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Skill-biased imports, skill acquisition, and migration[☆]Jingting Fan^a, Lei Li^b ^{*,*}^a Cheung Kong Graduate School of Business, China^b University of Göttingen, Germany

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ABSTRACT

Imported capital goods, which embody skill-complementary technologies, can increase the supply of skills in developing countries. Focusing on China and using a shift-share design, we show that city-level capital goods import growth increases the local skill share and that both skill acquisition and migration play a role. We develop and quantify a spatial equilibrium model with these two mechanisms to examine the aggregate effects of capital goods imports, accounting for trade and migration linkages between cities. Counterfactual experiments suggest that the growth in capital goods imports in China between 2000 and 2010 led to a 3.1–7.3 million increase in the stock of college graduates, representing 4.4–10.4% of the total increase over this period, with the increase disproportionately occurring in coastal regions. These endogenous skill supply responses reduce by half the increase in the aggregate skill premium due to capital goods imports.

1. Introduction

Developing countries often rely on imports of capital goods—such as advanced computers and sophisticated production machinery—from developed economies. Because these imports often embody technologies that complement high-skill labor more than low-skill labor, their adoption can significantly shift skill demand and widen wage disparities. Indeed, recent empirical and quantitative evidence shows that rising imports of capital goods have raised the skill premium in many developing countries (e.g., [Burststein et al. \(2013\)](#), [Parro \(2013\)](#), [Fan \(2019\)](#) and [Koren and Csillag \(2019\)](#)). In this paper, we build on this finding and go one step further to examine how imported capital goods—by increasing the demand for skill and driving up the skill premium—reshape both patterns of skill acquisition and the geographic distribution of skills within a country.

Our rationale is intuitive. When imported capital goods raise the skill premium, workers respond by acquiring more skills and by migrating to regions with stronger demand for skilled labor. Because the use of capital goods varies across locations, these responses—skill acquisition and migration—differ by region. As a result, rising capital goods imports can not only affect a country's overall skill level but also reshape the geographic distribution of skills. Understanding these impacts is crucial, both because they

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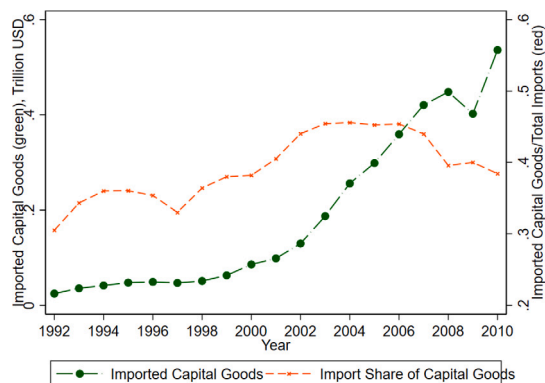


Fig. 1. Capital goods imports in China.

Note: The green line shows the pattern of China's capital goods imports (unit: 1 trillion USD) and the red line shows the share of imported capital imports in total imports. See Section 2 for the definition. Source of data: UN Comtrade. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

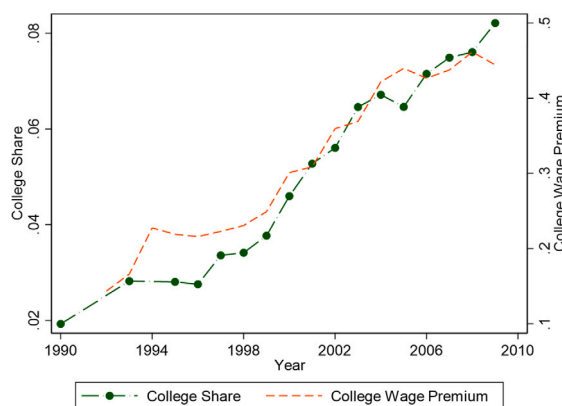


Fig. 2. China's rising college share and college wage premium.

Note: College share is the share of people above 15 years old with at least some college education. The college wage premium is the wage gap between people with at least some college education and those without, estimated using a Mincer-style OLS regression that controls for gender, working experience and its square term, employer ownership type, and industry fixed effects. Data: China Statistical Year Books (1990–2009) and the Urban Household Survey (1992–2009).

may shape the effect of capital goods imports on the skill premium and because human capital plays a fundamental role in fostering aggregate and regional economic growth (Gennaioli et al., 2013).

In this paper, we make two contributions. First, we present causal evidence that imported capital goods trigger the endogenous responses described above, exploiting cross-regional variation in capital goods imports. While these findings underscore the importance of local demand conditions in shaping the skill distribution, they do not reveal the full equilibrium effects. Our second contribution is to quantify a spatial equilibrium model that incorporates these mechanisms, with which we evaluate how capital goods imports ultimately affect both the aggregate level of skill and its spatial distribution, and how the endogenous skill distribution affects income inequality.

Our study focuses on China. The simultaneous increases in capital goods imports, the skill premium, and the number of college graduates in China over the past few decades make it a useful setting to test these mechanisms. As is well known, the Chinese economy experienced rapid integration with the global economy between 1978 and 2010. In particular, after Deng's 1992 Southern Tour, which reaffirmed the market reform policy, China's capital goods imports skyrocketed. This increase accelerated further in 2001 with China's WTO accession. During the period, capital goods imports account for up to 40% of total imports (Fig. 1). Accompanying this surge were the increases in the college wage premium and the share of college graduates in the population (the college share).¹ The college wage premium rose from 14.3% in 1992 to 44.4% in 2009, as shown in Fig. 2. Meanwhile, the college share quadrupled from 2% to 8.2%, consistent with rising demand for skill driving both the college wage premium and the college share.

¹ Throughout the paper, we define college shares based on people with any experience with college, including community college. We will use the terms skill premium and college wage premium interchangeably.

Our empirical analysis exploits the variations in the growth of capital goods imports across Chinese cities, drawing on several firm- and household-level datasets. In the data, cities with more rapid growth in capital goods imports over 2000–2010 experienced larger increases in college share. To establish a causal effect, we adopt a shift-share instrumental variable (IV) strategy, where we predict the growth in a city's capital goods imports using the inner product between the city's initial composition of imports across different capital goods and the (leave-one-out) national import growth rate in these goods over 2000–2010. In the IV regression, we view the national growth rate of the individual product imports as the result of random shocks. We calculate diagnostic statistics and conduct balancing tests following the recommendation of [Borusyak et al. \(2022b\)](#). These tests are generally supportive of the quasi-experimental national shock assumption. We also address the inference issues that arise in this setting ([Adao et al., 2019](#)).

Based on this research design, we estimate that between 2000 and 2010, an increase of 100 US dollars (USD) in a city's per-capita capital goods imports leads to a 0.16 percentage points increase in the city's college share. According to this estimate, capital goods imports increase can account for about 13% of differential increase in college share across cities. We provide suggestive evidence on the mechanism by documenting the relationship between capital goods imports, wage, and skill employment using firm- and city-level data. We find that, consistent with capital-skill complementarity, firms that use more imported capital are more skill intensive and pay higher wages; consistent with skill supply responding to higher skill premium, the increase in capital goods import leads to a short-run increase in the skill premium that attenuates over time.

Our interpretation of the mechanism is that by pushing up the skill premium, capital goods imports incentivize skill acquisition and migration—a story of labor market demand. A plausible alternative mechanism is that, with imported technologies, cities become more productive, and local households and governments have more resources to invest in higher education—an income effect on skill acquisition. We account for this mechanism by incorporating controls that speak directly to the income effects of households and city and provincial governments. The estimated effect of per capita capital goods import growth remains similar and statistically significant. Thus, while this mechanism may be important for the nation-wide college expansion, it cannot account for the *differential* effect across cities that we document. Additional analysis shows that other explanations also cannot account for our findings.

We further examine the effect of capital goods imports on college share by age and by channel. We find that the college share among young workers responds much more strongly to capital goods imports than that among old workers. This is perhaps unsurprising, as young workers can adjust through skill acquisition and migration, but old workers respond mostly through migration. Using newly constructed data on city-to-city individual migration, we decompose the increase in the number of college graduates into three components: the number of college graduates among stayers, immigrants, and emigrants, respectively. The decomposition shows that the estimate for migration is generally greater than the estimate for skill acquisition.

As is well recognized by the literature, in the presence of trade and migration linkages between cities, our reduced-form estimates do not recover the general equilibrium effect of capital goods imports. In the second part of the paper, we develop a simple spatial equilibrium model, with which we conduct counterfactual experiments. The model features capital-skill complementarity, endogenous skill acquisition, and costly trade and migration. To speak to the empirical patterns, we assume that there are two groups of people, young and mature. Young people decide whether to go to college and then make migration decisions; mature people also make migration decisions but treat their education as exogenous. In making these decisions, both groups consider the wage they will receive, which is determined in general equilibrium and can vary due to the cost of importing capital goods.

For transparency in estimation and counterfactual exercises, as well as to maintain a tight connection with the reduced-form exercises, we follow the [Adao et al. \(2022\)](#) approach and consider a linearized model around the 2000 baseline equilibrium. Our estimation rationalizes the differential increases in capital goods imports across cities through heterogeneous reductions in importing costs. We then estimate the key elasticities of the model—those that govern workers' skill acquisition and migration decisions—using an identifying assumption similar in spirit to the one in reduced-form analysis.

Through counterfactual experiments, We find that the decrease in capital goods import costs between 2000 and 2010 leads to between 3.1 million and 7.3 million increase in the stock of college graduates, accounting for between 4.4% and 10.4% of the 70 million increase in college graduates over this period—while imported capital goods are not the primary driver of the increase in skill supply, its role cannot be ignored either. Importantly, the increases in the college share are heterogeneous across locations. Dividing China into a coastal region and an interior region, we find that the coastal region experiences an around 16% increase in the college share. In contrast, the increase in the inland region is only modest (around 2%). Consistent with the reduced-form facts, we find that young workers' decisions are more important in driving the skill divergence between regions. The stark contrast between these two regions highlights the importance of imported capital goods for not only skill acquisition but also skill distribution within a country.

The endogenous changes in skill acquisition and distribution have important implications for the skill premium. We find that capital goods imports lead to a 5% increase in the average skill premium in China, with the increase substantially larger in the coast than inland. Without the response in migration or skill acquisition, the increase in the skill premium would have been twice as large. Thus, when thinking about how the progress affects wage inequality, accounting for the endogenous response in skill distribution is crucial. The two skill supply mechanisms, namely skill acquisition and migration, work in opposite directions both in the aggregate and along the spatial dimension: while skill acquisition moderates the increase in skill premium due to capital goods imports everywhere, migration increases the skill premium in the aggregate and in regions less exposed to the shocks, but moderates the increase in regions more exposed. Hence, in thinking about skill supply response, incorporating the spatial dimension and migration is important.

This paper is related to several strands of the literature. First, an influential literature has documented the effect of skill-biased technological change on the wage premium of college workers ([Katz and Murphy, 1992](#); [Berman et al., 1994](#); [Goldin and Katz, 1998](#); [Katz and Autor, 1999](#); [Krusell et al., 2000](#); [Acemoglu and Autor, 2011](#)). An immediate implication of the findings in this

literature for international trade—that importing capital goods embodying skill-biased technology can increase the wage premium in developing countries—has also been well studied.² Our contribution relative to existing studies is two folds. First, we test and quantify how this mechanism affects the acquisition and spatial distribution of skills within the importing country. Second, we show that once endogenous skill acquisition and migration are accounted for, the impact of capital goods imports on inequality decreases substantially, underscoring the importance of these general equilibrium forces. This second result complements a large literature on the role of endogenous skill supply on wage inequality (Galor and Moav, 2000; Goldin and Katz, 2018).

Of course, we are not the first to study how trade affects either human capital accumulation or migration. For example, Atkin (2016), Blanchard and Olney (2017), and Li (2018) estimate the impacts of trade on human capital accumulation; Facchini et al. (2019) estimate how trade affects migration in China. Relative to these works, which focus on either export opportunities or import competition, the main novelty of our analysis is that it focuses on a specific yet important type of trade—trade in capital goods. In addition, by combining causal estimates with a general equilibrium model, we quantify the aggregate effects of the mechanism.

In quantifying the mechanism, we build on recent development in spatial equilibrium models (Redding and Rossi-Hansberg, 2017). Our model is closest to that of Fan (2019), who himself builds on the models of Parro (2013) and Burstein et al. (2013). Our main departure from these existing models is that, motivated by the research question, we incorporate endogenous skill acquisition. Other recent works that consider skill acquisition to spatial equilibrium models include Ghose (2021) and Hsiao (2022).

The rest of the paper is organized as follows. Section 2 introduces the background and the data. Section 3 describes our empirical specification and reports the results. Sections 4 and 5 develop and quantify the model. Section 6 concludes.

2. Background and data

In this section, we briefly describe the trade liberalization episode and the institutional background of the higher education sector in China. We then explain the data used in our analyses.

2.1. Background

China's capital goods imports surge. Since 1949, China was largely isolated from the West, with its technology lagging behind. As part of the “reform and opening up” policy regime, the country started the “bring in advanced foreign technology” initiative in 1978. While technological transfer has been taking place in many forms, importing capital equipment that embodies advanced technologies has been particularly important for convenience and transparency. Hungry for advanced technology, the Chinese government gradually relaxed the constraints that impeded such imports by cutting tariffs, removing import quotas, and abolishing trade licenses. These efforts accelerated in 1992, when Deng Xiaoping, through the Southern Tour, signaled to the country (inside and outside the party elite circle) and to the world that China was going to continue market-oriented reforms (Vogel, 2011).

The result was a surge in capital goods imports, shown in Fig. 1. We define capital goods as durable machinery using the Broad Economic Classification (BEC). A Harmonized System (HS) product is classified as a capital good if it falls into BEC industry 41 (capital goods) or 521 (transportation equipment used for industrial purposes). From 1992 to 2000, capital goods imports grew by 16% per year; growth accelerated to 20% in 2001, when China joined the WTO.

These imports play a major role in China's overall investment. Figure A.1 shows the ratio of capital goods imports to aggregate investment in equipment and machinery. This share rose from around 60% to a peak of 90% in 2004 before gradually declining, yet remained above 40% throughout 2000–2010.³

Higher education in China. When the “reform and opening up” era began in 1978, China's higher education sector was small and still recovering from the disruptions of the Cultural Revolution. From 1978 to 1999, college admissions rose modestly from 0.4 million to 1 million.

In 1998, partly to meet the rising demand for skilled labor and partly to address youth unemployment amid widespread state-owned enterprise reform, the Chinese government launched a campaign to expand higher education. Admissions have steadily increased since then. According to the Education Statistical Yearbook of China, by 2010, total college admissions reached 6.6 million—an annual growth rate of 17% since 1998. About half of this growth came from establishing new colleges, while the rest resulted from expanding existing institutions.⁴

The implications of education policy for our study. Against the backdrop of the nationwide increase in college accessibility, we investigate whether regions that use more imported capital goods see a larger increase in college shares. We focus on the demand mechanism—rising demand for college graduates incentives more workers to acquire college education. A natural question is

² For example, Burstein et al. (2013), Parro (2013), and Fan (2019) incorporate capital-skill complementarity in trade models to study the impact of imported capital goods on the skill premium; Li et al. (2022) and Koren and Csillag (2019) provide empirical support for this mechanism in China and Hungary; Raveh and Reshef (2016) show in a sample of developing countries that R&D intensive capital goods imports are complementary to skills while other imports are complementary to unskilled labor. In addition to capital-skill complementarity, a broader literature studies how trade affects wage inequality through other channels, such as offshoring (Feenstra and Hanson, 1996, 1999), skill upgrading (Bustos, 2011; Verhoogen, 2008), and more (see Goldberg and Pavcnik (2007) for a review).

³ Our calculation does not adjust for quality. If foreign equipment is more advanced than domestic equipment, its true impact would exceed what the ratio implies.

⁴ Many new colleges affiliate with incumbent institutions, which helps bypass certain Department of Education restrictions on program offerings and size.

whether capital goods import growth can affect college shares through changes in higher education policy. This concern is especially relevant, as Chinese universities are predominantly financed by the government.⁵

As discussed, the expansion of higher education is a nationwide policy. To the extent that capital goods import—by fueling the overall economic growth and boosting skill demand—is part of the reason for the expansion, most of such response should operate at the national or provincial levels, instead of at the city that our identification strategy is suitable for. Thus, we do not attempt to measure capital goods imports' effects on higher education policy. Instead, our investigation will focus on how, given the overall expansion in higher education (or a fixed college seat supply curve), capital goods imports affect local college share through the demand channel.

Even with this focus, one might be concerned that if local governments' resources are affected by capital goods imports, then the increased higher education investment from the local government can partially explain our finding. In the empirical specification later, we will exploit the institutional setting of China's college admission and use additional controls to isolate the college seat supply mechanism.

2.2. Sample and data sources

This subsection outlines our regression sample and data sources.

Time horizon and regression sample. Our empirical analysis uses regional data from 2000–2010 to investigate the causal effects of capital goods imports on college shares. Following Topalova (2010), Autor et al. (2013), and Kovak (2013), we will adopt a local market approach. Our definition of local labor markets is prefecture cities. In the Chinese political hierarchy, prefectures are the administrative units between a province and a county. We choose prefectures as the units of analysis for both theoretical appeal and practical convenience. Specifically, prefectures are the closest counterpart to commuting zones often used in the studies of U.S. local labor markets, and they represent the most granular level at which some data are available. Moreover, within a prefecture, counties tend to be closely integrated economically through commuting ties and are governed by the same set of policies—many local government policies, such as those on hukou, land use, and investment, are made at the prefecture-city level. We refer to city-level prefectures and four municipalities under the direct administration of the central government simply as 'cities'. Over 2000–2010, there have been some changes in city boundaries through the reassignment of counties to cities. We account for such changes by constructing time-consistent county groups and matching cities across census years to the administrative division in 2000.⁶

Trade data. We construct prefecture-level capital goods imports from export and import transaction records provided by China's Customs Bureau, which covers 1998 to 2010. The data includes the importing/exporting firm's location, allowing us to calculate import growth by city. The summary statistics calculated from the microdata, reported in Appendix Table A.1, show considerable growth in per-capita capital goods imports during this period, with an average five-year (2000 to 2005, and 2005 to 2010) increase of 65 USD (for comparison, the average imports per capita in 2000 is 41 USD.) Importantly, the increase is highly heterogeneous across the population. For example, the people in the 90th percentile experience an average five-year increase of 138 USD, and the people in the 10th percentile experience a modest decrease.

We use product-level imports to implement our shift-share IV strategy. The raw data are at the HS 8-digit level, but product codes change over time, so we aggregate to HS 4-digit and use these national growth rates as the "shifters". There are 167 HS-4-digit products across 18 HS-2-digit segments. To have a sense of what is a 4-digit product, Appendix A.2 lists the number of HS-4-digit products and provides an example product within each HS-2-digit segment. As can be seen from the descriptions, an HS-4-digit code tends to contain products that serve a common, specialized function, supporting our later assumption of quasi-random national shocks at the HS-4-digit level.

We construct the "shares" in the shift-share instrument using the city-level importing data. Following Autor et al. (2013), we will fix the shares at pre-periods (at 1998 for the 2000–2005 period, and at 2003 for 2005–2010 period), but we note that under the maintained assumption introduced in the next section, our identification does not rely on the shares being exogenous.⁷

Population census. We use data from China's Population Census in 2000 and 2010, plus the 2005 Population Survey (the "Mini-Census"), to measure regional college shares and migration. All are created by the National Bureau of Statistics of China. The census covers the entire population, while the 2005 Mini-Census covers 1%. The sample available to us covers 0.1%, 0.2%, and 0.3% of the population in the three years, respectively. A representativeness check confirms that our subsample match official city-level statistics on demographic features.⁸

We also rely on these three samples to construct migration flows, which we use in the quantitative exercises as well as in the empirical decomposition. There are two ways of measuring migration from our micro data: one based on the location of a person five years ago (through a retrospective question in the census/survey), and one based on the birthplace of the person. The challenge is that for both definitions, the census microdata reports only the origin province, not the origin city. We rely on the output of a new data harmonization effort by Dorn and Li (2024) that creates city-to-city migration flows under both definitions. In this data project, we use auxiliary information to map all individuals living in a province five years ago to cities in that province, ensuring

⁵ According to China Educational Finance Statistical Yearbook, Chinese colleges at all tiers rely on governments, including central, provincial, and city governments, for more than half of their financing.

⁶ The construction of the county-level crosswalk is based on information on the administrative division changes published by the Ministry of Civil Affairs (www.mca.gov.cn/article/sj/xzqh/1980/).

⁷ We use two-year lagged shares, not shares further back, because the earliest year that we have city-level importing data is 1998.

⁸ We have excluded under-sampled cities from our analysis; collectively, these cities account for less than 5% of China's total population.

the population statistics in origin cities are consistent with our micro data and other official statistics. For example, in defining previous-to-current-residence migration from 2000 to 2005, we map individuals to their previous resident cities in 2000 so that the number of residents in city d for a given cohort in 2000 estimated based on the 2005 data is consistent with the actual number of residents in city d reported in the 2000 census. When defining birth-to-current-residence migration flows, we attribute individuals to birth cities based on these cities' share of total births in their province. See the appendix for additional details.

Our microdata confirm that the growing national skill share (Fig. 2) was accompanied by widening regional disparities. Table A.1 shows an average five-year growth in college share (population aged 15+) of 3.59 percentage points over 2000–2010, compared with an average college share of 4.30% in 2000. For the people at the 90th percentile, the average five-year increase is 7.24 p.p.; for people at the 10th percentile, the increase is only 0.7 p.p.

Supplementary data. We use additional datasets for auxiliary evidence for mechanism and to construct variables in our quantitative analysis.

We obtain information on wages from two sources. The first is the Urban Household Survey (UHS), available from 1992 to 2009. The survey provides detailed demographic, employment, and income information of urban residents. It is one of the most comprehensive household surveys in China and forms the basis for the wage and consumption information reported in the national statistical yearbooks. The full data cover 31 provinces; we have access to data from 18 of them. These 18 provinces are representative of the country in geographic location and economic development.⁹ We will primarily use this dataset for measuring city-level wage and skill premiums to provide suggestive evidence for the mechanism. In addition, our quantitative analysis requires wage information for the entire country. We will use the 2005 Mini Census to supplement the UHS to construct this measure, a process we describe in quantification.¹⁰

To examine the relationship between imported capital goods use and firm skill intensity, we will use the 2004 industrial census, which covers the universe of industrial firms, and the Annual Survey of Industrial Firms (ASIF), which covers all state-owned enterprises (SOEs) and non-state firms in the mining, manufacturing, and public utility sectors with annual sales above 5 million Chinese yuan. The balance sheet and production information in these firm-level data allow us to construct the city-level use of capital and equipment, which we will use in model calibration.

In addition to the aforementioned datasets, we use various statistical yearbooks, such as China Education Statistical Yearbooks, to measure city characteristics.

2.3. A first look from a regional perspective

Before proceeding to empirical analysis, we examine the cross-regional pattern in capital goods imports, the college share, and the skill premium.

Given China's widespread spatial disparity in international trade participation, it is perhaps unsurprising that coastal regions import far more than inland regions. Fig. 3 shows that coastal regions not only import more but also import more intensively in capital goods. Over 2000–2010, around 40% of coastal imports comprised capital goods, compared with only 30% for inland areas. Fig. 4 shows that over the same period, both the college share and the college premium increase more rapidly in the coastal regions. These spatial patterns align with our hypothesis that capital goods imports contribute to the increase in college share via capital skill complementarity. However, they could also reflect other confounding factors. In the next section, we will use a shift-share instrumental variable (IV) to estimate the causal effect of capital goods import growth on college shares.

3. Imported capital goods and college share

3.1. Empirical specification

Our regression specification is as follows:

$$\Delta Y_{it} = \beta_1 \Delta KIP_{it} + \alpha_{pt} + X'_{it} \delta + \epsilon_{it}, \quad (1)$$

where ΔY_{it} is the change in regional outcome variables—such as the share of people with some college education—in city i between $t-1$ and t , and ΔKIP_{it} is the increase in per-capita capital goods imports in city i between $t-1$ and t . Having at hand the data for 2000, 2005, and 2010, we estimate Eq. (1) through stacked 5-year first differences, that is, the difference from 2000 to 2005 and from 2005 to 2010.

College share. Our primary outcome is the change in a city's college share. We classify individuals as “college graduates” if they have any college education. The outcome variable is constructed as follows:

$$\Delta Y_{it}^g = \frac{Skill_{it}^g}{L_{it}^g} - \frac{Skill_{it-1}^g}{L_{it-1}^g}, \quad (2)$$

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

¹⁰ Among the three population censuses/surveys, only the one in 2005 contains wage information.

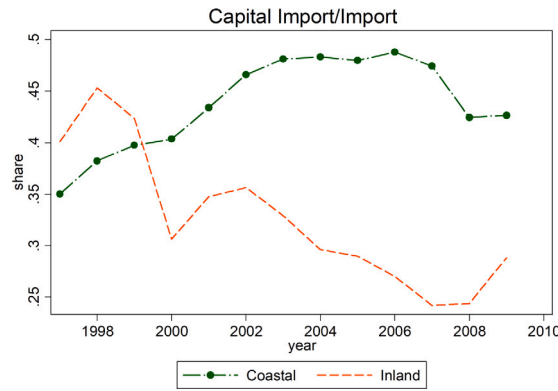


Fig. 3. Capital goods imports in all imports.

Note: The figure shows the share of capital goods imports in total imports for coastal and inland regions. Data: China General Administration of Customs, 1997–2009.

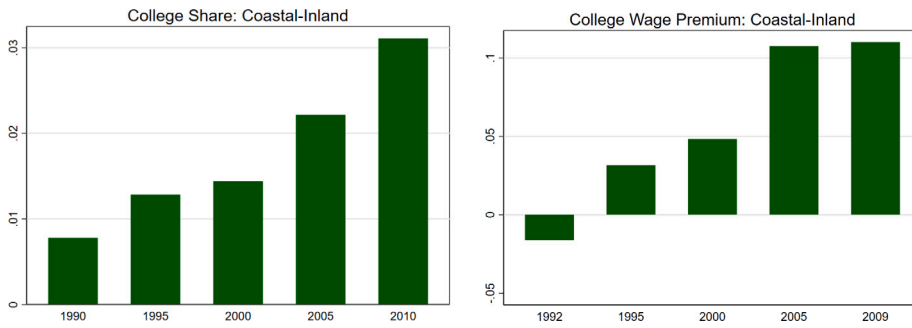


Fig. 4. The widening regional differences in college share and college wage premium.

Note: The college share is defined as the number of people with some any college education as a share of the population. The college wage premium is estimated via a Mincer-style OLS regression, controlling for gender, work experience and its square, employer ownership type, and industry dummies.

where ΔY_{it}^g is the change in the share of people in birth cohort g in city i with some college education, and $Skill_{it}^g$ and L_{it}^g denote the number of college-educated individuals and total individuals in cohort g in city i at time t .

Capital goods import growth. Our primary variable of interest is per-capita capital goods import growth, defined as

$$\Delta KIP_{it} = \frac{M_{it} - M_{it-1}}{L_{it-1}} = \frac{\Delta M_{it}}{L_{it-1}}, \quad (3)$$

where ΔM_{it} is the change in capital goods imports in city i between $t-1$ and t , and L_{it-1} is the city's population in $t-1$.

Control variables. Our first-difference specification removes time-invariant city-specific determinants of the outcome variables. To account for time-variant shocks, we include additional fixed effects and control variables. Specifically, to absorb variations across broad regions due to China's uneven spatial development and regional policies, we control for province $\times$ year dummies (α_{pt}). We accommodate the possibility that cities follow different time trends in both capital goods imports and college shares based on their (observable) features by controlling for a number of start-of-period city characteristics, including the minority population share, age structure (the fractions of people born in 1951–1960, 1961–1970, etc.), manufacturing employment share, and the shares of the cities' exports in the two major exporting industries of China between 2000 and 2010 (textile, and electronics & machinery).

We also address potential biases in the measure of capital goods import growth arising from wholesale and transit trade. Recall that we map imports to cities using the location of the importing firm.¹¹ While for the goods considered in this paper, capital machinery, the importer are most likely the user—or at least in the same city as the user—it is possible that some firms act as a wholesaler and re-sell the imported goods to firms in other cities, creating non-classical measurement errors. The data at hand does not allow us to directly correct for such biases, so in some specifications, we attempt to account for such biases by adding controls for the major transshipment cities with exceptionally high ratio of capital goods imports over input use.¹²

¹¹ There are two locations associated with an import transaction. The first is the city where the goods clear the customs, the second is the location of the importer. We use the latter location.

¹² To gauge the severity of such errors, we merge import transactions with the firm-level production data. We then calculate total imports as a share of a firm's total input use. Only 1% of the firms, most of them located in major ports, import more products than their reported input use.

3.2. Shift-share IV, diagnostics, and inference

Despite the rich set of controls, the OLS estimate of Eq. (1) suffers from simultaneity and reverse causality biases. To establish a causal interpretation, we use a shift-share IV strategy (Bartik, 1991). We construct the IV as:

$$\Delta KIP_{it}^{Bartik} = \left[\sum_j \frac{M_{ij,ini}}{M_{i,ini}} \left(\frac{M_{jt}^{-i} - M_{jt-1}^{-i}}{M_{jt-1}^{-i}} \right) \right] \frac{M_{i,ini}}{L_{i,ini}}, \quad (4)$$

where M_{jt}^{-i} is China's import of capital goods in product j and year t , calculated excluding the province where city i locates, $M_{i,ini}/L_{i,ini}$ is the imported capital goods per capita of city i in the initial period, and $M_{ij,ini}/M_{i,ini}$ is the share of an HS-4-digit product j in city i 's capital goods imports in the pre-period, which captures a city's initial reliance on a certain type of capital equipment.

Eq. (4) essentially predicts a city's per-capita capital goods import growth rate by combining its structure of imports across products in the pre period with the national growth in each product. As the predicted growth rate enters the IV in product with the initial per-capita imports, we also include the interaction between the latter and period dummies to absorb the variations in the pre-period per capita imports.

As illuminated by the recent methodological contributions on shift-share IVs, researchers can maintain one of the following two assumptions for this design to be valid: that the product-level import growth (the shifters) are generated by quasi-experimental shocks (Borusyak et al., 2022b), or that the shares in the pre-period are exogenous (Goldsmith-Pinkham et al., 2020). We will maintain the first assumption, viewing the shocks as generated by idiosyncratic foreign productivity growth/import cost reductions across small product categories.

Diagnostics. Following the recommendations of Borusyak et al. (2022b), we conduct three diagnostic tests on the validity of this assumption. Overall, we find the test to be supportive of the quasi-random national shocks assumption.

First, we assess the extent to which the variations among HS-4-digit capital goods are between versus within HS-2-digit segments. Appendix Figure A.3 depicts the growth rate for each HS-4-digit capital goods category. The goods within the same HS-2-digit segment tend to occupy a wide range on the vertical axis, indicating high variability in import growth among similar products. This figure is supportive of the quasi-randomness assumption of the shifters. It also suggests that the shocks are unlikely to have a strong correlation with the technological/industrial characteristics of the products—if that were the case, we would have seen a strong correlation in growth within the same HS-2-digit segment. We test this hypothesis formally in Table A.5, in which we map HS to four-digit Chinese industries (based on industry output) and then regress industry characteristics on capital goods imports growth. We find that the import growth is not systematically correlated with any of the industry characteristics.

Second, we calculate the expected HHI of average shock exposure (import share) to describe the effective sample size in Appendix Table A.3. The inverse HHI of the import shares is reasonably high and the shock dispersed: 25 when exposure is measured at the HS-4-digit level, with the largest weight being 14%.

Third, we conduct regional balance tests in Table A.4. Our IV, defined in Eq. (4), is the product between the predicted-growth rate $\sum_j \frac{M_{ij,ini}}{M_{i,ini}} \left(\frac{M_{jt}^{-i} - M_{jt-1}^{-i}}{M_{jt-1}^{-i}} \right)$ and initial import per capita $\frac{M_{i,ini}}{L_{i,ini}}$. We regress various city characteristics on both the predicted growth rate and the actual IV. In particular, given our focus on the change in college shares as the outcome variable and capital goods imports as explanatory variables, cities' initial urbanization rate, age structure (i.e., the shares of the population born in 1941–1950, 1951–1960, 1961–1970, etc.), the cultural value of education (proxied using minority share), manufacturing employment share, and the changes of China's import tariff between 2000 and 2010 are clearly relevant controls. None of these variables are statistically significantly correlated with the IV.

Inference. Under our identifying assumption, standard inference procedures may result in over-rejection due to correlation across cities in the shares (Adao et al., 2019). To assess the importance of this concern, we conduct a placebo analysis by running regressions using simulated data where we construct the shift-share explanatory variable by randomizing the nation-wide growth rates of different HS products. Figure A.2 reports the results of this analysis. Perhaps because the inter-regional correlation in importing shares is relatively low, the over-rejection of conventional clustered (by province) standard errors turn out modest. The resulting placebo instruments' coefficients are significant at the 1% level in 3.1% of cases, and at the 5% level in 8.7% of cases. Given this finding, we will use the clustered standard error.¹³

3.3. Baseline results

Table 1 Panel A presents the baseline results. All regressions are weighted by the city-level population in 2000. Columns (1) and (2) use the OLS specification. Both columns show a large and statistically significant correlation between the growth in capital goods imports and the change in college shares.

Columns (3) to (5) present the results from the IV specification, with the first-stage results reported in Panel B. Comparing the OLS estimate in Column (1) with the IV estimate in Column (3), we find that the coefficient of the IV estimation is slightly larger

¹³ The same capital goods are used in many sectors, and this might explain why the correlation in import shares can be lower than the correlation in employment shares in the setting considered in Adao et al. (2019). We use clustered standard errors because existing shift-share inference does not readily apply to our leave-one-out IV.

Table 1
Imported capital goods and college share.

Dependent variable: $100 \times \Delta$ (college share) (in % pts)					
Panel A: 2000–2010 Stacked first differences					
	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Δ Capital goods import per capita	0.29*** (0.09)	0.21*** (0.08)	0.44** (0.21)	0.24*** (0.08)	0.16** (0.07)
Dummy for period 2000–2005	✓		✓		
Province $\times$ period		✓		✓	✓
Dummies for major trans-shipment cities $\times$ period		✓		✓	✓
Start-of-period controls		✓		✓	✓
Pre-period imports per capita $\times$ period					✓
Panel B: 2SLS First stage estimates					
Δ Predicted imported capital goods per capita			1.03*** (0.06)	1.12*** (0.03)	1.05*** (0.05)

Note: $N = 652$. Regressions are weighted by city-level residence-based population in 2000. The start-of-period controls in 2000 and 2005 include the minority share, population shares by cohorts (e.g., people born before 1940, 1941–1950, 1951–1960, 1961–1970, 1971–1980, 1981–1990, 1991–2000), manufacturing employment share, the export share of textiles, and the export share of electronics & machinery. Dummies for major trans-shipment cities and their interactions with year are controlled in Columns (2), (4), and (5). Column (5) further controls for the pre-period (two-year lagged) capital goods imports per capita interacted with period dummies. Robust standard errors clustered at province are shown in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

than that in the OLS estimation. This difference can be explained either by attenuation bias or by households responding more to capital imports driven by national shifters than those driven by a city's idiosyncratic demand. In Column (4), when we include a richer set of controls, the coefficient declines to 0.24, similar to that in Column (2). In Column (5), we control for the interaction between city's initial per-capita imports and period dummies. The coefficient reduces but remain statistically significant.

Column (5), our preferred specification, implies that a 100 USD increase in imported capital goods per capita leads to a 0.16 p.p. increase in local college share. In the data, the standard deviation of five-year capital goods import growth and five-year change in college share is, respectively, 232 USD and 2.87 p.p. Our estimate implies the increase in the imported capital goods can account for 13% ($0.16 \times 2.32/2.87$) of the differential increase in skill shares across cities.

3.4. Suggestive evidence and alternative mechanisms

Auxiliary Evidence. Results in the previous subsection suggest that capital goods import growth has a statistically significant and economically meaningful effect on city differential increase in college share. Our preferred interpretation of the causal effect is that rising skill premiums motivate more workers to seek college education—a demand for skill channel. We use additional firm- and worker- level data to corroborate this interpretation with two sets of auxiliary evidence, which we report in the appendix.

First, in Table A.7, we use firm-level data to examine how a firm's production and demand for skill correlate with capital goods imports. We find that firms using imported capital are more productive, have a more skilled workforce, pay higher wages, and maintain a higher computer–worker ratio. These patterns are consistent with the notion of capital-skill complementarity and an increase in skill demand in response to an increase in imported capital goods.

Second, in Table A.6, we use the UHS panel to explore the impact of imported capital goods on the wage structure. We find that imported capital goods increase the skill premium, consistent with the findings of the literature. More importantly, the increases in skill premiums attenuate over time, in line with the gradual increase in college supply moderating the effects on skill premium.

Alternative Explanations. In the rest of this subsection, we discuss some alternative explanations for the finding.

The first alternative explanation is that capital goods may enhance the productivity of cities, bringing in additional revenue to local governments. As higher education in China relies heavily on government finance, more government investment in this sector can lead to an increase in the accessibility of college education, thereby increasing the local college share.

This is a very likely explanation for the *nationwide* increase in college share shown in Fig. 2. However, given the college admission institutions in China, it is unlikely to be a major driver for our reduced-form estimate, which focuses on *differential effects* exploiting variations between cities *within a province*. In China, high school graduates take the National College Entrance Exam (commonly known as “gaokao”). Their scores in these exams determine what kind of college they qualify for. Importantly, as college seats are allocated to provinces and the qualification cutoffs for each college are also set at the provincial level, students compete with all other students *from the same province*. For example, students from Guangdong Province would be ranked among all students from Guangdong to determine their eligibility and potential placement. Therefore, access to college varies largely by province, and these variations would be absorbed by our province $\times$ period fixed effects. As such, our estimates would not be affected by the concern that people from a province more exposed to capital goods have easier access to college and return to the home city after graduating from college.

Table 2

Alternative mechanisms.

Dependent variable: $100 \times \Delta$ (college share) (in % pts)	(1)	(2)	(3)	(4)	(5)	(6)
Δ Capital goods import per capita	0.13* (0.07)	0.16** (0.07)	0.18*** (0.06)	0.17** (0.07)	0.14* (0.08)	0.14** (0.07)
ln(total admission at local colleges)	0.20*** (0.04)					0.21*** (0.05)
Δ ln(GDP per capita)		−1.01 (1.52)				−0.05 (1.35)
Δ Imported raw inputs per capita			0.17 (0.15)			0.10 (0.13)
Δ Import weighted tariff				0.73 (1.13)		2.70 (1.68)
Employment share of state-owned enterprises					−1.14 (1.02)	−1.58 (1.25)
Employment share of foreign-owned enterprises					−3.02*** (0.73)	−2.77*** (0.76)
N	638	543	652	652	606	496
Dummy for period 2000–2005	✓	✓	✓	✓	✓	✓
Province $\times$ period	✓	✓	✓	✓	✓	✓
Dummies for trans-shipment cities $\times$ period	✓	✓	✓	✓	✓	✓
Start-of-period controls	✓	✓	✓	✓	✓	✓
Pre-period import per capita $\times$ period	✓	✓	✓	✓	✓	✓

Note: Regressions are weighted by city-level residence-based population in 2000. All columns are estimated using 2SLS. The start-of-period controls include the minority share, population shares by cohorts (e.g., people born before 1940, 1941–1950, 1951–1960, 1961–1970), manufacturing employment share, the export share of textiles, and the export share of electronics & machinery. The pre-period import per capita is also included. Dummies for major trans-shipment cities and their interactions with year are controlled. Robust standard errors clustered at province are shown in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We cannot rule out that *within* a province, students from a city with more colleges are more likely to go to college simply because they can stay close to home while in college. Students may also go to a city for college (and stay after graduation) if that city has more colleges. To account for this channel, we control for the total admission by local colleges in 2000 on the basis of the specification in Table 1 Column (5).¹⁴ The result is reported in the first column of Table 2. We find that the total admission by local colleges has a positive and statistically significant coefficient, but the coefficient for capital goods import growth does not change.¹⁵

The second alternative explanation, conceptually similar to the first, is that with an influx of imported capital goods, local residents' income rises, thereby increasing the demand for higher education via an income effect. To account for this channel, we control for the change in log GDP per capita in the second column of Table 2, with the caveat that GDP is itself an endogenous variable. Our sample shrinks somewhat due to the availability of local GDP data, but the primary result remains the same. As local government resources are also tightly connected to the local GDP, this control also alleviates the concern that in response to an increase in government revenue, the local government increases investment in other local public goods—such as by increasing the spending on the local K-12 education—which improves the readiness of local students for college.

The third alternative explanation suggests that perhaps capital goods imports are complementary to other imported goods and it is these other goods, rather than capital goods, that increase the college share. This complementarity could be direct—through production—or indirect; for example, cities importing more capital goods could lobby for lower tariffs on other goods they use. In Column (3), we control for the change in raw material imports per capita.¹⁶ In Column (4), we control for the change in city-level average import tariffs. These controls do not diminish the estimate for capital goods imports.

Finally, during the decade 2000–2010, China carried out major reforms in the state-owned enterprises sector and attracted many foreign enterprises. If—for reasons unrelated to capital-skill complementarity—these firms have a higher demand for both capital goods and skills, then the increase in capital goods imports can increase local skill demand in cities where SOEs and foreign firms have a bigger presence. To account for this mechanism, in Column (5), we control city-level employment shares of state-owned and foreign firms. Doing so does not affect the coefficient for capital goods imports.

In the last column, we include all these controls simultaneously. Our finding remains robust, suggesting that the estimated impact of capital goods imports on college share is unlikely to be driven by these alternative mechanisms.

¹⁴ Ideally, we would like to also control for the change in city-level admission, but we only have access to the city-level admission data in 2000. Using this as a control is still informative—as mentioned earlier, most of the increase in college admission is through either the expansion of incumbent institutions or the entry of new institutions that are affiliated with existing institutions. For this reason, initial college admission is likely to be highly correlated with the increase in college seats between 2000 and 2010. An added benefit of using 2000 admission is that it is less endogenous to the shock.

¹⁵ If not due to local college supply, how is the increase demand for college fulfilled? Given the institutional background of China, the increase in demand is likely fulfilled through provincial and national college expansion, which would be absorbed by our fixed effects. We also cannot rule out that the increase in college demand in one city crowds out the demand in other cities within the same province. For this reason, the estimate can only be interpreted as differential effect. We use the differential effect to identify skill supply elasticities in the structural estimation and then conduct counterfactuals (under additional assumption on college seat supply; see our discussion in Section 4.5).

¹⁶ The shift-share instruments for raw material imports are constructed similarly to the IV for the capital goods imports in Eq. (4).

3.5. Decomposition: Education vs. Migration

In a spatial setting, local college shares can respond to the rising capital goods imports through skill acquisition or migration. To inform the quantitative framework, we examine the response in these two margins across birth cohorts. To facilitate decomposition, we consider the following outcome variable:

$$\begin{aligned}\Delta Y_{it}^g &= \frac{Skill_{it}^g - Skill_{it-1}^g}{L_{it-1}^g} \\ &= \frac{Skill(Unskill_{it-1})_{it}^g - Skill(Deceased)_{it}^g}{L_{it-1}^g} + \frac{Skill(IM)_{it}^g}{L_{it-1}^g} - \frac{Skill(EM)_{it}^g}{L_{it-1}^g}\end{aligned}\quad (5)$$

where ΔY_{it}^g is the change in the number of people in cohort g with a college education between $t - 1$ and t over the population of the people in cohort g in $t - 1$.

ΔY_{it}^g can be conveniently decomposed into three margins of adjustment: the change in the number of people with a college education among the stayers (the first term in the second line, which, in turn, can be decomposed into skill acquisition and death), among the immigrants (the second term), and among the emigrants (the third term). We measure these terms using a newly constructed city-to-city, five-year migration flows, defined based on residents' current location in time t and their residence five years ago ($t - 1$). As our data are repeated cross-sectional, we have no information on total death by skilled stayers, so we report the sum of the two terms for stayers.

Table 3 reports the estimation results for the outcome variables defined in Eq. (5). The coefficients are generally positive and statistically significant and, with the exception of the 1974–1981 cohorts, tend to be larger for younger cohorts.¹⁷

Column (1) of Panel A shows the average effect of imported capital goods on all cohorts. The regression specification is the same as Table 1 Column (5), except for dependent variables. According to the summary statistics in Table A.1, the standard deviation of the outcome variable (skill share in *start-of-period* population) is 3.79 p.p. The estimate of 0.32 implies the increase in the imported capital goods can account for 19.6% ($0.32 \times 2.32 / 3.79\%$) of the differential increase in skill shares across cities.

In Columns (2) to (4), we decompose the estimates into the three components in Eq. (5). Aggregating across cohorts (Panel A), all three margins are statistically significant, with the net effect of migration ($0.23 = 0.19 + 0.04$) larger than that due to skill acquisition (0.09). Looking into individual cohorts, we see that the youngest cohort, 1986–1989 cohorts, have the largest local effect. Since at this age group, differential death is unlikely to be important, this local effect, which accounts for accounting for three quarters of the total effect ($1.07 / 1.41$), is best viewed as due to skill acquisition. This finding is intuitively sensible: most people attend college in 18 or 19 in China, but since the college entrance exam takes a years-long preparation process, the decision of whether to go to college is likely made earlier. In 2005, when some of the shocks have materialize, this cohort is 16–19 years old, exactly the age when the decision of going to college is being made. For older cohorts, the effect is by and large driven by net migration. Across all cohorts, the coefficients for immigration and emigration have expected signs, though immigration is generally more important quantitatively.

As noted by Borusyak et al. (2022a), in a spatial setting like ours, interpreting the coefficient for migration as capturing the true importance of migration might be misleading, as our exposure measure does not account for indirect exposure through labor market linkages between regions. Instead of an exact decomposition, our main takeaway from Table 3 is that migration could be an important mechanism for the change in regional college share.

Summary. Taking stock of the empirical section, we find that city-level capital goods imports lead to an increase in skill shares. The most likely explanation for this finding is that facing an increase in skill premium, people respond by going to college or through migration, with both mechanisms playing a statistically significant role.

Given the spatial linkages between cities, these reduced-form estimates do not recover the general equilibrium effect of capital goods imports on skill share, for two reasons. First, people can migrate from unaffected regions to regions affected by the shock, so the “control group” is affected by spillovers from the “treated group”. This suggests that our estimate tends to underestimate the true aggregate effect of capital goods imports on skill shares. Second, exactly because people anticipate they can migrate, people in untreated regions might also choose to go to college more often. This mechanism implies that the reduced-form estimates may overestimate the true aggregate effect. We now turn to the quantitative model to uncover how skill acquisition and distribution respond to capital goods imports, and how these responses moderate the impacts of capital goods imports on the skill premium.

4. The model

We consider an environment with domestic and international trade, capital-skill complementary, and education and migration choices. The trade block of our model builds on Burstein et al. (2013) and Parro (2013), which extends Eaton and Kortum (2002) and Caliendo et al. (2019) to incorporate capital-skill complementarity; the migration block of the model builds on the recent quantitative spatial model (see Redding and Rossi-Hansberg (2017) for a review). Our main departure from existing models is that we incorporate endogenous education choice, which allows the model to speak to the empirical patterns documented in Section 3.

¹⁷ These might be cohort specific shocks that shape the education decision, making it less or more sensitive to capital goods imports, but understanding why this might be the case is beyond the scope of this paper.

Table 3
Decomposition by birth cohort.

(1) = (2) + (3) – (4)	(1)	(2)	(3)	(4)
	Y = 100 × (no. people with some college or above) /population	Local	Immigration	Emigration
Panel A. all cohorts				
ΔCapital goods import per capita	0.32*** (0.09)	0.09** (0.04)	0.19*** (0.07)	–0.04* (0.02)
Panel B. 1986–1989				
ΔCapital goods import per capita	1.41*** (0.50)	1.07 (0.74)	0.17 (0.35)	–0.17*** (0.05)
Panel C. 1982–1985				
ΔCapital goods import per capita	0.88*** (0.20)	0.00 (0.25)	0.53*** (0.11)	–0.34*** (0.10)
Panel D. 1978–1981				
ΔCapital goods import per capita	–0.00 (0.35)	–0.48 (0.34)	0.32*** (0.05)	–0.16*** (0.04)
Panel E. 1974–1977				
ΔCapital goods import per capita	0.16** (0.07)	–0.10 (0.08)	0.24*** (0.02)	–0.01 (0.03)
Panel F. 1970–1973				
ΔCapital goods import per capita	0.29*** (0.06)	0.15** (0.07)	0.13*** (0.01)	–0.01** (0.01)
Panel G. 1960–1969				
ΔCapital goods import per capita	0.11* (0.06)	0.06 (0.06)	0.06*** (0.00)	0.01* (0.01)

Note: N = 652. Regressions are weighted by city-level population in 2000. Regression specification is the same as Column (5) of Table 1. Robust standard errors clustered at province are shown in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1

4.1. Environment

Our model is static. There are $d = 1, \dots, N$ locations, representing N Chinese cities and a synthetic rest of the World (the last location; hereafter RoW). Workers can migrate within China but not internationally. Chinese cities trade with each other and with the RoW.

There are three sectors, denoted by $s \in \{K, OT, NT\}$, which stand for capital goods (K), other tradable (OT), and non-tradable (NT), respectively. Within each sector, there is a continuum of intermediate goods, indexed by $\omega \in (0, 1)$. These intermediate goods are traded across regions (except for those in the NT sector, which are subject to infinite iceberg trade costs) and aggregated to make composite sector final goods. Composite final goods are not traded and used locally for consumption or as input for production.

In the rest of this section, we describe first production and trade decisions and then migration and education choices. Finally, we define the equilibrium and explain how we will bring the model to the data to quantify the impacts of imported capital goods (more precisely, the shock that drives the import growth) on skill acquisition and skill distribution within China.

4.2. Production and trade

Consider an intermediate variety $\omega \in (0, 1)$ in sector $s \in \{K, OT, NT\}$. Each region d draws variety-specific productivity $z(\omega)$ from a Frechet distribution with location parameter T_d^s and dispersion parameter θ . The production technology for ω is given by:

$$y_d^s(\omega) = z(\omega) \cdot [q_d^{s,KHL}(\omega)]^{\gamma_d^{s,KHL}} \cdot [q_d^{s,OT}(\omega)]^{\gamma_d^{s,OT}} \cdot [q_d^{s,NT}(\omega)]^{\gamma_d^{s,NT}}, \quad (6)$$

where $q_d^{s,OT}(\omega)$ and $q_d^{s,NT}(\omega)$ are the use of the final good in sector OT and NT, respectively, in the production of ω ; $q_d^{s,KHL}(\omega)$ is the use of “equipped labor”; $\gamma_d^{s,\bar{s}}$, $\bar{s} \in \{KHL, OT, NT\}$ is the output elasticity for these inputs.

Letting L_d^H and L_d^L be the number of high- and low-skill workers employed in d , the supply of “equipped labor”, denoted by q_d^{KHL} , is given by

$$q_d^{KHL} = \left[(\mu_d)^{\frac{1}{\rho_2}} [L_d^L]^{\frac{\rho_2-1}{\rho_2}} + (1 - \mu_d)^{\frac{1}{\rho_2}} [q_d^{KH}]^{\frac{\rho_2-1}{\rho_2}} \right]^{\frac{\rho_2}{\rho_2-1}} \quad (7)$$

$$q_d^{KH} = \left[(1 - \lambda_d)^{\frac{1}{\rho_1}} [L_d^H]^{\frac{\rho_1-1}{\rho_1}} + (\lambda_d)^{\frac{1}{\rho_1}} [q_d^K]^{\frac{\rho_1-1}{\rho_1}} \right]^{\frac{\rho_1}{\rho_1-1}}, \quad \rho_2 > \rho_1 > 0.$$

This nested-CES production function follows that of Krusell et al. (2000), which has been applied to trade settings by Parro (2013) and Burstein et al. (2013). In the inner nest, capital equipment is combined with high-skill labor to produce “equipped skill” q_d^{KH} ; in

the outer nest, q_d^{KH} is then further combined with low-skill labor to produce “equipped labor” q_d^{KHL} . λ_d and μ_d are location-specific technology shifters that determine the share of each factor in equipped labor q_d^{KHL} . Under the assumption that $\rho_2 > \rho_1 > 0$, the model displays complementarity between capital and high-skill labor, so a decrease in the price of capital equipment increases the skill demand and the skill premium. The unit cost for “equipped skill” and “equipped labor”, denoted by c_d^{KH} and c_d^{KHL} , respectively, are given by

$$c_d^{KH} = \left[(1 - \lambda_d)(w_d^H)^{1-\rho_1} + (\lambda_d)(P_d^K)^{1-\rho_1} \right]^{\frac{1}{1-\rho_1}}$$

$$c_d^{KHL} = \left[(\mu_d)(w_d^L)^{1-\rho_2} + (1 - \mu_d)(c_d^{KH})^{1-\rho_2} \right]^{\frac{1}{1-\rho_2}}.$$

Letting c_d^s be the production cost of a variety ω of a firm with unit productivity, w_d^e be the wage for workers of skill e , and P_d^s be the price for the sectoral final goods, Eq. (6) implies

$$c_d^s = \left[\frac{c_d^{KHL}}{\gamma_d^{s,KHL}} \right]^{\gamma_d^{s,KHL}} \cdot \left[\frac{P_d^{OT}}{\gamma_d^{s,OT}} \right]^{\gamma_d^{s,OT}} \cdot \left[\frac{P_d^{NT}}{\gamma_d^{s,NT}} \right]^{\gamma_d^{s,NT}}. \quad (8)$$

In each sector and each location, a representative sectoral final good producer combines intermediate varieties from the same sector using CES technology. The total sectoral final goods produced in sector s at location d , denoted by Q_d^s , is:

$$Q_d^s = \left[\int_0^1 [Q_d^s(\omega)]^{\frac{\sigma}{\sigma-1}} d\omega \right]^{\frac{\sigma-1}{\sigma}},$$

where $Q_d^s(\omega)$ is the use of variety ω by the final good producer. For each variety, the final good producer source from the country with the lowest shipping-cost inclusive price. The Frechet assumption implies that the trade shares and the sectoral price index are given by:

$$\pi_{do}^s = \frac{T_o^s(c_o^s \tau_{od}^s)^{-\theta}}{\Phi_d^s}, \text{ where } \Phi_d^s \equiv \left[\sum_o T_o^s(c_o^s \tau_{od}^s)^{-\theta} \right]$$

$$P_d^s = \left[\Gamma \left(\frac{\theta + 1 - \sigma}{\theta} \right) \right]^{\frac{1}{1-\sigma}} \cdot (\Phi_d^s)^{-\frac{1}{\theta}}, \quad (9)$$

where τ_{od}^s is the iceberg cost of shipping goods from o to d , and $\Gamma(\frac{\theta+1-\sigma}{\theta})$ is a constant that depends only on θ and σ .

4.3. Education, migration, and consumption decisions

The labor supply in the RoW is fixed. In China, the supply of high- and low-skill labor to cities is the result of individuals' skill and migration choices. We assume that each origin city i is home to two cohorts of people, the young and the mature, indexed by Y and M with their quantity denoted by $\underline{L}_{i,Y}$ and $\underline{L}_{i,M}$. Young people decide whether to receive a college education. Mature people take their skills as given, an assumption motivated by the fact that during our sample period, people above the conventional college enrollment age mostly do not respond through skill acquisition. Both groups can migrate. Thus, in response to a change in the wage premium across cities, mature people respond through migration, whereas young people respond through both education and migration. In what follows, we describe first the education choice of the young and then the migration of both groups.

Education. Consider a young worker v who is born in city i . Her decision about whether to receive a college education is described by:

$$\max \left\{ \frac{1}{\delta_i} \cdot u_{i,Y}^H \cdot \zeta_i^H(v), \quad u_{i,Y}^L \cdot \zeta_i^L(v) \right\}.$$

In this problem, $u_{i,Y}^H$ and $u_{i,Y}^L$ are the expected utility of young workers from location i with skill H or L , to be defined below. $\zeta_i^H(v)$ and $\zeta_i^L(v)$ are individual v 's idiosyncratic tastes for the two skill levels, drawn from a Frechet distribution with shape parameter ξ . δ_i represents the utility cost of a college education, encapsulating in a reduced-form way the effort, time, and monetary commitments involved in prepping for the National College Entrance Exam ('gaokao') and then pursuing a college degree. While the monetary and time cost of pursuing a college degree might not vary significantly across locations, the level of effort needed for college admission can vary markedly. In particular, as universities allocate more seats to the home province, the difficulty of qualifying for college depends on one's home location. We thus allow δ_i to be specific to i .

The fractions of young workers from i that chooses H and L , denoted by l_i^H and l_i^L are

$$l_i^H = \frac{(u_{i,Y}^H / \delta_i)^\xi}{(u_{i,Y}^H / \delta_i)^\xi + (u_{i,Y}^L)^\xi}, \quad l_i^L = \frac{(u_{i,Y}^L)^\xi}{(u_{i,Y}^H / \delta_i)^\xi + (u_{i,Y}^L)^\xi}.$$

The number of high- and low-skill young workers from i are $\underline{L}_{i,Y} \cdot l_i^H$ and $\underline{L}_{i,Y} \cdot l_i^L$, respectively.

Migration. Having made their education choice, young workers choose the location of work to maximize their utility, along with mature workers. The utility a worker in age group $a \in \{Y, M\}$ and skill group $e \in \{H, L\}$ obtains by moving from origin i to

destination d depends on three components: the indirect utility in the destination city, the “iceberg” migration cost from i to d , and the idiosyncratic preference draw of the worker for d . Formally, the location choice of worker v is represented by:

$$u_{i,a}^e \left(\epsilon_1^e(v), \epsilon_2^e(v), \dots, \epsilon_N^e(v) \right) = \max_d \left\{ \frac{v_{d,a}^e}{\kappa_{id,a}^e} \cdot \epsilon_d^e(v) \right\},$$

where $v_{d,a}^e$ is the indirect utility workers of type (a, e) derive from residing in d ; $\kappa_{id,a}^e$ is the migration cost from i to d , which can differ by both skill and age; $\epsilon_d^e(v)$ is a location-specific taste draw that is independent across individuals and locations. We assume $\epsilon_d^e(v)$ follows a Frechet distribution with a common location parameter across d and a shape parameter η^e .¹⁸

Workers choosing a city derive utility from local amenities and the consumption of sectoral final goods according to the following preference:

$$A_{d,a}^e \cdot (C_d^K)^{\alpha^K} \cdot (C_d^{OT})^{\alpha^{OT}} \cdot (C_d^{NT})^{\alpha^{NT}}.$$

$A_{d,a}^e$ is the amenities in location d for a worker of type (a, e) ; C_d^s is the consumption of sectoral final good in sector s . By allowing $A_{d,a}^e$ to depend on (a, e) , we capture that amenities that appeal to young low-skill workers might not be as attractive to mature high-skill people, and vice versa. This preference gives an indirect utility of

$$v_{d,a}^e = \frac{A_{d,a}^e \cdot w_d^e}{P_d},$$

where w_d^e is the earning in d and

$$P_d = \left(\frac{P_d^K}{\alpha^K} \right)^{\alpha^K} \cdot \left(\frac{P_d^{OT}}{\alpha^{OT}} \right)^{\alpha^{OT}} \cdot \left(\frac{P_d^{NT}}{\alpha^{NT}} \right)^{\alpha^{NT}}. \quad (10)$$

Under the Frechet assumption, the fraction of group (a, e) from i choosing d for work is

$$\lambda_{id,a}^e = \frac{\left(\frac{A_{d,a}^e \cdot w_d^e}{P_d \cdot \kappa_{id,a}^e} \right)^{\eta^e}}{\sum_{d=1}^N \left(\frac{A_{d,a}^e \cdot w_d^e}{P_d \cdot \kappa_{id,a}^e} \right)^{\eta^e}}. \quad (11)$$

The expected utility among workers in this group is

$$u_{i,a}^e = \tilde{\gamma} \left[\sum_{d=1}^N \left(\frac{A_{d,a}^e \cdot w_d^e}{P_d \cdot \kappa_{id,a}^e} \right)^{\eta^e} \right]^{\frac{1}{\eta^e}}, \quad (12)$$

with $\tilde{\gamma}$ being a constant. The supply of young and mature workers with skill e to location d is

$$L_{d,Y}^e = \sum_{i=1}^N \underline{L}_{i,Y} \cdot l_i^e \cdot \lambda_{id,Y}^e,$$

$$L_{d,M}^e = \sum_{i=1}^N \underline{L}_{i,M} \cdot \lambda_{id,M}^e$$

The total supply of workers in d with skill e is

$$L_d^e = L_{d,Y}^e + L_{d,M}^e.$$

Discussion on model assumptions. In our model, young workers make education choices before migration decisions and the realization of their location-specific preference draws ϵ_d^e . This setup might seem inconsistent with the observation that some people attend college in other cities and stay there after graduation. As noted earlier, a major component of college education cost, which we capture with δ_i , is the time commitment required to prepare for the entrance exam. This process starts long before college admission—see [Ash \(2016\)](#) for a description of the process and the stress it entails. During much of the preparation process, most students do not have a clear idea about which college they will get into, let alone where they will reside after graduation. In this sense, the education choice in our model is best thought of as the decision of whether to start the years-long preparation process. This interpretation, and the fact that college seats are allocated by province, also motivate an origin-specific—rather than destination-specific—cost for college education, introduced via δ_i .

4.4. The definition of equilibrium

The primitives of the model include the structural elasticities governing production, trade, and household choices $\{\theta, \sigma, \gamma^{s,s'}, \alpha^s, \rho_1, \rho_2, \xi, \eta^e\}$, CES production function share parameters $\{\lambda_d, \mu_d\}$, fundamental shifters including $\{T_d^s, \tau_{od}^s, A_{d,a}^e, \delta_d, \kappa_{od,a}^e\}$, and labor endowment $\{\underline{L}_{d,a}\}$. Given these primitives, a competitive equilibrium of the model is a set of prices and allocations so that (i) goods and labor markets are clear; (ii) all workers make optimal location choices; young workers make optimal education choices; and (iii) all firms are price takers and choose quantities to maximize profit. We describe the conditions that characterize the equilibrium in Appendix B.1.

¹⁸ Systematic differences in preference across cities will be captured in amenities.

4.5. First-order approximation for estimation and counterfactuals

We will use the model to examine how the acquisition and distribution of skills in China are affected by a change in the fundamentals of the economy, focusing on the cost of importing capital goods observed over 2000–2010. To this end, we first recover the primitives that govern the response of individual decisions to changing wage structures, η^e and ζ , among other model parameters. We use first-order approximations to write the changes in models' endogenous outcomes as linear combinations of the change in model fundamentals. As articulated by [Adao et al. \(2019\)](#) and discussed below, this approach will enable us to be precise about the identification assumption imposed while ensuring consistency with the previous reduced-form analysis.

To simplify the exposition, we use bold letters to denote vectors and matrices obtained from stacking variables by location (and sector). For example, We define $T_{(N \times 3 \text{ matrix})} \equiv [T_{(N \times 1)}^K, T_{(N \times 1)}^{OT}, T_{(N \times 1)}^{NT}]$, where the subscripts indicate the dimension of variables. Similarly, $\tau_{(N \times 3N)} \equiv [\tau^K, \tau^{OT}, \tau^{NT}]$, $A_{(N \times 4)} \equiv [A_Y^H, A_M^H, A_Y^L, A_M^L]$. We use $\bar{x}$ to indicate a variable x of a baseline competitive equilibrium and $\hat{x}$ to indicate the percentage change in variable x between two competitive equilibria. Lastly, we use $vec(x)$ to denote the vector formed by stacking matrix x by column. We have the following proposition.

Proposition 1. *Up to the first order, the percentage change from a baseline equilibrium to a counterfactual equilibrium in any outcome of the model—such as the skill share or total employment of a city—due to changes in the model's fundamentals can be expressed as a linear combination of the percentage change in these fundamentals, with the weight depending solely on outcomes in the baseline equilibrium and the models' structural elasticities. That is,*

$$\begin{aligned} \hat{y}_{(N \times 1)} = & B_{(N \times 4N)}^{y,A} \cdot vec(\hat{A}) + B_{(N \times 3N)}^{y,T} \cdot vec(\hat{T}) + B_{(N \times 3N^2)}^{y,\tau} \cdot vec(\hat{\tau}) \\ & + B_{(N \times 2N)}^{y,\delta} \cdot vec(\hat{\delta}) + B_{(N \times 4N^2)}^{y,\kappa} \cdot vec(\hat{\kappa}), \end{aligned} \quad (13)$$

where $\hat{y}_{N \times 1}$ is an N -by-1 vector representing a change in outcome y in each location, $vec(\hat{A})$, $vec(\hat{T})$, $vec(\hat{\tau})$, $vec(\hat{\delta})$, and $vec(\hat{\kappa})$ are vectors of fundamental changes, and matrices $B^{y,f}$, $f \in \{A, T, \tau, \delta, \kappa\}$ are non-linear functions of the baseline equilibrium and structural elasticities.

This proposition expresses the changes in model outcomes in a counterfactual experiment as a linear function of the changes in fundamentals. $B^{y,f}$, $f \in \{A, T, \tau, \delta, \kappa\}$ in Eq. (13) summarize the general equilibrium elasticities of endogenous outcome y with respect to the change in each of the fundamentals. For example, if y is the vector of high-skill worker employment $\{L_d^H\}$, the $(1, 1)$ th element of $B^{y,T}$ is the elasticity of outcome L_1^H with respect to the productivity in the capital industry in location 1. Such are general equilibrium elasticities, as they encapsulate the effects of a fundamental on y both direct and indirect through all endogenous prices and allocations.

According to [Proposition 1](#), conditional on the structural elasticities and the outcomes from the baseline equilibrium, the level of fundamentals in the baseline economy is not necessary for counterfactuals. This result bears a resemblance to the “exact-hat algebra” approach pioneered by [Dekle et al. \(2008\)](#). The difference here is that the impacts of the change in different model fundamentals are linearly separable, a result of the first-order approximation. As discussed below, this linear separability has implications for using [Proposition 1](#) for both identification and counterfactuals.

Implication for identification of structural parameters. Suppose we observe the outcome of the model in two periods and have measured the changes in model fundamentals between these two periods (e.g., $\hat{\tau}$), then Eq. (13) can be used to estimate the structural elasticities of the model. In particular, as the GE elasticity matrices $B^{y,f}$, $f \in \{A, T, \tau, \delta, \kappa\}$ are determined solely by the baseline equilibrium outcomes (the data) and structural elasticities, we can pick the structural elasticities by minimizing the differences between the actual change in an outcome variable and the model-predicted change according to Eq. (13).

A practical complication arises: given the dimension of the model, researchers rarely observe the changes in *all* fundamentals.¹⁹ If only a subset of the changes in fundamentals is observed, then the changes in $\hat{y}$ that is attributed to the unobserved components enter as a structural error in the estimation, resulting in an endogeneity concern. Following [Adao et al. \(2019\)](#), we will carry out our structural estimation using an identification assumption similar in spirit to that in the reduced-form analysis.

Let $\hat{\tau}_{Ni}^K$, the (N, i) th element of τ^K , denote the change in capital import cost of a Chinese location i from the RoW, and let $b_{(d,i \times N)}^{y,\tau}$ denote the $(d, i \times N)$ th element of $B^{y,\tau}$, which is the elasticity of y_d with respect to $\hat{\tau}_{Ni}^K$, with y being any endogenous outcomes of the model, then $\hat{y}_d$ can be expressed as:

$$\hat{y}_d = a + \sum_{i=1}^{N-1} b_{(d,i \times N)}^{y,K} \cdot \hat{\tau}_{Ni}^K + \epsilon_d^y, \quad (14)$$

Here, a is the mean difference in $\hat{y}$ between the two periods (i.e., $\frac{1}{N-1} \sum_{d=1}^{N-1} \hat{y}_d$), $\sum_{i=1}^{N-1} b_{(d,i \times N)}^{y,K} \cdot \hat{\tau}_{Ni}^K$ is the effect on outcome y in location d of the change in capital goods importing costs across the country, and ϵ_d^y is the structural residual that captures the general equilibrium effects of the changes in all fundamentals other than $\{\hat{\tau}_{Ni}^K\}_{i=1}^{N-1}$.

We assume that conditional on the outcomes of the baseline equilibrium $\bar{Y}$ and other controls X , the regional import cost shocks $\{\hat{\tau}_{Ni}^K\}_{i=1}^{N-1}$ and the structural error $\{\epsilon_d^y\}$ are independent. While this assumption can be strong, it is consistent with the identification

¹⁹ Under assumed values for structural elasticities, one can “invert” the data to obtain the changes in fundamentals. However, changes obtained through this inversion will satisfy Eq. (13) by design when structural elasticities take the assumed values, rendering Eq. (13) useless for estimation.

imposed for a causal interpretation of many recent studies applying a shift-share design to a spatial equilibrium setting, including the one presented in our empirical section. To see this, recall that in the empirical section, we predict the capital import growth of a city using the inner product between the city's composition of capital goods imports across product categories and the (leave-one-out) national import growth in these categories, viewing the source of variations as coming from quasi-random national shocks to product-level capital import costs. In the model, there is only one capital goods sector, so we view $\hat{\tau}_{Ni}^K$ as the weighted average capital import cost change across product categories and measure it as such.²⁰ If the shocks at the product category level are as good as randomly assigned, an assumption we have maintained and provided supported for, then conditional on the baseline equilibrium and other controls, the weighted average of these shocks are also randomly assigned—that is, $\hat{\tau}_{Ni}^K$ are conditional independent of the structural error term. This motivates the following moment condition

$$\mathbb{E}[\mathbf{I}_d^Y \cdot (\hat{\tau}_{Nd}^K - \bar{\tau}_{Nd}^K) | \mathbf{Y}, \mathbf{X}] = 0, \quad (15)$$

where $\bar{\tau}_{Nd}^K \equiv \frac{1}{N-1} \sum_{d=1}^{N-1} \hat{\tau}_{Nd}^K$ is the mean capital import cost shock.²¹ This moment condition is conceptually similar to, but distinct from the identifying assumption in the reduced-form analysis because here the assumption is on regional rather than product-level capital import costs. In the next section, we use this condition for identification, conditioning on the control variables Column (5) of Table 1. We also conduct balancing test for the structural shocks $\hat{\tau}_{Nd}^K$.

Implications for counterfactuals. Proposition 1 also shows that the impact of $\{\tau_{Ni}^K\}_{i=1}^{N-1}$ on equilibrium outcomes do not depend on the change in other fundamentals. In particular, as discussed in Section 2, China went through a higher-education expansion, which has major impacts on skill acquisition and distribution. Proposition 1 shows that to understand the impact of the change in capital goods importing cost, we do not have to back out the change in the other fundamentals—and our finding will have first-order accuracy.

Two caveats to this approach are noteworthy. First, one may think that part of the driving force of higher-education expansion, captured in our model by $\hat{\delta}_i$, is endogenous. For instance, the increase in capital goods imports could contribute to growth in household income and local government revenue. The former could make college more affordable, whereas the latter could increase the supply of college seats. While these two channels may be both important at the national level, our empirical evidence suggests that they do not seem to interact with capital goods imports at the local level, so in carrying out counterfactuals, we will assume that $\{\tau_{Ni}^K\}_{i=1}^{N-1}$ does not affect $\hat{\delta}_i$ —that is, capital goods imports do not affect the cost of attaining college. Of course, as more people decide to go to college, college seats will have to respond. Our assumption is essentially that the response is a movement along the same (perfectly) elastic college seats supply curve with province-specific exogenous costs. This assumption has two parts: that the college seat supply curve does not shift in response to capital goods imports, and that the supply curve is inelastic. We justify the first part of the assumption on the ground that the shocks we consider is relatively small and only second-order to education policy. To the extent that by increasing national income and government revenue, capital goods imports contributes to the expansion of college and the increase in subsidies for college students, which leads to either a shift or a tilt in the supply curve, our counterfactual findings can be viewed as a lower bound for the full effects of capital goods imports. We justify the second part of the assumption using the fact that the increase college enrollment predicted by our model is also a small share of baseline college shares—which means even if the college seats supply is upward-sloping, the increase in cost due to the increase in skill share would be relatively small.

Second, although first-order approximation simplifies the analysis—and has been shown by recent studies (e.g., Kleinman et al. (2020)) to be accurate for trade models—one might still be concerned that the higher-education expansion and other reforms (such as the hukou reform) carried out during this period can have a big impact on the economy, thereby interacting with $\{\tau_{Ni}^K\}_{i=1}^N$ nonlinearly. For example, when the cost of going to college is lower, the same increase in skill premium will have a bigger effect on skill acquisition than our model implies. To provide a bound for the importance of such nonlinear mechanisms, we will carry out a counterfactual analysis around the 2010 education and migration outcomes, which would account for the lower education/migration costs in the post-reform economy.

5. Quantification

5.1. Data

We use the data on China's spatial economy and international trade around the year 2000 to construct the outcomes in the baseline competitive equilibrium, which we denote by letters with an upper bar. Our structural estimation uses ten-year change between 2000 and 2010 because key data described below (trade flows between China, city-level migration based on birth places) are not available in 2005.

Employment and migration data. The demographic and migration data are constructed based on a 1% individual-level sample of the 2000 population census. We classify individuals aged between 18 and 60 into two groups, young (18–35) and mature (36–60), denoted by Y and M, respectively. For each individual, we observe their education and current location, which allows us to construct

²⁰ We chose to incorporate only one capital in the model because when we move to the quantification, the data on domestic trade is not as granular as for international trade, precluding us from accurately measuring domestic trade in narrowly defined capital goods in the baseline economy.

²¹ Adao et al. (2019) shows that under the orthogonality condition that we invoke, one can use a more general form of the specification, $\mathbb{E}[\mathbf{I}_d^Y \cdot \sum_i h_{di}(\hat{\tau}_{Ni}^K - \bar{\tau}_{Ni}^K)] = 0$, choosing h_{di} appropriately to increase estimation efficiency. We use an identity matrix both for simplicity and because we lack accurate first-hand data on trade between Chinese locations.

regional employment $\{\bar{L}_{d,a}^e\}$, $\forall a \in \{Y, M\}, e \in \{H, L\}$. We use the city-to-city migration flows from Dorn and Li (2024). As our model focuses on a one-shot long-term migration decision, the migration measure we will use is the one based on birthplace.

Factors shares in production and consumption. We assume that the shares of equipped labor and other final goods in the production of intermediate goods ($\gamma^{s,s'}$ in Eq. (6)) and the shares of household expenditures over final goods differ between China and the RoW but not between cities within China. We set these parameters using the corresponding values in Fan (2019), who calculates the values for China using the Chinese input–output table and the values for the synthetic RoW as the average values of major countries based on WIOD.

Equipped labor contains value added from capital equipment and high- and low-skill workers. We obtain the shares of capital in equipped labor as follows. For Chinese locations, we measure the capital share in value-added using the Annual Survey of Industrial Firms, calculating this share for each city by aggregating across firms there. For the synthetic RoW, we assume that 40% of the value added comes from capital, with the remaining from labor, a division close to that of the U.S. around 2000.

We then measure the relative share of high- and low-skill workers in equipped labor. For Chinese cities, these shares are calculated from the employment and wages of high- and low-skill workers using three sources of information: employment data from the population census and wage data from two sources—the 2002 UHS, which covers 181 cities (earlier UHS covers only half as many cities), and the mini census from 2005, which covers all Chinese cities. For cities covered by the UHS, we use the UHS to measure the average wage for high- and low-skill workers; for cities not covered by it, we infer their wages in 2002 using the wage in the 2005 mini census and the wage growth rate of similar cities between 2002 and 2005.²² For the synthetic RoW, we assume skilled workers account for about 73% of the labor value added, a share calculated based on the U.S. college share and skill premium around 2000.

Trade and production. We measure city-sector level trade shares and value-added using the model-based imputation of Fan (2019), who estimates a model of domestic and international trade with capital-skill complementarity using China's inter-provincial input–output table and city-sector level import, export, and value-added data. As the production of the model there is similar to the one adopted in this paper,²³ the values from Fan (2019) are consistent with what we would have obtained if we have repeated the same structural estimation process. This step gives us $\{\bar{\pi}_{od}^s\}$ and $\{\bar{X}_d\}$.

Measuring the change in capital goods import cost. To operationalize structural estimation, we need to take a stand on what drives the growth in capital goods imports—e.g., foreign capital goods sector productivity, changes in capital goods import costs, or other reasons. Given our focus on the outcomes within China, and considering that our model incorporates only one capital good sector, we assume that the import increase is driven by a location-specific decrease in importing costs. Thus, $\forall i = 1, \dots, N - 1$, we measure $\hat{\tau}_{Ni}^K$ as

$$\hat{\tau}_{Ni}^K = -\frac{1}{\theta} \cdot \widehat{KIP}_i^{IV}, \quad (16)$$

where $\widehat{KIP}_i^{IV}$ is the *percentage growth rate* in capital goods imports predicted by the shift-share formula (i.e., the term inside the square bracket of Eq. (4)), not including the initial imports-per-capita term), θ is trade elasticity, and $\hat{\tau}_{Ni}^K$ is the change in import cost necessary to account for $\widehat{KIP}_i^{IV}$.²⁴ As city-level capital goods import growth rates show a wide range of variations, the inferred $\hat{\tau}_{Ni}^K$ is widely dispersed. To reduce the impact of outliers, we winsorize $\hat{\tau}_{Ni}^K$ at -100 log points, which corresponds to approximately 64% decrease in capital goods importing cost (or a four-time increase in capital goods imports) over 2000–2010.

To corroborate the identification assumption for structural estimation, we conduct a balancing test by regressing regional characteristics on $\hat{\tau}_{Ni}^K$. As reported in Table B.1, none of the regional variables are statistically significantly correlated with $\hat{\tau}_{Ni}^K$.

5.2. Structural elasticities

In addition to the parameters in production functions, the model has the following structural parameters: ρ_1 and ρ_2 , which shape capital-skill complementarity; θ , the trade elasticity; ζ , which governs the dispersion in the taste draws in skill choice; η^e , $e \in \{H, L\}$, which govern the dispersion in workers' taste draws preferences for locations. Some of these parameters have been estimated in the literature, so we assign their values based on external estimates. In particular, we set $\theta = 4$ following Eaton and Kortum (2002). We set $\rho_1 = 0.67$ and $\rho_2 = 1.67$ following Krusell et al. (2000).²⁵

²² Using the 2005 mini census average wage for all cities leads to materially the same quantitative findings.

²³ The main difference is that the 'OT' sector in the present paper is split into agricultural and other manufacturing in Fan (2019). We use this estimate because the readily available inter-provincial input–output table is only at the provincial-pair level, but our reduced-form analysis and model quantification are at the city level, so model-based imputation is necessary.

²⁴ In a model that explicitly incorporates many capital goods varieties, the partial equilibrium change in capital goods imports in the region i can be written as $\widehat{KIP}_i^{IV} = -\theta \cdot \text{im}_i^j / \sum_j \text{im}_i^j \cdot \hat{\tau}_{Ni}^j$, where im_i^j is the baseline import of capital goods variety j , and $\hat{\tau}_{Ni}^j$ is the change in the importing cost of that variety. Thus, $\hat{\tau}_{Ni}^K$ in our model can be viewed as the weighted average of the changes in the cost of importing individual goods in a model with many capital goods.

²⁵ The estimates of Krusell et al. (2000) are based on an aggregate production function. One may be concerned that in our setting with many cities, these aggregate elasticities capture both the elasticities in a city-level production function and the substitution between cities with different factor shares, and therefore do not map into the elasticities in our city-level production function. See Oberfield and Raval (2021) for a discussion of this difference in the context of using firm-level data to estimate the aggregate elasticity. In the appendix, we exploit cross-region variations to estimate ρ_1 and ρ_2 internally at the city level under additional assumptions. We find that $\rho_1 = 0.425$ and $\rho_2 = 1.175$, implying slightly weaker capital-skill complementarity. We show that using these internally estimated values leads to similar counterfactual findings.

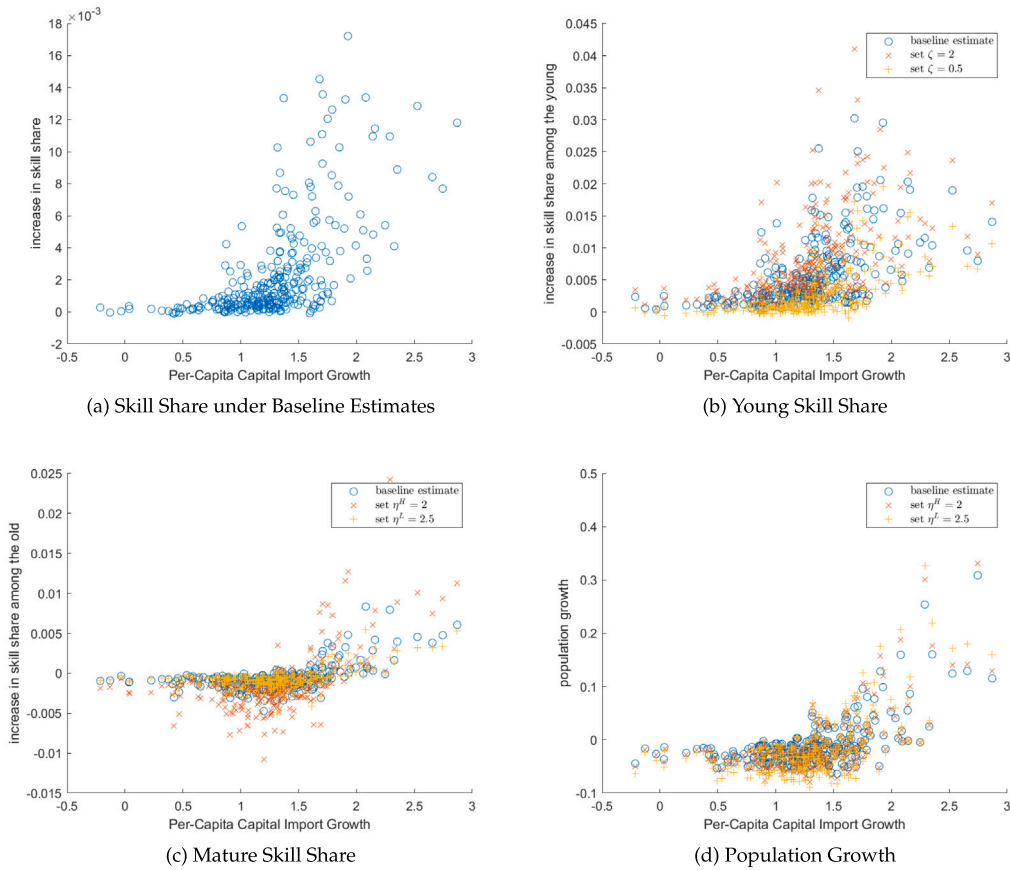


Fig. 5. Identification of structural parameters.

Note: The figures illustrate how city outcomes vary with key structural elasticities. In all panels, the horizontal axis is the per-capita capital goods import growth. The vertical axis is, respectively, the change in skill share (Panel a), the change in skill share among young workers (Panel b), the change in skill share among mature workers (Panel c), and the log difference in city population (Panel d).

The remaining elasticities, ζ , η^H , and η^L , are closely tied to the outcomes we seek to explain—the acquisition and spatial distribution of skills—and lack well-established estimates. We calibrate these internally. We identify these parameters using the changes in several outcome variables between 2000 and 2010, including the level and percentage increase in city skill share, and the percentage change in population and the skill shares among the young and the mature. Intuitively, the change in a city's overall skill share represents the net effect of both skill acquisition and migration. By targeting the changes in population and skill share simultaneously, we can differentiate the impact of acquisition from migration. Moreover, we can distinguish the migration parameters of high- and low-skill workers by matching the skill shares among different subgroups, for whom the two margins play varying roles.

Let $\hat{y}_d$ denote the change in these variables in the data, and let $\hat{y}_d(\theta, \hat{\tau}^K, \bar{Y})$ be the model-implied change under the measured $\hat{\tau}_{Ni}^K$ and the baseline equilibrium data $\bar{Y}$, and a particular set of structural parameters θ . Our moment condition is that the difference between $\hat{y}_d$ and $\hat{y}_d(\theta, \hat{\tau}^K, \bar{Y})$ —after residualized by the control variables in Column (5) of Table 1—being orthogonal to the residualized τ_{Nd}^K .

Identification of the elasticities. We illustrate how various outcomes assist in identifying the structural elasticities. Panel 5(a) of Fig. 5 shows that, under the baseline estimate (which we will discuss later), the increase in skill share is positively correlated with the growth of a city's per-capita capital goods imports. The cities with the most significant increase in imports see a rise in skill share by 1.8 percentage points, approximately two-fifths from the mean baseline levels. On the other hand, some cities with little increase in capital goods imports experience almost no change.

The changes in skill shares result from several decisions—the education decision of young workers, and the migration decision of both the young and mature. Since these decisions are governed by different parameters, we leverage the relative importance of these forces for identification. Panel 5(b) depicts the change in the skill share of the young, under both the baseline estimate ($\zeta = 1.15$) and alternative education choice parameters ($\zeta = 0.5$ or 2). As expected, the skill share among the young also increases the most in cities experiencing the biggest growth in capital goods imports. The increase becomes more pronounced with higher ζ . Panel 5(c) illustrates the change in skill shares among mature workers. In the most heavily exposed cities, skill shares in this age

Table 4
Summary of structural parameters.

Parameters	Descriptions	Source/Target	Value
A. Calibrated externally			
ρ_1	Capital-skill complementarity, lower nest	Krusell et al. (2000)	0.67
ρ_2	Capital-skill complementarity, upper nest	Krusell et al. (2000)	1.67
θ	Trade elasticity	Eaton and Kortum (2002)	4
σ	Demand elasticity	–	5.5
B. Determined internally			
ζ	Taste draws for education	Eq. (15)	1.15
η^H	Tastes draws for locations: high-skill workers	Eq. (15)	0.77
η^L	Tastes draws for locations: low-skill workers	Eq. (15)	1.60

Note: Panel A reports the parameters that are calibrated externally. Panel B reports the parameters that are calibrated internally.

group increase by about 1 percentage points. A higher migration elasticity for skilled workers compared to the baseline estimate ($0.77 \rightarrow 2$) increases this number, while a higher migration elasticity for low-skilled workers compared to the baseline estimate ($1.6 \rightarrow 2.5$) decreases it. Thus, mature skill shares provide insight into the *differential* mobility between high- and low-skill workers. To pinpoint the *level* of mobility, we rely on population growth. Panel 5(d) shows that increasing the migration elasticity for either high- or low-skill workers boosts the population growth in the most exposed cities.

Calibration Results. Panel A of Table 4 summarizes the sources and values of externally calibrated parameters. The lower panel summarizes the estimation results. We find that $\zeta = 1.15$, which means that a ten-percent increase in the skill premium leads to a 11.5% increase in $\log(\frac{\eta^H}{\eta^L})$. In the baseline economy, 5.6% of the people included in the analysis received college education, so the 11.5% increase in log odds ratio translates to around 0.64 p.p. increase in college share. Estimated in a static model with a one-shot education choice, this number is best viewed as a long-run semi-elasticity. It also fall in the same ballpark as Ghose (2021), who estimates a 1.6 dispersion parameter for education choice in the context of India. We find the dispersion parameters for location tastes to be 0.77 for skilled workers, and 1.61 for low-skill workers. These values are lower than the estimates in Fan (2019) and Tombe and Zhu (2015), both of which focus on China.²⁶ In the appendix, we report a sensitivity analysis of alternative migration parameters.

Comparison to the data. Before turning to counterfactuals, we assess, in two ways, the model's ability to account for the differential changes in skill shares across cities. In the first assessment, we regress the model-predicted changes in skill share on the model-implied increase in per-capita capital goods imports due to the $\{\hat{\tau}_{Nd}^K\}_{d=1}^{N-1}$ shock. We then compare the regression coefficient to the reduced-form estimates reported in Table 1. This comparison is informative about whether the model can produce the spatial correlation between these two variables in the data. We estimate a coefficient of 0.21 (s.e. 0.06) from model-generated data. This coefficient falls between the IV estimates in Columns (4) and (5) of Table 1. So under our parametrization, the model accounts for similar degree of the spatial correlation between the two variables to the data.

In the second assessment, as advocated by Adao et al. (2022), we regress the actual change in skill shares between 2000 and 2010 on the model-predicted changes. Under the null hypothesis that the model is correctly specified and parameterized and that the orthogonality condition holds, this regression should yield a coefficient of one. We find a coefficient of 1.44 (s.e. 0.43), unable to reject the null. This shows that our model yields a good *in-sample* fit for the key outcome of the empirical section.

This analysis suggests that the parameterized model can generate the differential effects of capital goods import growth on college share across locations observed in the data.

5.3. The impact of capital goods import on skill acquisition and distribution

We use the model to answer two questions: (i) how does an increase in capital goods imports affect skill acquisition and the distribution of skills across regions, and (ii) how do such endogenous responses shape the impact of capital goods imports on the skill premium. Our first set of counterfactuals addresses the first question.

As shown in Table 5, there was about 42 million college graduates in China in 2000, accounting for 5.6% of individuals aged 18 to 60. After applying the inferred $\{\hat{\tau}_{Nd}^K\}_{d=1}^N$ shock, we find an increase of 3.1 million college graduates, a 7.4% increase from the 2000 level. While significant, this number accounts for only a small fraction of the 70.3 million increase in college graduates seen from 2000 to 2010. Other factors, such as domestic productivity growth, reforms in the hukou system, and (especially) the broad expansion of higher education, likely had larger impacts.

To understand how these other changes shaped the effect of capital goods import on skill acquisition, we conduct a similar analysis using 2010 demographics, by which time the total skill count was 112 million, representing 13.15% of the population. Formally, we use 2010 migration, education, and age distributions instead of those from 2000 to conduct the counterfactual evaluations. Since 2010 data reflect the post-capital-good-imports-increase economy, in the counterfactual we increase (rather than

²⁶ The difference could arise from the variations exploited being different: Fan (2019) uses wage dispersions to estimate η^H and η^L ; Tombe and Zhu (2015) uses provincial level migration.

Table 5
Skill acquisition and distribution.

Skill acquisition and distribution				
	2000 demographics as baseline		2010 demographics as baseline	
Panel A: overall skill acquisition				
Baseline skill count (data)	41.69 million		111.98 million	
Skill share in population (data)	5.63%		13.15%	
Counterfactual skill count	44.75 million		104.73 million	
College graduate increase (%)	7.35%		6.92%	
Panel B: spatial distribution of skills				
	Coastal	Inland	Coastal	Inland
% increase in skill	15.62%	2.62%	15.99%	1.62%
% accounted for by				
Y, stayer	58.97%	126.20%	59.01%	146.50%
Y, migrant	32.41%	3.39%	32.76%	1.01%
M, stayer	2.43%	−21.25%	0.93%	−42.16%
M, migrant	6.19%	−8.34%	7.30%	−5.35%

Note: Panel A reports the number of high-skill workers and their share in the population in the baseline equilibrium (the first two rows), and the effect of the counterfactual change (the third and fourth rows). The lower panel reports the total increase in the number of high-skill workers in coastal and inland regions, and the contribution of four margins, young stayers, young migrants, mature stayers, and mature migrants, to this increase. The total shares of these four margins sum up to 100%. For each panel, we report the results separately for when 2000 or 2010 demographics (education, migration, young and old group size) are used as the baseline economy. When we use the 2000 as the baseline, the shocks are decrease in import costs; when the 2010 as the baseline, the shocks are increase in import costs.

decrease) the cost of capital goods imports. By using the data from 2010, we implicitly incorporate the possibility that, due to productivity growth, reforms, and higher education expansion, the costs of acquiring a college education and migration were lower than 2000.²⁷ Because these changes unfolded gradually over the decade, counterfactuals from the baseline equilibrium with 2010 demographics can be seen as an upper bound on the impact of imported capital goods when migration and education costs are gradually lowered by other reforms.

We find that, from the 2010 baseline, the reverse of the $\{\hat{\tau}_{Nj}^K\}_{j=1}^{N-1}$ shocks leads to an 7.25 million decrease (104.73 – 111.98) in college graduates, more than twice our baseline estimate, accounting for approximately 10% of the 70.3 million increase in college graduates over the decade. Treating the 2010 data as the post-shock economy and the counterfactual as pre-shock economy, we find that the increase in college graduates due to capital goods import liberalization leads to 6.9% (7.25/104.73) increase in the number of college graduates, similar to the percentage increase inferred using 2000 demographics. Hence, the larger estimates based on the 2010 demographics are due to a larger base number of college graduates (or alternatively, a lower implied college education cost), not a bigger percentage response to the same shock.

We also examine the spatial distribution of skills in response to the shock. We find a much larger increase in skill share in coastal regions (15.6%) than the hinterland (2.6%), which reflects that coastal region generally experienced a larger increase in capital goods imports over this period. We decompose the increase into four groups: young stayers, young migrants, mature stayers, and mature migrants. Young people from the coast (Y stayer) account for 59% of the total increase in college graduates there, while young migrants from inland contribute roughly 32%. Mature workers born on the coast and hinterland account for 2.43% and 6.19%, respectively. Recalling that mature workers do not make education choices, this change reflects that they disproportionately choose to stay in (or migrate to) coastal regions. This movement of mature workers contributes negatively to the skill share in the hinterland—the 2.62% increase in college graduate share there is entirely driven by young workers. We obtain similar decomposition results when focusing on the 2010 demographics as the baseline economy.

Taking stock, our model-based analysis suggests that, depending on the baseline year, the increase in capital goods imports raise college graduates by 3.1 to 7.3 million, accounting for between 4.4% and 10.4% of the total increase in college graduates over the period. We also find that because the increase is concentrated in the coastal region, it leads to a substantially larger increase in skill shares there than in the hinterland, potentially contributing to China's spatial disparities. Moreover, these findings are robust across a range of parameters, as we show in the sensitivity analysis reported in the appendix.

It is instructive to compare these results to aggregate impacts inferred from the reduced-form analysis. We estimate that each \$100 increase in capital goods imports leads local skill share to rise by 0.16 to 0.32 percentage points (depending on the specification; see Table 1 vs. Table 3). Multiplying this estimate by the average per-capita increase in capital goods imports (130 hundred USD) over ten years implies an increase in skill share of 0.2–0.4 percentage points—about 1.45–2.9 million college graduates. It turns out that the reduced-form analysis underestimates the effect of capital goods imports on skill acquisition.²⁸

²⁷ These changes are reflected in, for example, higher college and migration shares in 2010 than in 2000.

²⁸ As discussed earlier, one reason the differences-in-differences estimate can understate the true effect is that, because people anticipate they can migrate and because of trade linkages, even regions not directly affected by the shock experience a strengthened incentive to acquire skills. The counterfactual in Section 5.4 that shuts down education corroborates this mechanism.

Table 6
Comparison of skill premium changes (%).

	(1) Baseline model	(2) No edu	(3) No migration	(4) No edu and migration
Aggregate	4.95	13.35	3.09	10.75
Coastal	11.89	23.50	11.50	24.72
Inland	2.47	9.58	-0.17	5.32

Note: The numbers reported are the percentage change in the skill premium in the aggregate and in coastal and inland regions. The first column report the result from the baseline model; the second column reports the results from the same experiment with $\zeta \rightarrow 0$; the third column reports the result with $\eta^H, \eta^I \rightarrow 0$ (Column 3); the last column reports the results with $\zeta \rightarrow 0$ and $\eta^H, \eta^I \rightarrow 0$.

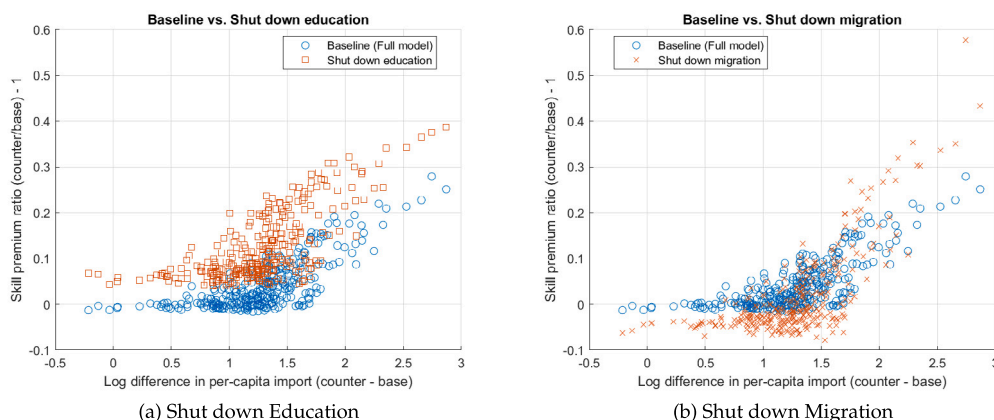


Fig. 6. Baseline vs. Alternative scenarios.

Note: Each panel compares the baseline model (circles) to a particular “shut down” scenario. The horizontal axis is the log difference in per-capita capital import (counterfactual minus baseline), and the vertical axis is the ratio between the skill premium impacts due to the counterfactual in the two economies minus one.

5.4. Capital goods and the skill premium: the roles of education and migration

We now discuss how the endogenous responses in skill acquisition and distribution moderate the impacts of capital goods imports on the skill premium. Since the previous section shows 2010 and 2000 as the baseline economies lead to largely the same percentage changes, we focus here on the 2000 as the baseline economy only.

Table 6 reports the results of capital goods imports on the skill premium. Column 1 presents the baseline model: the aggregate skill premium increases by 4.95%, with a larger gain in coastal regions (11.89%) than inland (2.47%). In Column 2, we conduct the same experiment in a hypothetical economy without an education response ($\zeta \rightarrow 0$). We find that the aggregate skill share rises more substantially, by 13.35%. Fig. 6(a) plots the skill premium increase in these two models against per-capita capital goods imports. Clearly, when the education response is absent, the skill premium rises more across the board—even in regions with minimal capital goods import growth. This broader rise suggests that capital imports can encourage skill acquisition in regions not directly importing capital goods.

Column 3 shows how the skill premium changes in a hypothetical economy where agents can choose education but do not migrate ($\eta^H, \eta^I \rightarrow 0$). In the absence of migration, capital goods imports increase the skill premium less overall. Fig. 6(b) shows that the skill premium rises more than in the benchmark for regions with greater capital goods imports and less in inland regions with small import growth. Intuitively, when agents can migrate, high-skill workers disproportionately move to regions with higher premiums, damping the skill premium at the destination but boosting it in their origin. Once migration is shut down, we see bigger premium increases in shock-exposed regions and smaller (or even negative) changes in non-exposed regions.

In Column 4, we carry out the same counterfactual in a hypothetical economy with education and migration both shut down. We find that, in the absence of these endogenous responses, the aggregate skill premium increases by 10.75%, twice as much as in the baseline. Importantly, in both coastal and inland areas, the skill premium response is substantially larger than in the baseline economy, reflecting the combined effect of education and migration channels. In Appendix Table B.6, we show the results are qualitatively and quantitatively similar when the relative complementarity between capital and skill (relative to low-skill labor) is weaker than the baseline value.

These exercises indicate that endogenous skill supply plays an important role in moderating the impact of capital-embodied technical progress or skill-biased trade liberalization. Failing to account for these mechanisms risks substantially overestimating the effect of such changes on the skill premium. Moreover, skill acquisition and migration operate in partly opposing ways across both aggregate and spatial dimensions: while education choices help temper the skill premium everywhere, migration tends to raise it in regions with lower import exposure but dampen it in regions more exposed to capital goods imports. Hence, it is important to incorporate the spatial dimension of the model and distinguish between these two margins of skill supply.

6. Conclusion

Human capital is a fundamental determinant of long-run economic growth. In a globalized economy, understanding how it is shaped by international trade is crucial. This paper has focused on imported capital goods—one of the main channels through which developing countries adopt advanced technologies—and has shown that these imports can increase the supply of high-skill workers as well as reallocate them across regions. Both mechanisms imply that capital goods imports can have long-lasting impacts on the spatial economy of the importing country.

Our quantitative analysis suggests that, depending on the baseline year considered (2000 or 2010 demographics), the growth in capital goods imports accounted for a 3.1–7.25 million increase in the number of college graduates between 2000 and 2010, representing 4.4–10.4% of the overall rise in college graduates during this period. The coastal region experienced the largest gains, which in turn amplified existing regional disparities in skill shares. The endogenous response in skill via education and migration reduces the rise in the aggregate skill premium by half. Hence, while capital goods imports raise overall demand for high-skill labor, the supply-side response through human capital investments and geographical mobility alleviates the wage inequality that such technological progress might otherwise generate.

Several exciting opportunities arise for future research. First, from a policy perspective, acknowledging and supporting these skill supply responses—for instance, by expanding access to education and facilitating worker mobility—can mitigate potential inequality effects. Studying policy interventions within a dynamic framework could clarify how measures such as targeted education subsidies, migration incentives, or labor-market regulations affect human capital accumulation and wage dynamics, thus influencing both aggregate outcomes and regional disparities. Second, while our model and data focus on regional outcomes, past research has suggested substantial firm heterogeneity in technology adoption and skill use. Integrating firm-level decisions into the framework and linking these decisions to local labor market outcomes could help bridge the regional perspective of our study and the crucial roles of firms emphasized in the empirical trade literature and policy discussions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jinteco.2025.104128>.

Data availability

Skill-Biased Imports, Skill Acquisition, and Migration (Original data) (Mendeley Data)

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