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

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Abstract

China has witnessed rising demand for skill in the last few decades, as evidenced by simultaneous rapid increases in both the college share and the college wage premium. This paper shows that capital goods imports, an important form of international technology diffusion, can explain the rising demand for skill in China. Using a shift-share instrument, I show that regions with faster growth in capital goods imports experienced greater increases in college share between 2000 and 2010. Analysis by cohort suggests that the impact of capital goods imports growth was stronger for young people. Furthermore, I quantify how skilled labor relocation can account for regional differences in college attainment. I find that growth in the import of capital goods not only encouraged local stayers to accumulate human capital but also attracted more skilled immigrants and ameliorated the brain drain of skilled emigrants. In addition, I supplement the above analysis by providing direct evidence on the positive impact of capital goods imports on firm’s demand for skill.

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1 Introduction

One of the most notable features of China’s labor market during the past few decades has been the rapid accumulation of human capital (Figure 1). The skill share in China, i.e., the number of people with at least some college education as a share of the number of people older than 15, quadrupled from 1.9% in 1990 to 8.2% in 2009. The skill premium for college-educated workers rose at a similar pace from 14.3% in 1992 to 44.4% in 2009.[1] These phenomena suggest that the demand for skill has increased dramatically in China’s labor market. Whereas skill-biased technological change at the technology frontier has been identified as a major driving force for rising skill demand in developed countries [Katz and Autor 1999; Autor, Katz and Kearney 2008; Acemoglu and Autor 2011], the impact of technology on the labor market may be even more dramatic for a developing economy like China that is in a process of catching up with the technology frontier.

In this paper, I argue that the import of capital goods such as modern production machinery and computers is an important driving force for the rising skill demand in China. The logic goes as follows: as a developing country, China’s technological advances mainly come from international technology diffusion rather than domestic innovation [Grossman and Helpman 1991; Coe and Helpman 1995; Eaton and Kortum 2001].[2] The import of capital goods which embodies the state-of-the-art technology is an important form of such technology diffusion. Due to the complementarity between capital and skill [Griliches 1969; Goldin and Katz 1998; Katz and Autor 1999; Krusell et al. 2000], capital goods imports drive up the demand for skill and thus encourage human capital accumulation and skill-biased migration to the regions where the demand for skill grows most.

China has experienced a surge in capital goods imports during the past several decades. Capital goods imports increased rapidly from 89 billion U.S. dollars in 2000 to 551 billion U.S. dollars in 2010, with an average annual growth rate of 20%.[3] Moreover, there are large

[1] I will use the terms skill premium and college premium interchangeably in later sections. Similarly, skill share and college share will also be used interchangeably.

[2] Because technology advances are highly concentrated in a handful of developed economies [Eaton and Kortum 2001], international technology diffusion plays a major role in shaping domestic technology in most countries. For most countries, about 90 percent of domestic productivity growth may be attributed to international technology diffusion [Keller 2004].

[3] The growth in capital goods imports 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%. The growth of the skill share was also slower in the 1990s.
regional differences in the amount of capital goods imported. The mechanism proposed in this paper suggests that regions with greater capital goods imports should see a stronger increase in their demand for skill. Indeed, this is what I observe in the data. From 2000 to 2010, the coastal regions experienced faster growth in capital goods imports than the inland regions (Figure 2). During the same period, the difference in the skill share between the coastal regions and the inland regions increased from 1.3 percentage points to 3.0 percentage points, while the difference in the skill premium increased from 5.7 percentage points to 11.6 percentage points. These two facts suggest that the demand for skill increased more in the coastal regions than in the inland regions.

To my knowledge, this paper is the first to investigate the impact of capital goods imports on skill supply. Taking the 330 Chinese prefectures as the unit of analysis, I exploit regional variations in initial trade patterns to analyze the relationship between the growth in per capita capital goods imports and the change in skill share of a prefecture. By using the population survey data collected by China’s National Bureau of Statistics, I am able to study the impact of capital goods imports with the economy-wide data. To tackle causality, I construct a shift-share instrument (Bartik, 1991) that is a prediction of the realized per capita capital goods imports growth for each prefecture. By combining each prefecture’s initial mix of capital goods imports and national-level data on import growth by product, I can characterize the exposure of a prefecture to national import growth. The shift-share instrument captures the demand-driven component of the capital goods imports and allows me to identify the causal link from capital goods imports to skill share.

The empirical results show that capital goods imports are indeed a key driving force for the regional differences in skill share in China. A prefecture at the 75th percentile of the distribution of capital goods imports growth per capita experienced a 0.2 percentage point larger increase in the skilled labor share (0.07 standard deviation) than a prefecture at the 25th percentile. The impact of capital goods imports was the strongest for young people born between 1982 and 1985 and gradually faded for older cohorts.

The granularity of my data allows me to quantify how skilled labor relocation can account than in the 2000s (2.7% percentage points vs 3.6% percentage points).

4 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).
for regional differences in human capital accumulation. To be more specific, I study how much of the rise in college share is due to the human capital accumulation of local stayers, skilled immigrants, and skilled emigrants; the last two components are less explored in the literature. Three waves of population surveys in 2000, 2005, and 2010 conducted by China’s National Bureau of Statistics collected information on individuals’ places of residence five years prior. Taking advantage of this information, 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. Using that information, I show that for young people between ages 15 and 18 at the start of a five-year period, skill acquisition of local stayers can account for 22% of the regional difference in the growth of college share that capital goods imports induce. Greater immigration and lower emigration of skilled individuals account for the remaining 58% and 20% of the regional differences, respectively. For older cohorts, the regional differences in the growth of skilled labor supply are almost entirely due to skilled labor relocation.

In addition to the skill share, this paper also explores the impact of capital goods imports growth on wage growth. More specifically, the average wage grew by 541 yuan, 9% of the overall increase in average wage, more in a prefecture at the 75th percentile of exposure to capital goods imports, compared to a city at the 25th percentile. Moreover, regions with faster growth in capital goods imports experienced faster wage growth among skilled labors and unskilled labors alike and the impact was stronger for skilled workers. When imported capital good growth per capita increased by a hundred U.S. dollars, the average wage of skilled labors increased by 2,634 yuan while the average wage of unskilled labors only increased by 761 yuan.

In the analysis, I also consider the spillover effects of capital goods imports. There would be more skilled emigrants and less skilled immigrants for a prefecture when other prefectures imported more capital goods. The decline in local skill supply increased the local skill premium and thus decreased the regional differences in skill premium. Compared with the impact of the local capital goods imports, the magnitudes of the spillover effects on skill share and skill premium are small.

Using firm data, I supplement the above analysis by providing evidence on how firms adjust production and how the import of capital goods affects firms’ demand for skill. Firms
that import more capital goods hire more skilled workers, use computers more intensively, pay higher wages, and have higher labor productivity. These findings support the notion that capital goods imports are complements to skilled labor.

The paper contributes to the literature by being the first to empirically quantify the impact of capital goods imports—a new channel—on human capital accumulation. While previous studies on developing countries find that both exports, which are usually less skill-intensive, and imports could lead to a decline in schooling [Edmonds, Pavcnik and Topalova, 2010; Atkin, 2016; Li, 2018], this paper shows that skill-complementary capital goods imports increase the demand for skill and encourages human capital accumulation.

This paper is also the first to quantify how skilled labor relocation can account for regional differences in human capital. The detailed information in the data allows me to decompose regional changes in the college share into the effects of skill acquisition among local stayers and changes in skill supply due to domestic migration; the latter is less explored in the literature. I find that the arrival of more skilled immigrants and the reduction in brain drain could explain much of the regional differences in college share. The findings of this paper suggest that the import of capital goods has played an important role in shaping regional differences in college share, which deepens our understanding of trade’s role in the widening human capital inequality between regions in China.

This paper has several implications. First, there has been a significant relocation of skilled laborers in response to the positive trade shocks, which is contrary to the observation that workers are reluctant to move when faced with adverse import competition shocks [Pavcnik, 2017]. Second, migration mitigates the regional inequality in the skill premium by increasing the relative supply of skilled laborers in the regions that are more exposed to capital goods imports shocks. 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.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the background, describe 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 capital goods imports on college share and college premium respectively. Section 7 supplements the above analysis by providing firm-level evidence. Section 8 concludes.
This paper relates to a growing body of literature on trade and 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 provide support for this argument. 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 to show that low skill-intensive exports depress educational attainment and skill-intensive export increase schooling. Li (2018) also reports similar findings using several waves of population survey data in China. Meanwhile, Topalova (2010) find that intensified import competition reduces job opportunities and increases 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.

This paper is the first to empirically quantify the impact of a new channel, namely capital goods imports, on human capital accumulation. While the previous studies find that both exports, which are usually less skill-intensive, and imports reduce schooling in developing countries, this paper shows that capital goods imports encourage skill acquisition in China. Moreover, this paper not only studies the impact of trade on the skill acquisition among local stayers but also considers the impact of trade on migrants.

This paper also complements studies on globalization and migration. While the impacts of negative trade shocks on internal migration are limited (Topalova 2010; Autor, Dorn and Hanson 2013; Kovak 2013; Dix-Carneiro and Kovak 2017) 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. Rising exports (Wang 2016), lower trade uncertainty (Potloga and Cheng 2017; Facchini et al. 2018) and the reduction of tariffs (Zi 2017) all contribute to greater internal migration and regional population growth. Relative to the literature, this paper explores a new channel, namely capital goods imports, which trigger a migration response. Furthermore, while previous
studies use regional aggregate data to analyze population growth or population inflows, the
detailed information in the microdata allows me to quantify the impacts of capital goods
imports on both population inflows and outflows with a focus on the different responses by
skill.

This paper also fits in the literature on globalization and demand for skill in developing
countries (Goldberg and Pavcnik 2007; Goldberg 2015; Pavcnik 2017). The workhorse
model of Heckscher-Ohlin along with the associated Stolper-Samuelson theorem predict
that the skill premium should decrease after a labor-abundant country opens to trade.
However, the empirical evidence reveals that the skill premium rises after trade liberal-
ization in developing countries. Motivated by this puzzle, researchers have relaxed the
assumptions in the Heckscher-Ohlin model and proposed alternative explanations for this
phenomenon (Bernard, Jensen and Redding 2007; Burstein and Vogel 2017). The first ex-
tension and modification of the Heckscher-Ohlin model is the well-studied channel which
allows trade-induced technology upgrading. Exporting to larger markets (Yaple 2005;
Bustos 2011b) or exporting to richer countries makes technological adoption more prof-
itable due to product quality considerations (Verhoogen 2008). Because the adoption and
operation of new technology requires skill (Bustos 2011a), exporting may increase demand
for skill. Imports can also raise skill demand if import competition encourages defensive
innovation that is skill-biased (Wood 1995; Thoenig and Verdier 2003; Teshima 2008).
The second deviation is the introduction of trade protection such as import restrictions.
Low skilled workers in developing countries will benefit less from international trade with
developed countries if the latter use tariff barriers to protect their unskilled-intensive in-
dustries (Attanasio, Goldberg and Pavcnik 2004). The third deviation is to incorporate
machinery or intermediate inputs into the production function and relax the assumption
that only final goods can be traded. Although substantial literature studies offshoring and
trade in intermediate inputs (Feenstra and Hanson 1996, 1997, 1999), the role of trade
in capital goods has not received much attention. The related theoretical papers include
Burstein, Cravino and Vogel (2013); Parro (2013) and Fan (2017) who build general equi-
librium models to show that capital goods imports can increase the skill premium. Despite

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5 Though the trade-induced technology upgrading channel and the channel of capital goods imports both
relate to technology adoption, the former explains why firms want to adopt technology while the latter
focuses on how firms acquire technology.

6 For the role of intermediate inputs, Amiti and Cameron (2012) set forth another explanation about how
the reduction in input tariffs and the import of intermediate inputs reduce skill premium in importing firms.
its importance, to my knowledge, only three recent papers provide empirical evidence on
the causal impact of capital goods imports on the skill premium (Raveh and Reshef, 2016; Koren and Csillag, 2017; Li, Li and Ma, 2018). Raveh and Reshef (2016) use a panel of 21
developing countries and show that R&D-intensive capital goods imports increase the skill
premium. Using the Hungarian linked firm-employee data, Koren and Csillag (2017) show
that operators of imported machines earn more than similar workers at similar firms and
that increasing exposure to imported machines explain a quarter of the rise of returns to
skill. Li, Li and Ma (2018) use household survey data and trade data to show that greater
increases in capital goods imports predicted by exchange rate fluctuations have been asso-
ciated with greater increases in the skill premium. This paper moves beyond the above
studies to examine how the supply of skilled labor reacts to regional increases in demand
for skill triggered by the surge in capital goods imports.

This paper also relates to broad literature concerning the impact of imports on local
labor markets. Most of the existing empirical studies show that imports that compete with
local outputs reduce employment and earnings in developed countries (e.g., Autor, Dorn
and Hanson, 2013) and increase the poverty rate, shift employment towards informal sectors,
and depress educational attainment in developing countries (e.g., Edmonds, Pavnik and
Topalova, 2010; Topalova, 2010; Dix-Carneiro and Kovak, 2017; Dai, Huang and Zhang,
2018). In contrast, Zi (2017) finds that input tariff reductions increase employment and
lead to welfare improvement in China; however, she does not provide evidence on the direct
impacts of imports. In this paper, I show that capital goods imports, a crucial way for devel-
op ing countries to acquire advanced technology, increase the demand for skill and encourage
human capital accumulation. In the Heckscher-Ohlin model, trade liberalization decreases
the demand for skill in developing countries because the production of skill-intensive goods
is shifted to developed countries. However, the negative import competition effect of skill-
intensive imports, such as machinery, will be quite modest if the skill-intensive goods were
not mass-produced in developing countries before trade liberalization. This explains why
the positive impact of capital goods imports on the demand for skill dominates its negative
impact. Furthermore, the findings of this paper also contribute to the understanding of
trade’s role in China’s widening regional differences in human capital.
3 Institutional Background and Data

In this section, I introduce the background, summarize the data used in the analysis, and document several stylized facts.

3.1 China’s import of capital goods

One remarkable feature of China’s trade liberalization has been the surge of capital goods imports (Figure 4). As technology advances are highly concentrated in a handful of developed economies [Eaton and Kortum 2001], international technology diffusion has been an important way to transfer among most countries [Keller 2004]. China was isolated from the rest of the world since 1949 and its technology level greatly lagged. Given the strong demand for advanced technology, China named “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 is particularly popular for its convenience and transparency. As shown in Figure 3, China’s imports in capital goods increased rapidly with an average annual growth rate of 20% after China entered the World Trade Organization (WTO). In 2010, China’s total import of capital goods imports was as much as 551 billion U.S. dollars. The fast globalization has been accompanied by rapid economic development, which has been driven by productivity growth [Zhu 2012].

Moreover, there have been substantial variations in the imports of capital goods across regions. Panel A of Figure 2 shows that most of the growth in capital goods imports occurred in coastal areas. Panel B continues to emphasize that coastal regions’ share in capital goods imports also increased, while inland regions experienced a decline in the share of capital goods imports relative to total imports. The large disparity of capital goods imports across local labor markets provides the identifying variations for the empirical analysis.

Figure 4 shows that there were large regional variations in changes in capital goods import per capita between 2000 and 2010. Prefectures in coastal regions had higher growth in capital goods import. Table 1 further presents the summary statistics. The average growth in capital goods imports per capita across prefectures was 0.7 (measured in units of 100 US dollars, and thus corresponding to $70 per person), with an inter-quartile range of 0 to 0.3, implying substantial skewness in this measure. I address skewness by presenting
results with and without outlier cities that have exceptionally high levels of exposure to capital imports growth, 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 capital goods imports growth are cities that have access to major international ports and that were among the earliest prefectures with special economic zones ([Wang 2013] [Alder, Shao and Zilibotti 2016]).

[INSERT Figure 4 and Table 1]

I also make international comparisons to examine the importance of capital goods imports for other countries. Figure 5 compares the import shares of capital goods between China, seven developed countries, newly industrialized countries with high manufacturing shares, and newly industrialized countries with low manufacturing shares. As shown, China’s import share of capital goods has risen 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. The international comparison reveals that newly industrial countries which have a comparative advantage in manufacturing, also tend to have a higher share of capital goods imports during the economic take-off. However, capital goods import share was much lower for newly industrialized countries with low manufacturing shares and the G7.[7] For the G7, the import share of capital goods was 29 percentage points in 1998, which was 10 percentage points smaller compared to 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, which was 22 percentage points smaller compared to China.

[INSERT Figure 5]

The above analysis is based on trade data from the UN Comtrade database and China’s Customs Bureau. The latter gives details 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. In the following empirical analysis, I focus on the period between 2000 and 2010, which spanned the most intense phase of China’s post-WTO

[7]The seven developed countries include Canada, France, Germany, Japan, Italy, the United Kingdom, and the United States.
import growth. Prefecture-level trade data are available as of 1997, and I use that year to construct the shift-share instrument.

### 3.2 The fast human capital accumulation in China

The overall education level of China was low before the 1978 “reform and opening”. According to the World Bank, China’s tertiary enrollment was as low as 0.1% in 1970, while the world’s tertiary enrollment rate was 10.1%. Despite the low level of education, China’s higher education system experienced several structural changes. One important reform was the college 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 capital goods imports on human capital.

China saw a modest increase in the number of college students after the economic reform in 1978; the increase in college enrollment has accelerated since 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%. In 2017, the number of college admissions was as high as 7 million. Between 1998 and 2017, the annual growth rate in college admissions was 11%.

The increase in college enrollment could well be a result of the rising demand for skilled workers (Li et al. 2017). As shown in Figure 1, the return to college education in China has continued to increase rapidly despite the unprecedented increase in college enrollment, implying a strong demand-side force. A possible reason for the rising demand for skill is the surge in capital goods imports. Moreover, 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. This indicates that the demand-side force also plays a role in those newly industrialized economies.

Along with the rapid increases in college enrollment, widening regional disparities have developed. As shown in Appendix Figure A1, college enrollment rates differ across regions
and are higher for coastal regions compared with inland regions. A possible explanation is that coastal regions have a higher demand for skill. As pointed out by Lanqing Li, then Vise Premier of China, in 2003, one of the main objectives of China’s college expansion policy was to meet the increasing demand for skilled workers. Although most of the colleges and universities in China are public and the Ministry of Education has played an important role in the allocation of college admissions quotas, the quota for each province is allocated according to the local demand for skill.

In the empirical analysis below, I use population survey in 2000, 2005, and 2010 to study the regional differences in human capital. The available samples cover between 0.1%, 0.2%, and, 0.3% of the Chinese population in each year. To test the representativeness of the data, 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 China’s National Bureau of Statistics. The comparison results suggest that samples are representative of national data. Additional details on the comparison are displayed in the Appendix. In the subsample of the 2010 census, there are 7 cities that are heavily under-sampled. To alleviate the concern that data for these cities are not representative, I delete the 7 cities and use data for the remaining 330 cities in the analysis.

3.3 China’s rising skill premium

Over the past several years, China has experienced a fast rise in the skill premium. As shown in Figure 1, the skill premium, or the wage gap between workers with college or above education and those with less education, widened between 1992 and 2009. In 1992, skilled workers earned 14% more than unskilled workers. The wage gap has widened since China entered the WTO in 2001, rising to 44% in 2009.

Meanwhile, the regional differences in the skill premium have also widened as shown in Figure 6. 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 re-
gional disparity in the skill share, which increased from 1.3 percentage points in 2000 to 3.0 percentage points in 2010.

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 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. To ensure representativeness, the NBSC adopts a probabilistic and stratified multistage sampling method when selecting households. The second advantage of the UHS data is its long time span, which allows me to study the labor market dynamics of China. Another advantage of the UHS data is comparability. Because the NBSC uses similar sampling methods and questionnaires for each survey, the data are comparable over time and across regions. The data cover 31 provinces in China; I have access to data covering 18 provinces, which are representative regarding geographic location and economic development. For my purposes, I focus on employed people between ages 16 and 60. To calculate the prefecture-level skill premium, I separately estimate a Mincerian wage regression \(^{[Mincer\ 1974]}\) for each prefecture in each year.

3.4 Supplementary data

To provide additional evidence for capital-skill complementarity, I use the Annual Survey of Industrial Production (ASIP) data, which is collected by the NBSC. This firm-level data contain balance sheet information and production information for all state-owned enterprises (SOEs) and all non-state firms with annual sales above 5 million RMB, in the mining, manufacturing, and public utility sectors.\(^{12}\) In addition, the 2004 version of the survey, as part of the 2004 industrial census of China, reports employment by workers’ education and

\(^{12}\)As documented in Brandt et al. (2012), firms in the ASIP data set account for 90%, 91%, 97%, and 70% of the gross assets, sales, exports, and employment respectively in the manufacturing sector.
also the number of computers used by each firm. 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 each prefecture is calculated using information from China Data Online.13

4 Empirical Approach

This section presents the empirical approach that links the growth of imports of capital goods to changes in the skill share in China. I adopt the local-labor-market approach following Chiquiar (2008), Topalova (2010), Autor, Dorn and Hanson (2013) and Kovak (2013) and deal with endogeneity problems by using the shift-share instrument.

4.1 Defining local labor markets

In the analysis, I use prefectures as the unit of analysis, which is also a common practice in the literature (Zi, 2017; Autor et al., 2018; Dai, Huang and Zhang, 2018; Li, 2018; Li, Li and Ma, 2018). A prefecture in China is an administrative unit ranking below a province and above 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 2000.14 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.15 For comparison, prefectures in China are roughly twice as large as 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, 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, it is not feasible to use county or township level data because prefectures or

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13http://chinadataonline.org/
14The 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/zzgh/1980/). The Appendix provides additional details on this process.
15The province-controlling counties (accounting for 1% 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.
provinces are the basic units for reporting most of the regional economic indicators, and data quality makes it even less appealing to use data at the county or township level.

4.2 Econometric specification

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

\[ \Delta Y_{it} = \beta_1 \Delta KIP_{it} + \alpha_{pt} + X_{it}' \beta + \epsilon_{it}, \]  

(1)

where \( \Delta Y_{it} \) is the change of regional outcome variables such as the change in the college share in prefecture \( i \) between \( t - 1 \) and \( t \), and \( \Delta KIP_{it} \) is capital goods imports growth 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-period fixed effects model. To account for the time-variant shocks in each province where prefecture \( i \) is located, I include province \( \times \) year dummies \( (\alpha_{pt}) \). 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.\[16]\n
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. This census definition is broader than the definition in which educational attainment is measured by the highest diploma that a person has received.\[17]\n
\[16\] For regressions run for each age/cohort group separately, the weights used are the start-of-period population shares by age/cohort group.

\[17\] 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 differences in college attainment.
above definition, I construct the key outcome variable as follows:

\[
\Delta Y_{git}^g = \frac{\text{Skill}^g_{it}}{P^g_{it}} - \frac{\text{Skill}^g_{it-1}}{P^g_{it-1}}
\]  

(2)

where \(\Delta Y_{git}^g\) is changes of college share of group \(g\) (certain birth cohort) in prefecture \(i\) between 2000 and 2005 or between 2005 and 2010, \(\text{Skill}^g_{it}\) is the number of people with some college education or above living in prefecture \(i\) in year \(t\), and \(P^g_{it}\) is the residence-based population of group \(g\) in prefecture \(i\) in year \(t\).\(^{18}\) For people who have not reached the college age in \(t - 1\), \(\Delta Y_{git}^g\) captures the skill acquisition effect. For older cohorts, \(\Delta Y_{git}^g\) captures the relocation effect.

### 4.4 Import demand shocks

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

\[
\Delta KIP_{it} = \frac{M_{it} - M_{it-1}}{P_{it-1}} = \frac{\Delta M_{it}}{P_{it-1}},
\]  

(3)

where \(\Delta M_{it}\) is changes of capital goods imports 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 \(t - 1\).\(^{19}\) The above definition makes clear that the variations in capital goods imports growth per capita across regions arise from two sources: differential growth in capital goods imports and differential population. The latter is not the primary source of variation, as the growth in total capital goods imports and the population in China between 2000 and 2010 were 520% and 5.8% respectively.

\(^{18}\)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.\(^{19}\) 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 capital goods imports. 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](#).
4.5 Shift-share approach

It is possible that the establishment of the causal link from capital goods imports to skill supply may be hampered. One concern for the subsequent estimation is that capital goods imports may be correlated with some regional confounding factors such as productivity growth and public investment on education, in which case the OLS estimate may underestimate the true effects. Another concern is reverse causality—firms may choose to locate in regions with abundant skill supply and thus import more skill-complementary capital goods. To identify the causal impacts of rising capital goods imports on human capital accumulation, I employ an instrumental-variable strategy by adopting the shift-share approach (Bartik, 1991) to account for the above concerns.

\[
\Delta KIP_{it}^{Bartik} = \sum_j \frac{M_{ijt-1}}{M_{it-1}} \left( \frac{M_{ijt}^{-i} - M_{ijt-1}^{-i}}{M_{ijt-1}^{-i}} \right) \frac{M_{it-1}}{P_{it-1}},
\]

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, \(M_{ijt-1}/M_{it-1}\) is last period’s share of product \(j\) in region \(i\)’s imports which captures a region’s reliance on certain type of capital equipment, and \(M_{ijt-1}/P_{it-1}\) is capital goods imports per capita of region \(i\) in year \(t-1\). To avoid introducing a common source of measurement error on both sides of the equation, I measure the weight \(M_{ijt-1}/M_{it-1}\) and the scaling variable \(M_{it-1}/P_{it-1}\), using values from pre-sample years (1997 for the period of 2000-2005, and 2000 for the period of 2005-2010). 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 I have region-level trade data. Because residence-based regional 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 capital goods imports growth by combining each region’s initial import structure with the national import growth for each type of capital goods. The import of capital goods grows faster in regions that initially demand more capital goods of certain types that experienced rapid growth at the national level.
5 Effects of capital goods imports on college share

This section examines changes in skill share over the 2000—2010 period that are associated with exposure to growing capital goods imports. The empirical strategy identifies the responses of human capital accumulation to the demand-driven component of capital goods imports. The context for the analysis is that the initial import pattern exposes the regions to national-level shocks more in some industries than in others.

5.1 First stage results

The instrumental variable strategy as outlined above isolates China’s national demand for capital goods imports from other factors that may also be associated with the growth of capital goods imports. The predicted capital goods imports 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 capital goods imports 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 initial view of the data, Figures 7 plots the instrument variable in Equation (4) against capital goods imports growth per capita in Equation (3). It reveals the substantial predictive power of the Bartik instrument for the changes in capital goods imports per capita without the presence of the outlier cities in terms of import growth. A $100 predicted increase in capital goods imports 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 shows the corresponding result of the bivariate linear regression. In Appendix Figure A2, I further examine the relationship by period, 2000-2005, 2005-2010, and the positive correlations are robust across different periods. 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 1.66 to 1.84. In Figure 7, I exclude the outlier cities from the sample. The correlation between predicted and observed capital goods imports growth remains strongly positive. The corresponding regression result is displayed in column (4) of Table 2, where the correlation coefficient is 1.29 and R-square rises to as much as 0.89. This relationship remains quite stable with the inclusion of province dummies (column (5)) and province × year dummies (column (6)).
5.2 Baseline results

Table 3 presents the initial estimates of the relationship between changes in capital goods imports 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. As shown in column (1), there is a positive correlation between the two variables in the OLS estimation. Figure 8 plots the corresponding reduced form regression. The positive correlation between the change in college share and the change in capital goods imports per capita is 0.5.\footnote{In Appendix Table 1 and Appendix Figure 1, the correlation between predicted and observed capital goods imports growth remains strongly positive when the outlier cities are dropped from the sample.} In column (2), I present the 2SLS estimation results. A one-hundred dollar increase in a prefecture’s capital goods imports exposure per capita is associated with an increase in college share of 0.7 percentage points. The coefficient in column (2) is slightly larger than that in the OLS estimation. The downward bias in the OLS estimation suggests that college share grows faster in cities that have faster growth in capital goods imports due to national trends, but less so in cities that have greater growth in capital goods imports due to city-specific shocks. A possible explanation is that city-level shocks are short-term fluctuations that have less impact on education and mobility choices. Another explanation is that local government policies that encourage capital goods imports have more modest impacts on human capital accumulation than national trends. In column (3), I further control for province-year fixed effects and the estimation result remains almost the same. In column (4), I further control for the dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with the year dummy. The impact of capital goods import increased dramatically. The likely cause is as follows. While the change in skill share can not exceed 1, the change in capital goods imports per capita has no upper bound. This suggests that prefectures with extremely fast growth in capital goods imports had smaller growth in skill share.

[INSERT Figure 8 & Table 3]

From column (5), I augment the first-difference model for the period of 2000—2010 with a set of start-of-period measures which test the robustness and eliminate the potential confounding factors. In column (5), I add the share of people for each cohort and the share
of minorities to absorb cohort-specific trends and changes in college share that are related to races. Minority share is included because the government may provide more favorable education policies to regions with higher minority shares. The specification finds a slightly smaller effect of import exposure on college share, but the relationship remains economically large and statistically significant.

To address the concern that a prefecture’s initial import structure may correlate with the local unobserved time-varying demand-side forces such as exports, I augment the model by adding three additional controls. In column (6), I include the start-of-period share of people with urban hukou, employment share of manufacturing sectors, and export share of textile, electronic, and machinery into the regression. As industrialization is usually associated with urbanization, prefectures with higher urban shares demand more capital goods imports. In addition, urban areas have better education infrastructure which facilitates future improvement in educational attainment. Thus, the inclusion of urban share absorbs the changes in college share that are related to urbanization and is expected to correct the upward bias. The manufacturing sector, especially textiles and electronics, is China’s major exporting sector. Controlling for the start-of-period employment and export structures addresses the concern that the import exposure may in part capture the impact of exports on changes in college share. Indeed, the estimated result in column (5) shows that prefectures with higher urban share, higher manufacturing share, and higher export share of textiles and electronics had faster growth in college share. More specifically, a prefecture with a ten percentage point higher urbanization rate at the start of the period had an increase of 0.5 percentage points in college share in the subsequent period. A prefecture with a ten percentage point higher manufacturing share at the start of the period had an increase of 0.2 percentage point in college share in the subsequent period. When these variables are included, the coefficient of capital goods import declines.

In addition to the demand-side forces, a second potential threat to the identification is that a prefecture’s initial import structure may be correlated with the local unobserved time-varying forces which affect skill supply. In column (7), I control for the start-of-period average years of schooling. Adding the average years of education into the regression addresses the concern that the import exposure may in part be picking up an overall trend in changes in educational attainment. This specification finds a modestly smaller effect of capital goods imports on college share than that in column (6) and the positive relationship

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21 People who are classified as being in the same cohort are those who were born in the same decade.
remains statistically significant.

To further examine the impact of supply-side forces, I capture the exogenous changes in college supply by utilizing a novel dataset released by Glaeser and Lu (2018). In the early 1950s, there was a radical college reallocation in China. Utilizing this quasi-experiment, I study the impact of department reallocation in the 1950s on the changes in college share between 2000 and 2010. As shown in column (8), regions with more departments moved in had faster growth in college share. Meanwhile, the impact of capital goods imports remains robust. I choose column (8) as the preferred benchmark results.

5.3 Analysis by cohort

To examine the heterogeneous impacts of capital goods imports, I calculate changes in the college share for each birth cohort. As shown in Figure 9, the impacts of capital goods imports are mainly concentrated among young people born between 1978 and 1986, who were between ages 14 and 22 in 2000 and between ages 19 and 27 in 2005. This result is quite intuitive, as young people have much lower migration costs and it is easier for them to acquire higher education compared with senior people.

[INSERT Figure 9 & Table 4]

5.4 Decomposition

In this section, I quantify how labor relocation can account for the regional differences in skill composition. 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:

$$\Delta Y'^g_{it} = \frac{\text{Skill}^g_{it} - \text{Skill}^g_{it-1}}{P^g_{it-1}} = \frac{\text{Skill} (\text{Unskill}_{it-1})^g_{it} - \text{Skill} (\text{Dead})^g_{it}}{P^g_{it-1}} + \frac{\text{Skill} (\text{IM})^g_{it}}{P^g_{it-1}} - \frac{\text{Skill} (\text{EM})^g_{it}}{P^g_{it-1}}$$ (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, $\text{Skill}^g_{it}$ and $P^g_{it}$ are as defined in Equation
\( \text{Skill} (\text{Unskill}_{it-1})^g_{it} \) is the number of people of group \( g \) living in prefecture \( i \) who did not attended college in in year \( t - 1 \) but have received some college education or above in year \( t \). \( \text{Skill} (\text{Dead})^g_{it} \) 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 \( t \). \( \text{Skill} (\text{IM})^g_{it} \) 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 \( t \). \( \text{Skill} (\text{EM})^g_{it} \) 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, \( \frac{\text{Skill} (\text{Unskill}_{it-1})^g_{it} - \text{Skill} (\text{Dead})^g_{it}}{P^g_{it-1}} \), is the combined effect of the skill acquisition of local unskilled laborers and the death of local skill laborers. 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 older cohorts, the college share mainly reflects the relocation of incumbent skilled laborers across regions. We learn from the above breakdown about how much the rise in the skill share 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 in capital goods imports enjoy faster growth in skill share, as shown in Figure 10. For young people, the effects mainly come from the skill acquisition of local stayers and skilled immigrants. As for older cohorts, capital goods imports have no effect. The regression for these people serve as counter-factual tests and the results alleviate the concern that capital goods imports are correlated with confounding factors that affect skill supply.

[INSERT Figure 10]

5.5 Spatial spillover effects

The identification strategy relies on the assumption that prefecture \( i \)'s skill share is not affected by the labor market conditions in other prefectures. Nevertheless, the import of capital goods import elsewhere can also affect people’s education decisions and work
decisions. To quantify the spillover effects and estimate the “total” impacts of capital goods imports, I need to use a different source of variation. As with most of the spatial problems, the skill share in prefecture $i$ could be a function of the capital goods imports of all the other prefectures. Because it is difficult to estimate the functions precisely, I adopt three approaches to examine the impact of non-local import shocks.

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

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

(6)

where $D_{ij}$ is the spatial distance between prefecture $i$ and prefecture $j$ and $\Delta KIP_{jt}$ is the capital goods imports growth per capita in prefecture $j$ between $t-1$ and $t$.

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

$$\Delta KIP_{it} = \frac{\text{Employment}_j}{\sum_{j\in \text{neighbor}} \text{Employment}_j} \Delta KIP_{jt}$$

(7)

where $\text{Employment}_j$ is the employment of prefecture $j$ and $\Delta KIP_{jt}$ is the capital goods imports growth per capita in prefecture $j$ between $t-1$ and $t$.

Third, I construct prefecture $i$’s share of neighboring prefectures with larger capital goods imports 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.\(^{22}\) To test the sensitivity of the results to the definition of neighborhoods, I also try various radii and the results are robust.

Table 5 presents the results incorporating the spillover effects of capital goods imports. Panel A shows the results using the first approach. There is a strong negative spillover effect on the skill share and it works through the channel of immigration. Using the two sets of spillover indicators yields similar results.

\[^{22}\text{The radii is set based on the average size of provinces and prefectures in China. China covers roughly 9,600,000 km}^2\text{. There are 31 provinces and the average radii is about 314 km ((9600000/31/3.14)^{0.5})}. \text{There are 337 prefectures and the average radii is about 95 km ((9600000/337/3.14)^{0.5})}.\]
5.6 Robustness: Imports of non-capital goods

There is concern that the capital goods imports may partly capture the impacts of other imported products. To verify that the above results are driven by the imports of other products, I conduct a falsification exercise to examine the impact of non-capital goods imports on skill supply in Table 6. Panel B displays the corresponding second-stage results. In column (1), the specification finds a larger effect of changes in capital goods imports per capita when including non-capital goods imports; this could result from the multi-collinearity problem given that the correlation between capital goods imports 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 skill share. The results suggest that the various kinds of non-capital goods imports, including imported intermediate inputs, do not increase skill share and they have either no effect or a negative effect on skill supply. Panel C shows the first-stage results. As shown in column (1), there is a strong correlation between the predicted and the realized change in non-capital-goods-imports per capita. Similarly, the instruments for other types of imports growth also have good predictive powers for the corresponding realized import growth.

[INSERT Table 6]

6 Effects of capital goods imports on wage

Despite college share, I also explore the impact of capital goods imports growth per capita on the changes in average wage, the changes in wage of skill workers, the changes in wage of low skilled workers and the changes in skill premium.

Following the specification in Table 3 column (8), I first present the benchmark result in Table 7 panel A. In column (1), I report an 2SLS regression with the the changes in average wage as the dependent variable, and the capital good imports growth per capita, as well as province-year fixed effect, and a set of the start-of-period controls as independent variables. The coefficient on the capital good imports growth per capita is positive and significantly different from zero, suggesting that imports of capital goods have a positive
and significant effect on wage. The point estimate of 1804 is also quite large economically. When imported capital good growth per capita increased by 100 dollars, the average wage increased by 1804 yuan. Putting this into context, for a city at the 25th percentile of the distribution of capital goods imports, its average wage will rise by 541 yuan or 9% of the increase in average wage, if its import growth per capita increases to the level of the city at the 75th percentile.

In column (2) and (3) of panel A, I examine the impact of capital good imports growth per capita on the changes in wages by skill level. Regions with faster growth in capital goods imports experienced faster wage growth among skilled labors and unskilled labors alike and the impact was stronger for skilled workers. When imported capital good growth per capita increased by 100 dollars, the average wage of skilled labors increased by 2634 yuan while the average wage of unskilled labors only increased by 761 yuan. Moreover, the results in column (4) show that capital goods imports increased skill premium. The magnitude of the coefficient is 3%, though it is noisily estimated. The above findings confirm that capital goods imports are indeed a key driver for the rising demand for skill.

In panel B, panel C and panel D, I further consider the spillover effect following the specifications in Section 5.5. When other prefectures imported skill-complementary capital goods, there would be more skilled emigrants and less skilled immigrants. The relative decreasing skill supply would increase local skill premium and narrow down regional differences in skill premium. Indeed, this is what I find in column (4) of panel B, panel C and panel D.

[INSERT Table 7]

7 Effects of capital goods imports on firms’ demand for skill

I supplement the above analysis by providing direct evidence on how firms adjust production and how capital goods imports 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 allows me to control for time-invariant firm fixed effects. 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).
specification has the following form:

\[ y_{ikmt} = \beta_1 K_{ikmt} + X_{ikmt} \delta + \mu_i + \gamma_m + \gamma_t + \varepsilon_{ikmt} \]  

(8)

where \( y_{ikmt} \) includes a set of dependent variables for firm \( k \) in industry \( m \) at city \( i \) in year \( t \), \( K_{ikmt} \) is the ratio of imported capital goods over its capital stock, \( X_{ikmt} \) is a set of firm-level controls, \( \mu_i \) and \( \gamma_m \) are city fixed effects and industry fixed effects respectively. For regressions in which data are available for more than one year, I also control for year fixed effects and firm fixed effects (Table 7 columns (3) and (4)).

Column (1) of table 8 suggests that firms with more capital goods imports have higher shares of skilled laborers (as measured by the share of workers with a college degree or above) using 2004 data. While the coefficient on imported input intensity is also positive, the effect is more pronounced for capital goods imports. However, export intensity has a negative association with the share of college workers, consistent with the observation that Chinese manufacturers’ comparative advantage is labor intensive.

Capital goods importers use more computers, which are generally considered to be embedded with skill-biased technology. More specifically, increasing capital import intensity by 10 percentage points is associated with a 1.8 percentage point increase in the number of computers per worker, as shown in column (2), using data in 2004. A large body of literature has used computerization of US firms as reflecting skill-biased technology change (Berman, Bound and Griliches [1994] Autor, Levy and Murnane [2003]).

Capital goods importers pay higher wages and have higher labor productivity. Although I am unable to examine the relationship between capital goods imports and the skill premium because the national survey does not have wage data by education, using firm survey data from 2000 to 2007, I find supportive evidence that firms with more capital goods imports tend to pay higher wages and have higher labor productivity. This is consistent with the findings by Bernard and Jensen [1997], who shows 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 wage and labor productivity of the firm after controlling for firm fixed effects. The above findings are consistent with the findings by Dai, Maitra and Yu [2016].

In Table 8, I control for firm size using total employment, and for the city- and industry-specific factors. Although I cannot rule out the possibility of endogeneity in the OLS
regressions, the results indicate that imported capital goods are skilled-biased and thus increase demand for skill.

[INSERT Table 8]

8 Conclusion

Human capital is an important determinant of the long-run economic growth. It is crucial to understand how trade affects human capital accumulation as countries are becoming more globalized. This paper argues that capital goods imports are an important force to drive up demand for skill and thus encourages human capital accumulation in newly industrialized countries. Drawing on several rich data sets, I examine how the skill share and skill premium respond to changes in capital goods imports. By taking the regional economy as the unit of analysis, I identify the combined effect of the direct impact of capital goods imports as well as the spillover effects across regions. To tackle causality, I construct a shift-share instrument for the changes in capital goods imports 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 more capital goods imports growth per capita experienced faster increases in skilled labor share. 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 college share, I quantify how skilled labor allocation can explain regional differences in college share. Moreover, the effects of capital goods imports spill over across regions. The capital goods imports in other regions mitigate the impact of local capital goods imports via the migration channel. Furthermore, I supplement the above analysis by providing firm-level evidence and show the same story also holds at the firm level.

The findings have several implications. I find that people, especially skilled workers, are quite responsive to positive trade shocks, which contrasts to the fact that people are less responsive to negative trade shocks. Moreover, the findings suggest that migration mitigates the regional inequality in the skill premium by allowing skilled workers in regions that are less exposed to capital goods imports to earn higher wages in more exposed regions. Meanwhile, it also aggravates the regional inequality in human capital by intensifying the brain drain.
References


Figure 1 The Increasing Regional Differences in College Shares


Note: Skill share is defined as the number of people with at least some college education or above as a share of the number of people aged above 15 years old. 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.
Figure 2 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 3 Capital Goods Imports

Data: UN Comtrade Database, 1992-2017

Note: This 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 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). Prefecture-level population is the residence-based population in 2000.
Figure 5 Import Share of Capital Goods: International Comparison

Data: UN Comtrade Database, 1992-2010

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 (RSA).
Figure 6 The widening regional differences in skill share and skill premium


Note: Skill share is defined as the number of people with some college education or above as a share of 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 Urban 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 7 First Stage

Whole sample

Dropping outliers

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

whole sample

$y = 2.5572 + 4.6959 \times \quad R^2 = 11.8\%$

Dropping outliers

$y = 2.3761 + 11.679 \times \quad R^2 = 14.4\%$

Note: The binned scatter plots display the relationships between the capital goods imports growth per capita and changes in skill share.
Figure 9 Imported Capital Goods and Allocation of Skilled Labors: by Birth Year

Note: I regress the changes in skill share for each cohort on capital goods import growth per capita. Each cohort group include people born in two adjacent years.
Figure 10 Decomposition of Changes in Skill Share: by Birth Year

ΔCapital Goods Imports per Capita and (ΔCollege)/Population (%)

ΔCapital Goods Imports Capita and Emigrant/Population (%)
Note: I first decompose the changes in skill 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.
Appendix Figure A1 Spatial Distribution of College Admission Rate in 2007

Data: China’s Statistical Yearbook.

Note: The college admission rate is at province level.
Appendix 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 1 Summary Statistics

<table>
<thead>
<tr>
<th>Panel A: Dependent Variables</th>
<th>mean</th>
<th>sd</th>
<th>min</th>
<th>p25</th>
<th>p75</th>
<th>max</th>
</tr>
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<td>ΔCollege share, %</td>
<td>3.96</td>
<td>2.89</td>
<td>-7.31</td>
<td>1.74</td>
<td>5.55</td>
<td>23.08</td>
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<table>
<thead>
<tr>
<th>Panel B: Key Independent Variable and IV</th>
<th>mean</th>
<th>sd</th>
<th>min</th>
<th>p25</th>
<th>p75</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔImported capital goods per capita (ΔK)</td>
<td>0.70</td>
<td>2.31</td>
<td>-6.96</td>
<td>0.00</td>
<td>0.30</td>
<td>22.77</td>
</tr>
<tr>
<td>ΔPredicted imported capital goods per capita (ΔIVK)</td>
<td>0.39</td>
<td>1.14</td>
<td>0.00</td>
<td>0.00</td>
<td>0.20</td>
<td>12.02</td>
</tr>
<tr>
<td>Spillover (inverse distance weighted)</td>
<td>0.61</td>
<td>1.85</td>
<td>-0.45</td>
<td>0.02</td>
<td>0.28</td>
<td>15.18</td>
</tr>
<tr>
<td>Spillover (employment weighted)</td>
<td>0.48</td>
<td>0.25</td>
<td>0.15</td>
<td>0.33</td>
<td>0.54</td>
<td>1.91</td>
</tr>
<tr>
<td>Spillover (share of neighboring cities with larger ΔK, R=200km)</td>
<td>0.30</td>
<td>0.36</td>
<td>0.00</td>
<td>0.00</td>
<td>0.50</td>
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<td>0.01</td>
<td>0.16</td>
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<td>Minority share</td>
<td>0.09</td>
<td>0.18</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>1.00</td>
</tr>
<tr>
<td>Manufacturing employment share</td>
<td>0.14</td>
<td>0.13</td>
<td>0.00</td>
<td>0.05</td>
<td>0.16</td>
<td>0.79</td>
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<tr>
<td>Textile and electronics’ export share</td>
<td>0.40</td>
<td>0.25</td>
<td>0.00</td>
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<td>1.00</td>
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<tr>
<td>Average years of education</td>
<td>8.46</td>
<td>0.96</td>
<td>1.74</td>
<td>7.92</td>
<td>8.99</td>
<td>11.40</td>
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<td>No. of reallocated departments</td>
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<td>-20.00</td>
<td>0.00</td>
<td>0.00</td>
<td>35.00</td>
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Note: N=660. Imported capital goods growth per capita and predicted imported capital goods growth are both measured in 100 U.S. dollars. The statistics are weighted by residence-based population in 2000.
Table 2 First Stage

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tr>
<td>ΔImported capital goods per capita (ΔK)</td>
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<td></td>
</tr>
<tr>
<td>ΔPredicted imported capital goods per capita (ΔIVK)</td>
<td>1.56***</td>
<td>1.66***</td>
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<tr>
<td></td>
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<td>(0.40)</td>
<td>(0.28)</td>
<td>(0.30)</td>
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<td>Y</td>
<td>-</td>
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<td>Y</td>
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<tr>
<td>Province-year FE</td>
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<td>-</td>
<td>Y</td>
<td>-</td>
<td>-</td>
<td>Y</td>
</tr>
<tr>
<td>Dummies for outliers &amp; interactions with year</td>
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<td>-</td>
<td>-</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>R-squared</td>
<td>0.59</td>
<td>0.66</td>
<td>0.70</td>
<td>0.89</td>
<td>0.94</td>
<td>0.95</td>
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</table>

Note: N=660. Dummies include Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai. All observations are weighted by city-level residence-based population in 2000. Robust standard errors in parentheses are clustered on province. *** p<0.01, ** p<0.05, * p<0.1
### Table 3 Imported Capital Goods and College Share

<table>
<thead>
<tr>
<th>Y=100×Δ (no. people with some college or above/population)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<th>(7)</th>
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<td>OLS</td>
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<td>IV</td>
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<td>IV</td>
<td>IV</td>
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<td>IV</td>
</tr>
<tr>
<td>ΔCapital goods import per capita</td>
<td>0.50***</td>
<td>0.70***</td>
<td>0.67***</td>
<td>2.10***</td>
<td>1.67***</td>
<td>0.88***</td>
<td>0.73**</td>
<td>0.74**</td>
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<td>(0.10)</td>
<td>(0.15)</td>
<td>(0.06)</td>
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<td>(0.42)</td>
<td>(0.33)</td>
<td>(0.33)</td>
<td>(0.38)</td>
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<tr>
<td>Share of minority</td>
<td>-0.89*</td>
<td>-0.56</td>
<td>-0.06</td>
<td>-0.08</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(0.49)</td>
<td>(0.36)</td>
<td>(0.37)</td>
<td>(0.37)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Share of people with urban <em>hukou</em></td>
<td>5.33***</td>
<td>2.43*</td>
<td>2.49*</td>
<td></td>
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<td>(0.87)</td>
<td>(1.48)</td>
<td>(1.43)</td>
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<tr>
<td>Manufacturing employment share</td>
<td>2.42*</td>
<td>2.39**</td>
<td>2.37**</td>
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<td></td>
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<tr>
<td>(1.24)</td>
<td>(1.10)</td>
<td>(1.15)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Export share of textile, electronic &amp; machinery</td>
<td>0.21</td>
<td>0.07</td>
<td>0.06</td>
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<td></td>
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<td>(0.26)</td>
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<tr>
<td>Average years of education</td>
<td>0.66***</td>
<td>0.65***</td>
<td></td>
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<tr>
<td>(0.13)</td>
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<td></td>
<td></td>
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<tr>
<td>Share of senior high</td>
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<td>-0.02</td>
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<td>No. of reallocated departments</td>
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<tr>
<td>Province-year FE</td>
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<td>Y</td>
<td>Y</td>
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<td>Y</td>
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<td>Dummyes for outliers</td>
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<tr>
<td>Cohort fixed effects</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Note: N=660. All the control variables are values at the start of each period (2000-2005 or 2005-2010). Dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by residence-based population in 2000 using the tabulated city-level data. The analysis is conducted based on people’s resident prefectures in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1
### Table 4 By-cohort Analysis

<table>
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</thead>
<tbody>
<tr>
<td>ΔCapital goods import per capita</td>
<td>0.45</td>
<td>9.75***</td>
<td>-1.27</td>
<td>0.94</td>
<td>0.61</td>
<td>1.03***</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>(2.85)</td>
<td>(1.19)</td>
<td>(0.61)</td>
<td>(0.53)</td>
<td>(0.31)</td>
<td>(0.27)</td>
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<tr>
<td>Mean of Y</td>
<td>13.71</td>
<td>9.99</td>
<td>3.47</td>
<td>2.62</td>
<td>1.69</td>
<td>0.93</td>
<td>0.35</td>
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Note: N=660. The start-of-period minority share, urban share, industry structure, educational attainment, and province-year fixed effect are controlled. Dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by residence-based population in 2000 using the tabulated city-level data. The analysis is conducted based on people’s resident prefectures in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1
**Table 5 Spillover Effects**

<table>
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<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)=(2)+(3)-(4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( Y = 100 \times (\Delta \text{no. people with some college or above})/\text{population} )</td>
<td>( = \text{Local} + \text{Immigration} - \text{Emigration} )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel A. Inverse distance weighted \( \Delta \) capital goods import per capita of all the rest prefectures**

| \( \Delta \text{Capital goods import} \)  | 0.84***       | 0.43         | 0.28         | -0.14        |
| \( \text{per capita} \)                    | (0.27)        | (0.65)       | (0.46)       | (0.09)       |
| \( \text{Spillover effect} \)              | -0.36         | 1.21         | -1.42**      | 0.14         |
| \( \text{per capita} \)                    | (0.48)        | (0.80)       | (0.59)       | (0.18)       |

**Panel B. Employment share weighted \( \Delta \) capital goods import per capita of neighboring prefectures**

| \( \Delta \text{Capital goods import} \)  | 0.83***       | 0.52         | 0.17         | -0.13        |
| \( \text{per capita} \)                    | (0.26)        | (0.63)       | (0.43)       | (0.09)       |
| \( \text{Spillover effect} \)              | -0.06         | 0.04         | -0.08        | 0.01         |
| \( \text{per capita} \)                    | (0.04)        | (0.09)       | (0.05)       | (0.01)       |

**Panel C. Share of neighboring cities with larger \( \Delta \) capital goods import per capita**

| \( \Delta \text{Capital goods import} \)  | 0.84***       | 0.75         | -0.02        | -0.11        |
| \( \text{per capita} \)                    | (0.27)        | (0.70)       | (0.51)       | (0.10)       |
| \( \text{Spillover effect} \)              | 0.03          | 0.20*        | -0.16*       | 0.01         |
| \( \text{per capita} \)                    | (0.05)        | (0.11)       | (0.09)       | (0.02)       |

Note: N=660. The start-of-period cohort dummies, urban share, minority share, industry structure, educational attainment, and province-year fixed effect are controlled. Dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by residence-based population in 2000 using the tabulated city-level data. The analysis is conducted based on people's resident prefectures in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th>Panel</th>
<th>Stage</th>
<th>Equation</th>
<th>( \Delta \text{Imported Capital goods per capita} )</th>
<th>( \Delta \text{Other imported goods per capita} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A</td>
<td>Correlation</td>
<td>(\Delta \text{Imported capital goods per capita vs. } \Delta \text{Other imported goods per capita})</td>
<td>0.69</td>
<td>0.42</td>
</tr>
<tr>
<td>Panel B</td>
<td>Second Stage</td>
<td>( \Delta Y = 100 \times \Delta \text{College Share} )</td>
<td>0.65</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-0.06</td>
<td>-4.12</td>
</tr>
<tr>
<td>Panel C</td>
<td>First Stage</td>
<td>( Y = \Delta \text{Other imported goods per capita} )</td>
<td>0.41</td>
<td>0.17**</td>
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<tr>
<td></td>
<td></td>
<td>( \Delta \text{Predicted imported Capital goods per capita} )</td>
<td>1.27**</td>
<td>0.57*</td>
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<tr>
<td></td>
<td></td>
<td>( \Delta \text{Predicted other imported goods per capita} )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: N=660. The start-of-period cohort dummies, urban share, minority share, industry structure, educational attainment, and province-year fixed effect are controlled. Dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by residence-based population in 2000 using the tabulated city-level data. The analysis is conducted based on people’s resident prefectures in 2000. Standard errors clustered at province are shown in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
Table 7: The Impacts of Imported Capital Goods on Wage

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Baseline</th>
<th>Panel B. Inverse distance weighted Δcapital goods import per capita of all the rest prefectures</th>
<th>Panel C. Employment share weighted Δcapital goods import per capita of neighboring prefectures</th>
<th>Panel D. Share of neighboring cities with larger Δcapital goods import per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Δ Wage (1)</td>
<td>Δ(Δ capital goods per capita) (2)</td>
<td>Δ(Δ capital goods per capita) (3)</td>
<td>Δ(Δ capital goods per capita) (4)</td>
</tr>
<tr>
<td>ΔCapital goods import per capita</td>
<td>1804.28**</td>
<td>2634.00**</td>
<td>761.35</td>
<td>0.03</td>
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<tr>
<td></td>
<td>(701.71)</td>
<td>(1291.11)</td>
<td>(468.91)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>ΔCapital goods import per capita</td>
<td>1575.60**</td>
<td>2346.60*</td>
<td>516.02</td>
<td>0.03</td>
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<td></td>
<td>(668.21)</td>
<td>(1241.21)</td>
<td>(415.79)</td>
<td>(0.03)</td>
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<tr>
<td>Spillover effect</td>
<td>2671.83***</td>
<td>3357.82***</td>
<td>2866.36***</td>
<td>-0.04</td>
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<tr>
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<td>(579.75)</td>
<td>(1027.75)</td>
<td>(483.82)</td>
<td>(0.04)</td>
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<tr>
<td>ΔCapital goods import per capita</td>
<td>1678.28**</td>
<td>2426.56*</td>
<td>662.13*</td>
<td>0.03</td>
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<tr>
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<td>(692.79)</td>
<td>(1281.08)</td>
<td>(397.04)</td>
<td>(0.03)</td>
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<tr>
<td>Spillover effect</td>
<td>259.54***</td>
<td>427.29***</td>
<td>204.38***</td>
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<td>(65.65)</td>
<td>(69.45)</td>
<td>(40.57)</td>
<td>(0.00)</td>
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</table>

Note: N=346. I use data between 2002 and 2009 because the number of prefectures before 2002 was small. In the analysis, there are two periods, namely 2005-2005 and 2005-2009. The start-of-period cohort dummies, urban share, minority share, industry structure, educational attainment, and province-year fixed effect are controlled. Wages are set at constant national level (in 1992 yuan). Dummies for outliers (Dongguan, Guangzhou, Haikou, Jiayuguan, Shenzhen, Suzhou, and Xiamen and Zhuhai) and their interactions with year are controlled. Regressions are weighted by residence-based population in 2000 using the tabulated city-level data. The analysis is conducted based on people’s resident prefectures 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

<table>
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<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Workers with College Degree</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computer per Worker</td>
<td>0.15***</td>
<td>0.18***</td>
<td>0.04***</td>
<td>0.17***</td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
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<tr>
<td>Ln(Value-added per Worker)</td>
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<td></td>
</tr>
<tr>
<td>Export/Sales</td>
<td>-0.01***</td>
<td>0.00***</td>
<td>0.03***</td>
<td>0.01***</td>
</tr>
<tr>
<td>Non-Capital Goods Import/Inputs</td>
<td>0.06***</td>
<td>0.07***</td>
<td>0.07***</td>
<td>0.19***</td>
</tr>
<tr>
<td>Ln(Employment)</td>
<td>-0.01***</td>
<td>-0.01***</td>
<td>-0.15***</td>
<td>-0.42***</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>CIC 4-digit Industry Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>City Fixed Effects</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Observations</td>
<td>216,932</td>
<td>216,932</td>
<td>1,482,241</td>
<td>1,482,241</td>
</tr>
</tbody>
</table>


Note: Skilled worker is defined as people 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 by firm. *** p<0.01, ** p<0.05, * p<0.1.
### Appendix Table A1

<table>
<thead>
<tr>
<th>Whole sample</th>
<th>ΔCapital goods import per capita</th>
<th>ΔExport per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔCapital goods import per capita</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>ΔExport per capita</td>
<td>0.81</td>
<td>1.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Dropping outliers</th>
<th>ΔCapital goods import per capita</th>
<th>ΔExport per capita</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔCapital goods import per capita</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>ΔExport per capita</td>
<td>0.69</td>
<td>1.00</td>
</tr>
</tbody>
</table>