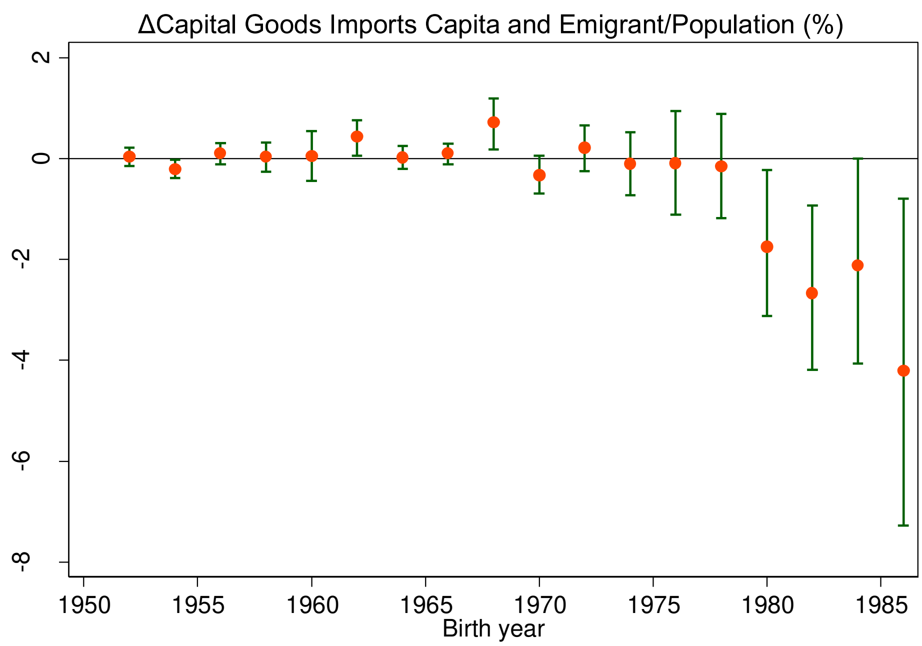
Figure 8 Imported Capital Goods and Allocation of Skilled Labors: by Birth Year

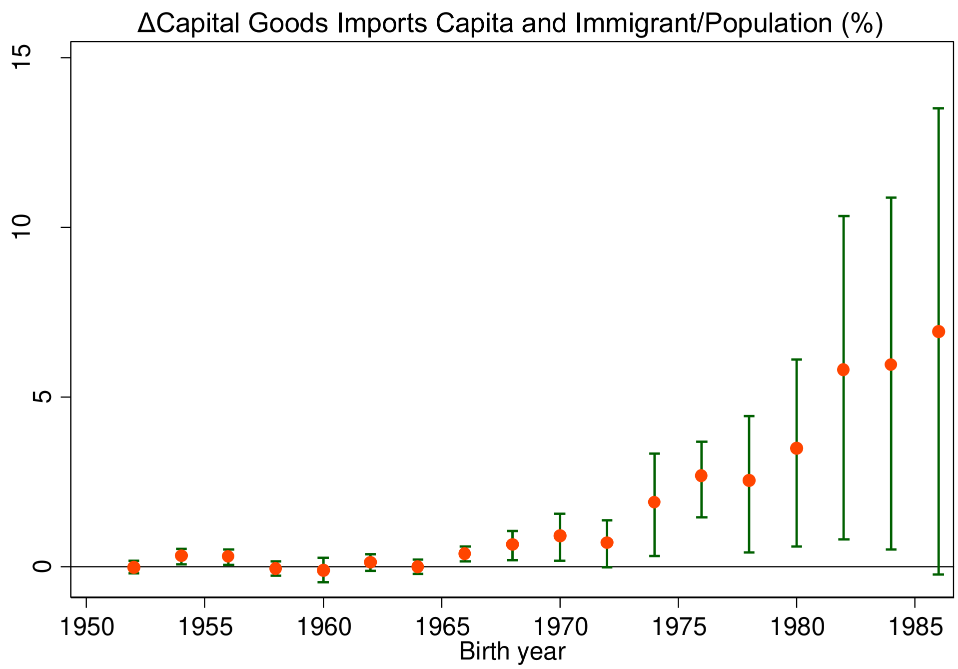


Note: I regress the changes in college share for each cohort on capital goods import growth per capita. Each cohort group includes people born in two adjacent years.

Figure 9 Decomposition of Changes in College Share: by Birth Year

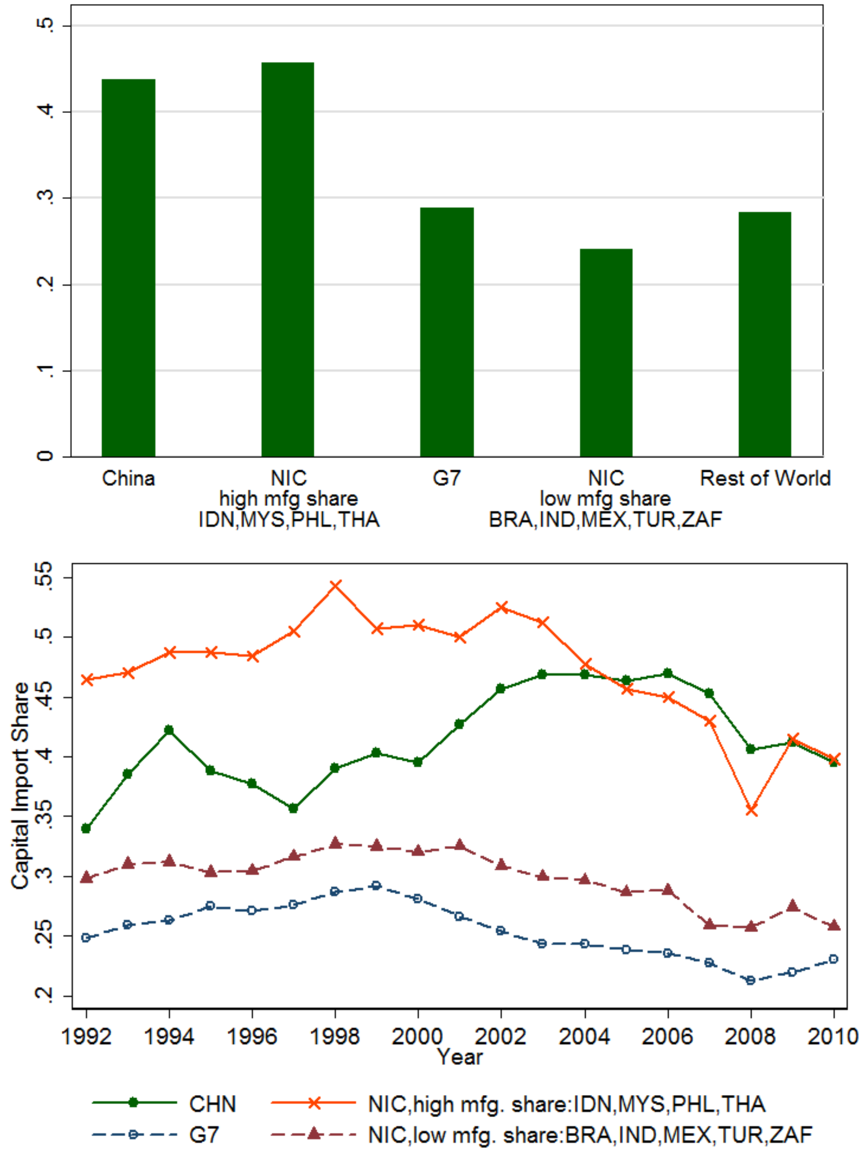






Note: I first decompose the changes in college share for each cohort into three components, namely immigration component, emigration component, and skill acquisition component. Then I regress the three components on capital goods import growth per capita.

Figure 10 Import Share of Capital Goods: International Comparison



Data: UN Comtrade Database

Note: Capital goods are defined as the sum of ISIC Rev. 3 codes 29-33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry). The seven developed countries include Canada (CAN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the United Kingdom (GBR), and the United States (USA). The four developing countries with high manufacturing shares include Indonesia (IDN), Malaysia (MYS), Philippine (MEXPHL, and Thailand (THA). The five developing countries with high manufacturing shares include Brazil (BRA), India (IND), Mexico (MEX), Turkey (TUR), and South Africa (RUS).

Table 1 Summary Statistics

	mean	std	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	N
Panel A: College share and college premium (%)								
College share, 2000	4.33	3.38	1.65	2.24	3.09	5.06	9.58	330
△College share, 00-05	2.20	1.88	0.43	0.98	1.76	2.97	4.59	330
△College share, 05-10	5.01	3.12	2.07	3.17	4.17	6.11	8.92	330
△College share, 00-10	3.61	2.93	0.70	1.54	3.05	4.72	7.24	660
(△College)/population, 00-10	3.90	3.82	0.56	1.42	2.84	4.88	8.93	660
△College premium, 00-10	2.12	14.21	-12.30	-7.28	0.11	10.84	21.88	341
Panel B: Capital goods imports (100 U.S. dollars)								
△Imported capital goods per capita (△K), 2000	0.32	0.89	0.00	0.00	0.03	0.15	0.92	330
△Imported capital goods per capita (△K), 00-05	0.74	2.66	0.00	0.01	0.04	0.23	1.28	330
△Imported capital goods per capita (△K), 05-10	0.66	1.91	-0.03	0.00	0.06	0.33	1.73	330
△Imported capital goods per capita (△K), 00-10	0.70	2.31	-0.02	0.00	0.05	0.30	1.46	660
△Predicted imported capital goods per capita (△IV)	0.39	1.14	0.00	0.00	0.04	0.20	0.94	660
Panel C: Start-of-period controls								
Minority share, (%)	0.09	0.18	0.00	0.00	0.01	0.06	0.30	660
Manufacturing employment share, (%)	0.12	0.11	0.03	0.05	0.08	0.15	0.28	660
Textile and electronics' export share, (%)	0.40	0.25	0.02	0.16	0.43	0.61	0.71	660
No. of reallocated departments	-0.99	6.04	-3.00	0.00	0.00	0.00	0.00	660

Note: The statistics are weighted by prefecture-level residence-based population in 2000.

Table 2 Growth in Imported Capital Goods and Change of College Share

Dependent Variable: 100 × △(college share) (in % pts)

Panel A: 2000-2010 Stacked First Differences	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV
△Capital goods import per capita	0.32***	0.47**	0.33***	1.97***	1.44***	1.57***	1.39***
	(0.10)	(0.21)	(0.10)	(0.49)	(0.43)	(0.49)	(0.49)
Dummy for period 2000-2005	√	√	√	√	√	√	√
Province-year fixed effects			√	√	√	√	√
Dummies for large ports and their interactions with time				√	√	√	√
Demographic features					√	√	√
△College departments in 1952						√	√
Industry structure & export structure							√
Panel B: 2SLS First Stage Estimates							
△Predicted imported capital goods per capita		1.60***	1.84***	1.25***	1.02***	0.98***	0.80**
		(0.21)	(0.29)	(0.33)	(0.32)	(0.34)	(0.31)
R-squared		0.57	0.69	0.95	0.95	0.95	0.95

Note: N=660. The control variables are values at the start of each period (2000-2005 or 2005-2010). Demographic features include the initial population share of minority and the population shares of each cohort (e.g., people born before 1940, 1941-1950, 1951-1960, 1961-1970). Industry structures include the employment share of manufacturing, export share of textile, and export share of electronic & machinery. Major port cities include Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai. Models are weighted by prefecture-level residence-based population in 2000. Robust standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3 By-Cohort Analysis

Dependent Variable: 100 × △ (no. people with some college or above)/population (in % pts)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Born 1986-1989	Born 1982-1985	Born 1978-1981	Born 1974-1977	Born 1970-1973	Born 1960-1969	Born 1950-1959
△Capital goods import per capita	18.64***	13.09***	-2.44	2.95***	1.77**	2.02***	1.05*
	(5.30)	(4.80)	(1.53)	(0.98)	(0.83)	(0.63)	(0.61)
Mean(Y)	2.06	7.87	11.28	9.40	7.68	6.17	3.69
Mean(△Y)	14.55	11.09	4.28	3.09	1.85	0.87	0.29

Note: N=660. The start-of-period minority share, the share of people by cohorts, and province-year fixed effects are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 Growth in Imported Capital Goods and Change of College Share

Dependent Variable: 100 × △ (no. people with some college or above)/population (in % pts)

Born between 1986 and 1989	(1)	(2)	(3)	(4)	(5)	(6)
△Capital goods import per capita	18.64***	14.20***	14.54***	18.63***	21.70**	15.16**
	(5.30)	(4.94)	(4.91)	(5.29)	(8.44)	(6.96)
Years of schooling		7.94***				4.71***
		(1.38)				(1.50)
Share of people with urban *hukou*			45.99***			28.03***
			(7.20)			(7.57)
Trade policy uncertainty				2.62		1.87
				(3.45)		(3.53)
Employment share of State-owned enterprises					9.31**	3.84
					(4.37)	(3.80)
Employment share of Foreign-owned enterprises					-17.68	-10.10
					(22.30)	(16.08)
N	660	660	660	660	612	612
Dummy for period 2000-2005	√	√	√	√	√	√
Province-year fixed effects	√	√	√	√	√	√
Dummies for large ports and their interactions with time	√	√	√	√	√	√
Demographic features	√	√	√	√	√	√
Industry structure & export structure	√	√	√	√	√	√
△College departments in 1952	√	√	√	√	√	√

Note: N=660. The control variables are values at the start of each period (2000-2005 or 2005-2010). Demographic features include the initial population share of minority and the population shares of each cohort (e.g., people born before 1940, 1941-1950, 1951-1960, 1961-1970). Industry structures include the employment share of manufacturing, export share of textile, and export share of electronic & machinery. Major port cities include Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai. Models are weighted by prefecture-level residence-based population in 2000. Robust standard errors clustered at province are shown in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5 Decomposition

(1)=(2)+(3)-(4)	(1) Y=100×(△no. people with some college or above)/population	=	(2) Local	+	(3) Immigration	-	(4) Emigration
Panel A. 1986-1989							
△Capital goods import per capita	18.64***		15.76***		1.76		-1.11**
	(5.30)		(5.01)		(1.21)		(0.54)
Panel B. 1982-1985							
△Capital goods import per capita	13.09***		9.52**		3.33***		-0.24
	(4.80)		(3.84)		(0.91)		(0.57)
Panel C. 1978-1981							
△Capital goods import per capita	-2.44		-4.31***		1.73***		-0.13
	(1.53)		(1.56)		(0.43)		(0.22)
Panel D. 1974-1977							
△Capital goods import per capita	2.95***		1.76**		1.29**		0.10
	(0.98)		(0.90)		(0.60)		(0.20)

Note: N=660. The start-of-period minority share, urban share, industry structure, college reallocation, average years of schooling, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6 Spillover Effects

(1)=(2)+(3)-(4)	(1) Y=100×(△no. people with some college or above)/population	=	(2) Local	+	(3) Immigration	-	(4) Emigration
Panel A. 1986-1989							
△Capital goods import per capita	15.01***		13.26***		0.43		-1.33**
	(4.68)		(4.47)		(1.42)		(0.58)
Spillover of neighboring prefectures	-1.39**		-0.75		-0.43*		0.21***
	(0.64)		(0.67)		(0.22)		(0.04)
Panel B. 1982-1985							
△Capital goods import per capita	10.11***		7.12**		2.31**		-0.68**
	(3.88)		(3.17)		(1.01)		(0.28)
Spillover of neighboring prefectures	-0.37		-0.05		-0.15***		0.17***
	(0.55)		(0.59)		(0.06)		(0.06)
Panel C. 1978-1981							
△Capital goods import per capita	5.21**		3.46		1.21**		-0.54
	(2.34)		(2.21)		(0.47)		(0.36)
Spillover of neighboring prefectures	-0.21		-0.11		-0.10***		-0.00
	(0.40)		(0.43)		(0.02)		(0.05)
Panel D. 1974-1977							
△Capital goods import per capita	2.97**		1.89		0.91***		-0.17
	(1.24)		(1.18)		(0.27)		(0.23)
Spillover of neighboring prefectures	-0.34*		-0.29		-0.03		0.02
	(0.18)		(0.18)		(0.03)		(0.03)

Note: N=660. The start-of-period minority share, industry structure, college reallocation, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7 Growth in Imported Capital Goods and Growth in Wage

	(1) △log(Wage)	(2) △log (Wage: skill workers)	(3) △log (Wage: low skilled workers)	(4) 100*△log (Skill premium)	(5) 100*△log (Skill premium): controlling for individual features
Panel A: one-year difference					
△log(Capital goods import)	0.00	0.06**	-0.01	0.23***	0.20**
	(0.02)	(0.03)	(0.02)	(0.07)	(0.08)
N	1617	1617	1617	1605	1564
Panel B: three-year difference					
△log(Capital goods import)	0.02	0.07*	0.01	0.24**	0.33***
	(0.02)	(0.04)	(0.03)	(0.09)	(0.06)
N	507	507	507	501	492
Panel C: seven-year difference					
△log(Capital goods import)	0.05	0.07	-0.00	0.14**	0.09
	(0.04)	(0.04)	(0.04)	(0.06)	(0.11)
N	169	169	169	168	167

Note: In the analysis, I use wage information in the Urban Household Survey. Panel A uses data from 1997 to 2009. Panel B uses data in 1997, 2000, 2003, 2006, and 2009. Panel C uses data in 2002 and 2009. The province-year fixed effects are controlled for Panel A and B. Wages are measured in yuan and deflated to the 1992 level. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

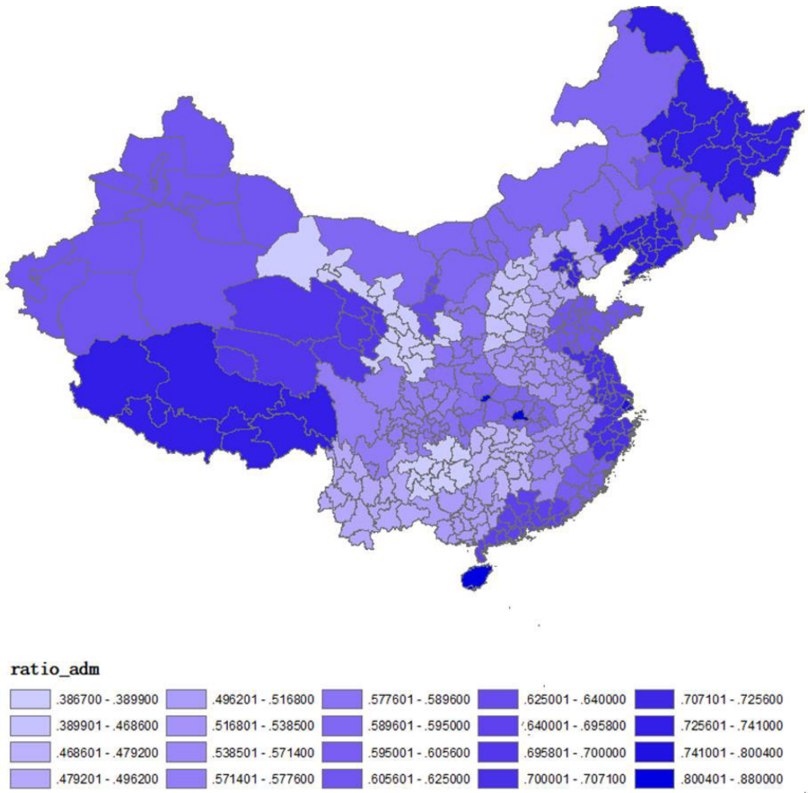
Table 8 Imported Capital Goods and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	100*Ln (Wage)	100*Ln(Value-added per Worker)	100*Share of Workers with College Degree	100*Computer per Worker	100*Profit/ Sales	100*Operation Profit/Sales
	2000-2007	2000-2007	2004	2004	2004	2004
Imported Capital Goods/Imports	2.47***	6.25***	5.31***	6.28***	1.03***	0.93***
	(0.36)	(0.56)	(0.24)	(0.25)	(0.28)	(0.24)
Export/Sales	3.04***	1.41***	-1.89***	-0.75***	-0.63**	-0.56**
	(0.34)	(0.52)	(0.11)	(0.10)	(0.26)	(0.24)
Import/Inputs	4.66***	14.79***	3.07***	5.01***	0.12	0.21
	(0.86)	(1.39)	(0.37)	(0.37)	(0.74)	(0.67)
Foreign-owned firm indicator	2.66***	0.98*	4.18***	4.12***	0.46***	0.67***
	(0.39)	(0.59)	(0.11)	(0.10)	(0.13)	(0.12)
State-owned firm indicator	-1.59***	-5.63***	3.49***	1.29***	-4.32***	-4.62***
	(0.51)	(0.76)	(0.23)	(0.17)	(0.35)	(0.32)
Ln(Employment)	-14.79***	-42.33***	-0.88***	-1.56***	0.20***	0.11**
	(0.19)	(0.27)	(0.04)	(0.03)	(0.05)	(0.04)
City-Industry(4-digit) Fixed Effects			√	√	√	√
Firm Fixed Effects	√	√				
Year Fixed Effects	√	√				
Mean: Imported Capital Goods/Imports	0.03	0.03	0.03	0.03	0.03	0.03
Mean: Dependent Variable	246.90	401.29	11.48	7.48	3.48	3.34
Observations	1,482,241	1,482,241	216,932	216,932	216,995	216,995

Note: I use the data from the Survey of Industrial Production and the China General Administration of Customs. A skilled worker is defined as someone with a college degree or above. Imported capital goods intensity is defined as the share of imported capital goods out of capital stock. Reported standard errors are robust and are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

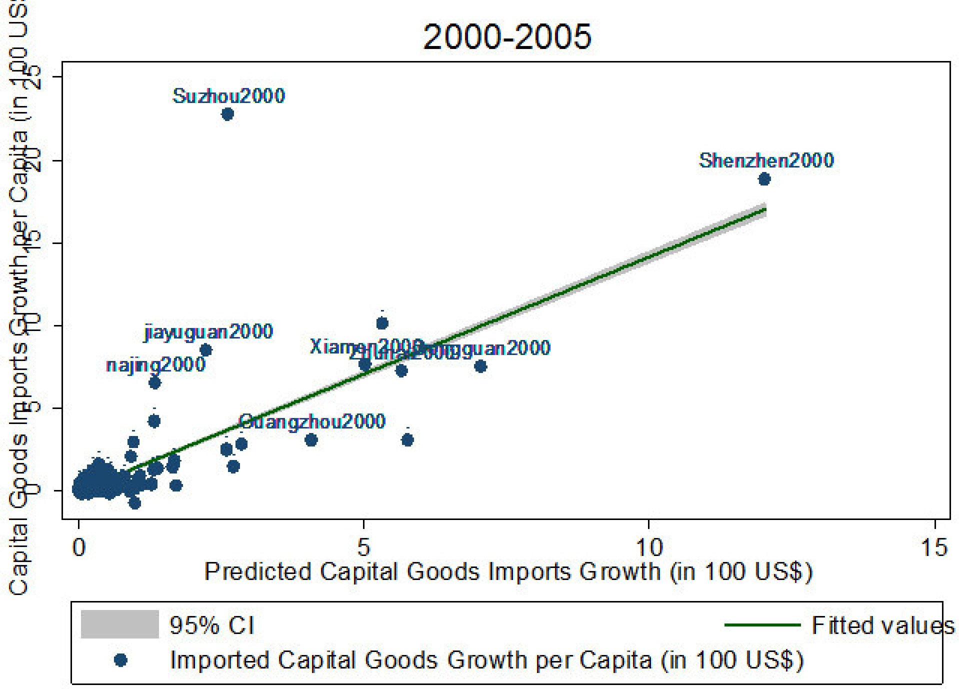
Figure A1 Spatial Distribution of College Admission Rate in 2007

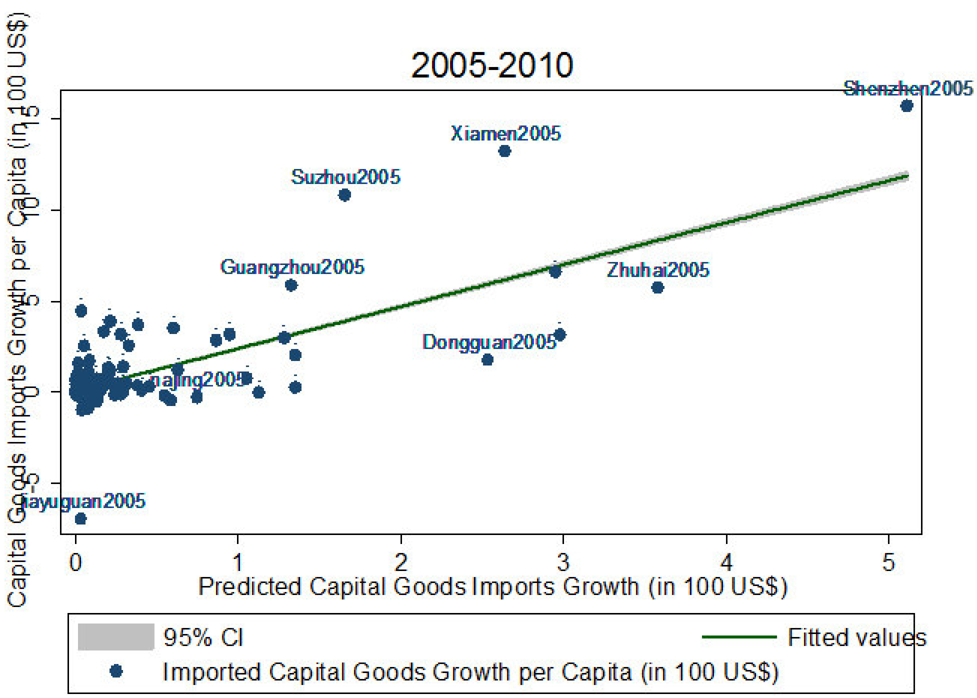


Data: China's Statistical Yearbook.

Note: The college admission rate in mainland China is at the province level. Due to data limitations, the data in 2007 is the latest data available.

Figure A2 First Stage by Period





Note: the figure on the top shows the first stage between 2000 and 2005, and the figure on the bottom shows the first stage between 2005 and 2010.

Table A1 Robustness: Non-Capital Goods Imports and Exports

(1)=(2)+(3)	(1) Export	(2) All Non-K	(3) Consumption goods & others	(4) Inputs & Raw Material
Panel A Correlation				
△Imported capital goods per capita vs. △Other imported or exported goods per capita	0.84	0.69	0.42	0.67
Panel B Second Stage △Y=100×△College Share				
△Imported Capital goods per capita	2.43	1.15	2.45	1.04
	(2.57)	(1.43)	(3.39)	(1.30)
△Other imported or export goods per capita	-0.31	-0.10	-4.38	-0.09
	(0.31)	(0.14)	(6.58)	(0.13)

Note: N=660. The start-of-period cohort dummies, minority share, industry structure, college reallocation, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A2 FDI and SOE Reform

Dependent Variable: 100 × △ (no. people with some college or above)/population (in % pts)

	(1) Born 1986-1989	(2) Born 1982-1985	(3) Born 1978-1981	(4) Born 1974-1977	(5) Born 1970-1973	(6) Born 1960-1969	(7) Born 1950-1959
△Capital goods import per capita	15.56**	13.45*	-2.12	3.07*	1.89*	2.86**	1.76*
	(6.77)	(7.29)	(1.68)	(1.62)	(1.06)	(1.24)	(1.03)
Employment share of state-owned firms	3.95	-2.92	1.73	1.13	0.50	-0.31	-0.77*
	(3.53)	(3.14)	(1.52)	(1.26)	(0.69)	(0.54)	(0.45)
Employment share of foreign-owned firms	-9.51	-14.61	10.01*	-1.88	-2.67	-5.72*	-3.41
	(16.10)	(15.34)	(5.67)	(3.67)	(2.29)	(3.14)	(2.24)
Mean(Y)	2.13	8.09	11.58	9.58	7.81	6.25	3.76
Mean(△Y)	14.96	11.35	4.31	3.12	1.86	0.87	0.29

Note: N=612. There are 48 cities whose employment shares by ownership have missing values. The start-of-period urban share, minority share, average years of schooling, college share, senior high school share, the number of moved-in departments in 1952, the share of people by cohorts, manufacturing share, export share of textile, export share of electronic and machinery, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3 Spillover Effect: by-cohort Analysis

Dependent Variable: 100 × △ (no. people with some college or above)/population (in % pts)

	(1) Born 1986-1989	(2) Born 1982-1985	(3) Born 1978-1981	(4) Born 1974-1977	(5) Born 1970-1973	(6) Born 1960-1969	(7) Born 1950-1959
Panel A. Baseline							
△Capital goods import per capita	13.85***	9.25***	4.77**	2.76**	0.07	0.63	-0.02
	(4.49)	(3.46)	(2.09)	(1.20)	(0.62)	(0.42)	(0.25)
Panel B. Inverse distance weighted △capital goods import per capita of all the rest prefectures							
△Capital goods import per capita	15.20***	10.01***	5.12**	3.05***	0.07	0.82*	0.08
	(4.55)	(3.69)	(2.09)	(1.14)	(0.69)	(0.42)	(0.25)
△Capital goods import in other prefectures per capita	-15.94**	-8.94	-4.15	-3.39**	0.06	-2.25***	-1.14**
	(7.90)	(6.09)	(4.27)	(1.38)	(1.10)	(0.74)	(0.53)
Panel B. Inverse distance weighted △capital goods import per capita of all the neighboring prefectures							
△Capital goods import per capita	14.19***	9.37***	4.80**	2.84**	0.09	0.67*	0.00
	(4.24)	(3.43)	(2.05)	(1.11)	(0.63)	(0.40)	(0.24)
△Capital goods import in neighboring prefectures per capita	-1.19*	-0.40	-0.11	-0.28*	-0.06	-0.16***	-0.07**
	(0.66)	(0.58)	(0.41)	(0.16)	(0.11)	(0.05)	(0.03)
Panel C. Share of neighboring cities with more △capital goods import per capita							
△Capital goods import per capita	14.47***	9.44**	4.84**	2.74**	-0.03	0.60	-0.04
	(4.89)	(3.82)	(2.29)	(1.31)	(0.71)	(0.45)	(0.27)
Spillover effect (R=200km)	4.07	1.21	0.49	-0.12	-0.67	-0.16	-0.15
	(3.00)	(2.68)	(1.70)	(1.04)	(0.51)	(0.34)	(0.18)
Mean of Y	14.63	12.19	9.65	5.39	2.18	1.07	0.40

Note: N=660. The start-of-period minority share, industry structure, college reallocation, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A4 Spillover Effects and Decomposition

(1)=(2)+(3)-(4)	(1) Y=100×(△no. people with some college or above)/population	=	(2) Local	+	(3) Immigration	-	(4) Emigration
Panel A. Inverse distance weighted △capital goods import per capita of all the rest prefectures							
△Capital goods import per capita	1.77**		1.31***		0.38		-0.07
	(0.79)		(0.47)		(0.41)		(0.13)
△Capital goods import in neighboring prefectures per capita	-0.12		-0.22***		0.08		-0.03**
	(0.12)		(0.08)		(0.05)		(0.01)
Panel B. Employment share weighted △capital goods import per capita of neighboring prefectures							
△Capital goods import per capita	1.88**		1.49***		0.34		-0.06
	(0.84)		(0.51)		(0.40)		(0.12)
△Capital goods import in other prefectures per capita	-1.63		-2.71***		0.78		-0.30*
	(1.22)		(0.85)		(0.66)		(0.17)
Panel C. Share of neighboring cities with more △capital goods import per capita							
△Capital goods import per capita	1.67*		1.19**		0.39		-0.09
	(0.87)		(0.57)		(0.42)		(0.13)
Share of neighboring cities with larger imports (R=200km)	-0.35		-0.17		-0.24		-0.06
	(0.59)		(0.43)		(0.27)		(0.12)

Note: N=660. The start-of-period cohort dummies, minority share, industry structure, college reallocation, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A5 Spillover Effects and Decomposition: by-cohort Analysis

(1)=(2)+(3)-(4)	(1) Y=100×(△no. people with some college or above)/population	=	(2) Local	+	(3) Immigration	-	(4) Emigration
Panel A. 1986-1989							
△Capital goods import per capita	15.20***		14.30***		-0.43		-1.33**
	(4.55)		(4.40)		(1.35)		(0.63)
△Capital goods import in other prefectures per capita	-15.94**		-19.58***		5.10*		1.46
	(7.90)		(7.25)		(2.83)		(1.06)
Panel B. 1982-1985							
△Capital goods import per capita	10.01***		7.55***		1.83		-0.64**
	(3.69)		(2.91)		(1.15)		(0.30)
△Capital goods import in other prefectures per capita	-8.94		-9.17*		0.96		0.73
	(6.09)		(5.51)		(1.05)		(1.02)
Panel C. 1978-1981							
△Capital goods import per capita	5.12**		3.38*		1.06**		-0.68*
	(2.09)		(1.87)		(0.50)		(0.37)
△Capital goods import in other prefectures per capita	-4.15		-3.38		-0.29		0.48
	(4.27)		(4.57)		(0.49)		(0.86)

Note: N=660. The start-of-period cohort dummies, minority share, industry structure, college reallocation, and province-year fixed effect are controlled. Dummies for major port cities (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by the residence-based population in 2000 using the tabulated city-level data. Models are weighted by prefecture-level residence-based population in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A6 Correlation

Whole sample	△Capital goods import per capita	△Export per capita	Average years of schooling	College share	Senior high share	Mfg. share	Textile	Electronic
△Capital goods import per capita	1.00							
△Export per capita	0.84	1.00						
Average years of schooling	0.21	0.25	1.00					
College share	0.25	0.23	0.72	1.00				
Senior high school share	0.28	0.31	0.85	0.70	1.00			
Manufacturing employment share	0.49	0.69	0.40	0.29	0.47	1.00		
Export share of textile	-0.01	0.04	0.04	0.03	0.06	0.11	1.00	
Export share of electronic and machinery	0.41	0.48	0.27	0.23	0.27	0.49	-0.03	1.00

Dropping outliers	△Capital goods import per capita	△Export per capita	Average years of schooling	College share	Senior high share	Mfg. share	Textile	Electronic
△Capital goods import per capita	1.00							
△Export per capita	0.68	1.00						
Average years of schooling	0.25	0.24	1.00					
College share	0.31	0.20	0.71	1.00				
Senior high school share	0.32	0.29	0.85	0.70	1.00			
Manufacturing employment share	0.49	0.74	0.38	0.27	0.45	1.00		
Export share of textile	0.04	0.11	0.04	0.03	0.08	0.14	1.00	
Export share of electronic and machinery	0.33	0.37	0.24	0.20	0.23	0.41	-0.02	1.00