HCEO WORKING PAPER SERIES

Endogenous Skill-Biased Technology Adoption: Evidence from China's College Enrollment Expansion Program

Shuaizhang Feng
Xiaoyu Xia

Working Paper

2018-099

12/2018

HUMAN CAPITAL AND
ECONOMIC OPPORTUNITY
GLOBAL WORKING GROUP

The University of Chicago
1126 E. 59th Street Box 107
Chicago IL 60637

www.hceconomics.org

Endogenous skill-biased technology adoption: Evidence from China's college enrollment expansion program*

Shuaizhang Feng† and Xiaoyu Xia‡

December 19, 2018

Abstract

China's college expansion program, which was implemented in 1999 significantly increased the share of college-educated workers in the urban labor force. We find that returns to education were not responsive to changes in local skill supply between then and 2009. To explain the trend, we develop a model of endogenous technology adoption and predict that increasing the share of college-educated workers leads firms to adjust their use of production technology. We construct supply shocks in local labor markets based on policy-driven variations in the changes of college enrollment quotas across cities. Using panel data from over 20,000 large manufacturing firms, we find that an enlarged college-educated labor force causes skill-intensive firms to invest more in capital and R&D as well as employ more workers, evidence that supports the theory of endogenous technology adoption.

Keywords: human capital; endogenous technology adoption; college education; Chinese economy.

---

*For insightful suggestions, we thank Enrico Moretti, David Card, Giovanni Peri, Lars Lefgren, Yifan Zhang, Pauline Leung, and various seminar participants at the University of California, Berkeley; National University of Singapore; University of Technology Sydney; Tsinghua University. We also thank Gaojie Tang, Peng Xu and Minzhi Liu for their excellent research assistance. All errors are our own. Feng acknowledges financial support from the Chinese National Science Foundation for distinguished young scholars (Project Number: 71425005) and the Yangtze River Scholars Program (Project number: T2012069). Xia acknowledges financial support from the Research Grants Council of Hong Kong (ECS Grant 24500416).

†Institute for Economic and Social Research, Jinan University. 601 Huangpu W. Ave, Guangzhou 510632, China

‡Corresponding author, Department of Decision Sciences and Managerial Economics, Chinese University of Hong Kong. Rm 901 Cheng Yu Tung Bldg, 12 Chak Cheung St., Hong Kong SAR, China. Email: xiaoyuxia@cuhk.edu.hk.

I Introduction

Over the past several decades, returns to college education have steadily increased in many countries despite an increased supply of college graduates.[1] While researchers reason that recent technological changes are skill-biased, shifting the relative demand for highly educated workers, it is possible that skill-biased technological changes (SBTC) are actually caused by increases in the supply of skilled labor, an idea introduced in theories of endogenous growth (Romer, 1990), endogenous technological change (Acemoglu 1998, 2007) and endogenous technology adoption (Beaudry et al., 2010).

Testing theories of endogenous technology adoption, however, requires understanding how firms choose production inputs after changes in their local labor market. While existing studies mainly use immigration waves as the source of exogenous increases in low-skilled labor (e.g. Lewis, 2011), this paper focuses on how firms adjust their inputs as the share of high-skill labor increases. We use data from a large-scale natural experiment in China that took place in 1999. We adopt a firm-level approach that provides more granular evidence to an endogenous technology adoption model, extending city-level evidence reported in previous studies such as Beaudry et al. (2010). A firm-level analysis also helps us to rule out the possibilities that previous city-level results are solely driven by the relative expansion of capital-intensive sectors or export-intensive industries. Although firms' adjustments in production technology may happen through exits and entries, previous work has shown that within-firm adjustments are the main mechanism through which labor supply shocks are absorbed by the economy (see Lewis, 2013 and Dustmann and Glitz, 2015).

The Chinese college enrollment expansion program was implemented by the Chinese central government unexpectedly in 1999 and became one of the biggest expansions of post-secondary education in the world.[2] By 2009, annual post-secondary school enrollment increased six-fold, from 1 million students to 6 million, and the share of college-educated workers in the urban labor force increased by more than 60% (Table 1). The college wage premium remained stable despite the sharp and persistent increase in the relative supply of college-educated workers (Figures 1 and 2).[3] This suggests that a rightward shift occurred in the labor demand curve and motivates us to consider an endogenous technology adoption model as a potential explanation.[4]

We develop a framework with the coexistence of two types of production technologies,

[1]See Bekman et al. (1998), Card and Lemieux (2001), Acemoglu (2002), Autor et al. (2008), and Walker and Zhu (2008) for example.

[2]We calculate that China's college expansion program generates an average increase of 0.6 year of education for cohorts born in 1990 compared with cohorts born in 1980.

[3]Carneiro et al. (2018) studied the change of college wage premiums after the construction of new colleges in several cities in Norway in the 1970s. Although their setting is very different from ours, the results regarding changes in college wage premium are similar.

[4]Acemoglu (2002) proposes a theoretic framework of directed technology change.

characterized by two different types of capitals, one skill-biased and the other labor-biased. Our model is an extension of the models in Beaudry et al. (2010) and Lewis (2013), which include two types of capital (skill-biased and labor-biased) and two types of labor (high-skill and low-skill).[5] In our model, firms employ both high- and low-skill workers and choose either type of capital to produce the same output across two types of firms. To achieve a new equilibrium, firms adjust every input when the local labor market skill-mix changes. As high-skill labor becomes more abundant, firms using skill-biased capital invest more in capital and hire more workers, while firms using labor-biased capital reduce capital investment and workforce size as the relative supply of low-skill workers decreases. The model predicts that college wage premiums do not change, as the endogenous shifts in labor demand exactly compensate for the increases in skilled labor.

To test this model empirically, we treat cities as individual labor markets and use variations in the college enrollment expansion of each city to identify shocks in the supply of college-educated workers. More specifically, we construct an instrumental variable for the local skill mix based on a city's predicted college enrollment quota, which was determined by the Ministry of Education (MOE). Using the firm-level panel data on all large manufacturing firms in China from 1998 to 2008, we show that firms hiring more high-skill labor, which are more likely to use skill-biased capital in production, are more likely to increase their capital, R&D spending, and employment when the local share of skilled labor increases. We control for confounding factors such as state-owned enterprise (SOE) reform, rural-to-urban migration, and industry-specific time trends that might have been influenced by China joining the World Trade Organization (WTO) in 2001.[6] Finally, using worker-level wage data from the Urban Household Survey (UHS), we verify that the estimate for the slope of the relative labor demand, or the inverse elasticity of substitution between college- and high-school-educated workers, is close to zero. All findings are aligned well with the predictions of our endogenous technological adoption model.

Previous studies that have used SBTC to explain increasing college wage premiums often assume that technological changes are exogenous, e.g. Katz and Murphy (1992), Krueger (1993), Bekman et al. (1998), and Autor et al. (2008). There are only a handful of empirical studies that test endogenous adoption of technologies with respect to skill-mix shocks. Examples include Goldin and Sokoloff (1984), Krusell et al. (2000), Beaudry

[5]We use a nested CES production function which is a more general function form than that in Beaudry et al. (2010). Nevertheless, all predictions of the model are unchanged if we use exactly the same functional form as that in Beaudry et al. (2010).

[6]Previous evaluations of China's college enrollment expansion program mainly use a difference-in-differences design that cannot rule out industry-specific time trends. For example, Li et al. (2014) and Li et al. (2017) describe how the college expansion program changes the return to education; Che and Zhang (2018) study the growth of firms' total factor productivity after the college enrollment expansion program.

et al. (2010), and Lewis (2011).[7] We contribute to this literature by suggesting a specific mechanism that could explain how SBTC happens when different technologies coexist: as high-skill labor share increases, the overall labor demand becomes more skill-biased because firms that adopt skill-biased technologies grow faster than firms that use labor-biased technology. Our finding complements that of Lewis (2011), which models an economy with only one type of capital that is skill-biased.

By examining one of the largest educational promotion programs, our study also adds more micro-foundations to the "human capital engine" theory (Lucas, 1988). Instead of the cross-country comparison approach, we adopt a local labor market approach that is less limited by reverse causality.[8] In particular, to explain China's phenomenal growth in the past several decades, existing literature emphasizes drivers such as the reallocation of resources from the public sector to the private sector (Song et al., 2011), access to international trade (Brandt et al., 2017), capital formation (Chow, 1993), and institutional reform (Xu, 2011). We suggest a human capital channel that has been overlooked previously. If enrollments of college students were strictly controlled by the government, relaxing the supply constraints of college-educated workers could have triggered technological progress and economic growth.[9]

Our study also contributes to the understanding of the general equilibrium effects of education. While a vast amount of literature estimates the returns to education in various countries (see a survey in Card, 1999), there are far fewer studies that discuss the general equilibrium effects of education and even fewer that study countries other than the United States (studies on human capital spillovers include Moretti 2004b, 2004a, Ciccone and Peri, 2006, and Iranzo and Peri, 2009). Our results show that endogenous labor demand shifts may offset the wage effects of the supply increase, which provides an alternative channel to understanding the general equilibrium effects of educational promotion programs.

The remainder of this paper is organized as follows. Section II discusses the policy background and examines aggregate college wage premium trends before and after the college enrollment expansion. Section III outlines a simplified model of endogenous technology adoption. Sections IV and V discuss data and our empirical strategies, followed by our empirical results in Section VI. Section VII concludes our paper.

[7]A related example on endogenous technological change with respect to endowment shocks is Hanlon (2015) which tested how the shock to the relative supply of cotton (an input to production) affects the direction of technological progress in textile industry of US.

[8]Examples of cross-country comparisons include Benhabib and Spiegel (1994), Barro and Lee (1994), Gregorio and Lee (2002), Barro et al. (2013), and Nicola Gennaioli and Shleifer (2013). Critiques of the cross-country comparison approach include Bils and Klenow (2000), Chevalier et al. (2004), and de la Fuente and Doménech (2006).

[9]From Chinese import competition, there can also be technology spillover effects in other countries as studied by Bloom et al. (2016).

II Policy background

Each higher-education institution's enrollment in China is managed by the MOE, a branch of the Chinese government that falls below the State Council. However, a policy change originating in the State Council in 1999 started the college expansion program, which deviated from the MOE's five-year plan for 1996-2000 (and since the State Council manages the MOE, the State Council's policy took precedence over the MOE plan).[10] To achieve the ambitious goal set by the State Council, the MOE modified its college education enrollment plan abruptly. On June 24, 1999, only two weeks before the national college entrance exam, the MOE announced a 38 percent increase in the admissions quota. Since then, college enrollment has increased dramatically in China.

The MOE sets a binding enrollment quota for each college every year. If a college plans to make any adjustment, it needs to seek approval from its provincial government and the MOE. As each college follows the pre-assigned quota closely, the MOE plays the main role in determining the total enrollment of a college and therefore the total college enrollment of the country. To formulate the enrollment quota for each college, the MOE issues a plan every five years that outlines the growth of college enrollment for an upcoming five-year time frame. To do this, the MOE audits the on-campus infrastructure at each of the country's colleges and then constructs benchmark enrollment quotas accordingly. For example, the MOE used the auditing results from 1996 to compute the benchmark college enrollment quotas for each college from 1997 to 2004. The MOE sets annual enrollments based on the benchmark quotas and the country's overall growth plan. After the State Council unexpectedly raised the target gross college admission rate in 1999, the MOE did not revise the benchmark enrollment quota but only increased the growth rate of annual enrollment at the national level.

Figure 1 shows that the annual college admission growth rate was 2 percent on average between 1993 and 1998 based on the data published by the National Bureau of Statistics (NBS) of China. However, from 1999 to 2001 it suddenly increased by 30 percent per year. It slowed to a 15 percent annual growth rate in the following 5 years. As a result, the average proportion of workers with any college education between 15 and 64 years of age in China's urban labor force increased from 17.9 percent in 1993-1999 to 29.5 percent in 2003-2009, according to the UHS (see Table 1).

How does the enlarged college-educated workforce affect the equilibrium wage in the labor market? To document the change in the college wage premium at the national

[10]Based on the "Blueprint for the Ninth Five-Year Plan for Education" published in 1996, the MOE originally planned to raise the gross college enrollment rate (college enrollment among those in the same age group) from 6.5 to 8 percent by 2000. However, in December of 1998, the State Council released a special issue of the policy book "Plan to Revitalize Education for the 21st Century," which sought to raise the target gross college admission rate further to 11 percent, tripling the original growth goal year-over-year from 1.5 to 4.5 percent.

level, we run an ordinary least squares (OLS) regression. This allows us to estimate the college wage premium each year and the results of this can be seen in Figure 2.[11] We restrict the sample to workers between 20 and 40 years of age at the time of the survey because workers in this age group have similar work experiences and they were directly affected by the college expansion program.[12] In Figure 2, the squares represent the point estimates for the estimated college wage premium from 1993 to 2009 for workers aged 20-40. During this period, the increase in the supply of college-educated workers accelerated. However, the average college wage premium remained steady. Also of note is that unemployment rate of college-educated workers decreased compared to workers without any college education (see Feng et al., 2017 and Figure A1).

This college expansion program also increased variation in the skill mix across cities. Although the MOE did not publish details of how the college expansion program was implemented, the data suggests that the MOE likely increased each college's enrollment quota using a national growth rate. Figure 3 shows that changes in a city's college enrollment between 1998 and 2009 is highly correlated to the city's initial college enrollment in 1998. Therefore, cities that had higher college enrollments before 1999 were likely to have faced larger influxes of college-educated workers compared to others after the college expansion program.

While the relative supply of college-educated workers quadrupled from 1993 to 2009 for 20 to 40-year-olds based on UHS data, the college wage premium during this period did not decrease. The national acceptance rate of the college entrance exam nearly doubled from 34 percent in 1998 to 62 percent in 2009. This change in selection cutoff decreases the average unobserved abilities of college graduates (e.g., Juhn et al., 2005). As colleges had insufficient infrastructure in the first few years to accommodate so many new students, the quality of college education could decline during the beginning of the college expansion program (see Meng et al., 2013). Overall, changes in students' unobserved abilities or quality of college education during this period were likely to decrease rather than increase the college wage premium holding the relative labor demand constant.

Our explanation for the observed college wage premium trend is a shift in the labor demand that was likely caused by endogenous skill-biased technology adoption. In the following sections, we develop a model with two production technologies to illustrate how firms adjust capital and labor demand when faced with an exogenous change in the skill mix of a local labor market.

[11] The dependent variable is the log of a worker's annual earnings in each year, which consists of basic wages, bonuses, subsidies, and other labor-related income. The explanatory variables include a dummy variable that indicates whether a worker is college educated and other control variables that include demographics, provincial-fixed effects, and years of experience by education levels.

[12] Li et al. (2017) suggest that the college expansion program has different effects on labor market performance across workers in different age groups. We also verify that the pattern holds for college wage premium of workers aged 15-64.

III Model

There are four possible elements in a production function: low-skill labor (L), high-skill labor (H), skill-complementing capital (K_h), and labor-complementing capital (K_l). We define workers who received any college education as high-skill labor, and workers who have received high-school education or below as low-skill labor. We define capital in our model as a generalized machinery input in the production function, which can be measured by the total value of capital in firm-balance sheet or other related variables such as R&D expenditure. Motivated by observed heterogeneity in production technology among firms in a large developing country like China, we assume that there are two types of firms: firms that use skill-biased capital and firms that use labor-biased capital. Both types of firms employ a mix of high- and low-skill labor.

Consider an environment in which two types of firms both produce one final good denoted by Y. Each type of production technology follows a nested constant elasticity of substitution (CES) production function (see Equations 1-2), which has been widely adopted in economics literature since Sato (1967). In particular, Y_1 equals the amount of output produced by firms using technology 1 and Y_2 represents the total output of firms using technology 2.

$$Y_1 = [\alpha_1 (K_h^{\rho_1} + L_1^{\rho_1})^{\frac{\mu}{\rho_1}} + (1-\alpha_1) H_1^{\mu}]^{\frac{1}{\mu}},\ 0 < \alpha_1 < 1,\ \rho_1, \mu \leq 1 \tag{1}$$

$$Y_2 = [\alpha_2 (K_l^{\rho_2} + H_2^{\rho_2})^{\frac{\mu}{\rho_2}} + (1-\alpha_2) L_2^{\mu}]^{\frac{1}{\mu}},\ 0 < \alpha_2 < 1,\ \rho_2, \mu \leq 1 \tag{2}$$

In these production functions, the elasticity of substitution between labor and capital is fixed. For example, the elasticity of substitution between L_1 and K_h is $\frac{\mu}{1-\rho_1}$ under the first production technology. When ρ_1 is equal to 1, L_1 and K_h are perfect substitutes, see example in Autor et al. (2003). When ρ_1 is equal to μ, capital is skill-neutral, i.e. the elasticity of substitution between L_1 and K_h is equal to that between H_1 and K_h. If $\rho_1 > \mu$, capital is generally a substitute to low-skill labor and a complement to high-skill labor.

Capital is not always skill complementing. Acemoglu (2002) summarizes studies such as Goldin and Katz (1998) on how machines invented in the 19th Century were non-skill-biased. An example from today's economy is that sewing robots and sewing machines are simultaneously used in the textile industry. Sewing robots require high-skill workers to program designs while sewing machines simply assist low-skill workers in making clothes. In this example, the second type of production technology, sewing machines, is an illustration of capital (K_l) as a complement to low-skill labor (thus $\rho_2 > \mu$), as opposed to the more generally assumption that capital only complements to high-skill labor.

In this economy, we further assume that the price of capital is exogenous (denoted as r_h and r_l); and the sum of each type of labor is exogenous ($H_1 + H_2 = H$ and $L_1 + L_2 = L$).

Both types of firms maximize their profits by choosing the optimal amount of capital and labor. As the production functions in our model satisfy constant returns to scale, we can normalize the number of firms to be 1 under each type of production technology. In this case, a price-taking firm aims to maximize profits by solving the problems in Equations (3-4) after we normalize the product price to be 1 as well.

$$max\,\Pi_1 = Y_1 - w_H H_1 - w_L L_1 - r_h K_h \tag{3}$$

$$max\,\Pi_2 = Y_2 - w_H H_2 - w_L L_2 - r_l K_l \tag{4}$$

We define a competitive equilibrium as a situation when firms maximize profit, labor markets clear, and each type of firm earns the same profit for a given output price and input price. The constant returns to scale of the production function imply that each type of firm earns zero profit. In equilibrium, we can solve how a firm allocates inputs by taking the first-order derivative of a firm's profit with respect to each input. In particular, we propose the following:

Proposition 1: When firms can adjust capital freely and the range of parameters allows an interior solution for the equilibrium, the relative wage of high-skill workers compared to that of low-skill workers, $\ln(\frac{w_H}{w_L})$, only depends on exogenous production function parameters ($\mu, \alpha_1, \alpha_2, \rho^h$ and ρ^l) and capital rental price (r_h, r_l). See proof in Appendix A1.

To see the adjustment of relative wages of high- and low-skill workers in each type of firm, we can focus on the first-order conditions summarized in Equation (5).

$$\begin{aligned}\ln(\frac{w_H}{w_L}) &= \ln\frac{(1-\alpha_1)}{\alpha_1} + (1-\frac{\mu}{\rho_1})\ln(1+\frac{K_h^{\rho_1}}{L_1^{\rho_1}}) + (\mu-1)\ln\frac{H_1}{L_1} \\ &= \ln\frac{\alpha_2}{(1-\alpha_2)} + (\frac{\mu}{\rho_2}-1)\ln(1+\frac{K_l^{\rho_2}}{H_2^{\rho_2}}) + (\mu-1)\ln\frac{H_2}{L_2}\end{aligned} \tag{5}$$

Suppose firms do not adjust capital (i.e. K_h and K_l are fixed). According to Equation (5), the relative wage of high-skill workers compared to that of low-skill workers, $\ln(\frac{w_H}{w_L})$, decreases as the relative supply of college-educated workers ($\ln\frac{H_1}{L_1}$ or $\ln\frac{H_2}{L_2}$) increases when $\mu < 1$. However, if the price of the capital is constant and firms can adjust the quantity of capital freely, Proposition 1 shows that the relative wage keeps constant regardless of skill-mix changes under both technologies.

While our model is an extension of Beaudry et al. (2010) and Lewis (2011), it is different in three aspects: 1) Lewis (2011) points out skill-capital complementarity can explain why low-skill immigration has little effect on wages. Our model, however, exhibits that adjustment in both skill- or labor-biased capital can explain the observed constant wage premium after relative labor supply shocks; 2) our model allows for the co-existence of different types of production technologies and predicts a zero response in college wage premium instead of a diminished response as that in Beaudry et al. (2010);[13] 3) in this model, we assume that firms are endowed with different production technologies, whereas firms in Beaudry et al. (2010) and Lewis (2011) are homogeneous.

In addition, Equation (5) indicates that a sufficient condition for $\frac{H_1}{L_1} > \frac{H_2}{L_2}$ is $\alpha_1 + \alpha_2 < 1$. This is aligned with previous estimates. For example, Stokey (1996) finds $\alpha_1 = 0.38$ and Duffy and Papageorgiou (2000) use $\alpha_1 = \alpha_2 = 0.4$ in the estimation of nested CES production functions. This observation provides a method for how to identify firms that are using skill- or labor-biased capital and motivates our next proposition.

Proposition 2: When more high-skill workers enter the labor market, firms that use skill-biased capital hire more workers and invest more in capital. Correspondingly, firms that use labor-biased capital employ fewer workers and divest in capital. However, the capital intensity measured by the value of capital per worker remains constant among both types of firms. For proof, see Appendix A2.

IV Data

The main data sets used in this study are micro-level surveys conducted by the National Bureau of Statistics (NBS) of China. The first data set comes from the Urban Household Survey (UHS), which is China's largest nationally representative urban household data set. It is a repeated cross-sectional survey similar to the March Current Population Survey Income Supplement in the United States. We have access to the UHS data from 1993 to 2009, which provides the most complete information on the urban labor market in China to our knowledge (Feng et al., 2017). The second data set is the Annual Survey of Industrial Firms (ASIF), which consists over 2 million observations of large domestic- and foreign-invested manufacturing firms in China from 1998 to 2008.[14] In addition, we use aggregated summary data from 2000, 2005 and 2010 Census as supplementary information on city-level skill-mix. We chose the Census data for the years that most closely align with the data from our other sources. By combining all these data, we can connect large manufacturing firms with local labor-force compositions before and after the college expansion program.

UHS data includes information on employment, earnings, expenditures, and demographic characteristics of urban residents in China. In addition to labor market outcomes,

[13]As a robustness check, we use the production functions in Beaudry et al. (2010) (both firms use skill-biased capital but with different substitution elasticities) to replace our Equations (1-2) and we obtain the same set of results.

[14]Examples of recent works that use the ASIF data include Brandt et al. (2017) and Che and Zhang (2018).

the UHS also records detailed information about school completion levels and residential locations. The education levels of workers are grouped into the categories of "high school and below" and "college or above."[15] To be consistent with the workforce definitions in the Census data (where workers are grouped by aged below 15, aged 15 to 64 and aged above 65), we restrict our UHS sample to urban workers who are between 15 to 64 years old to calculate each city's share of college-educated workers at the prefecture-level.[16]

We list the summary statistics of workers in the UHS by separating the sample into two comparable periods (see Table 1). The first period is from 1993 to 1999, when the college expansion policy was not implemented. The second period is from 2003 to 2009, when the affected cohorts started entering the labor market. The four-year gap between 1999 and 2003 accounts for the affected cohorts' time in college, which was on average four years. Table 1 shows that the composition of education levels in urban labor market changed substantially between the two periods. The share of workers with a college degree or above increased from 17.9 percent in the first period to 29.5 percent in the second period.[17]

The ASIF contains information on the income statements and balance sheets of each large manufacturing firm in China from 1998 to 2008. The ASIF includes all firms that are either state-owned or are non-state firms with current-year sales over CNY 5 million in the manufacturing sector. Our unit of analysis in this data set is at a plant level, as we observe one firm having multiple plants in different cities. Among all the firms, more than 90 percent of all observations in our sample are single-plant firms. For firms with multiple plants, we treat each plant as an independent unit and assign them separate IDs. The definition of unit ID is by a firm's tax filer number and location code (or 6-digit administration code). For simplicity of notation and emphasizing the fact that most of our observations in the data are at a firm-level, we refer the unit of analysis as a "firm" regardless whether it is from single- or multiple-plant firms. To measure firms' real capital stock, we follow Brandt et al. (2012) by using the perpetual inventory method. We exclude firms with missing, zero, and negative values for real capital stock and employment, as well as firms with fewer than eight employees (such firms are considered individually-owned businesses in China).

We then drop firms that did not enter the ASIF in 2004. We impose this restriction as firm-level skill mix is crucial for our analysis and we can only track the skill-mix information of any firm in the ASIF that existed in 2004 using the 2004 Economy Census.

[15] The category of "college or above" includes workers who have received any post-secondary education.

[16] Individuals who are retired, disabled, students, or working at home are not considered to be a part of the labor force.Feng et al. (2017) provides a more detailed description of the UHS. We confirmed that using weighting in the UHS sample does not change our empirical results. Likewise, we found that restricting the data to 20- to 40-year-olds did not change our empirical results.

[17] Part of the observed change may be explained by the lower levels of education achieved by people who were college-aged during the Cultural Revolution. During that time, college enrollment was nearly halted.

Table 2 lists the summary statistics for all firms in our analysis sample. All of the firms surveyed by the ASIF are quite large in scale of employment due to the design of the data collection. In our sample of interest, the annual real value added is CNY 33 million (as measured in 1998) and the average workforce size is 289.

As supplementary data, we use city-level outcomes that from the statistical yearbooks published by the NBS. The city-level college enrollment and graduate data are from the "Statistical Yearbook of Regional Economy". One control we have is based on the city macroeconomic indicator data from the "City Statistical Yearbooks". In addition, we use micro-level data from the 1995 and 2004 Economy Censuses. We also use export and import records from the General Administration of Customs (GAC) from 1998 to 2008 to provide additional controls and tests.

To capture the likelihood of a firm's use of skill- or labor-biased capital (K_1 or K_2), we use the share of college-educated workers in a firm based on the 2004 Economy Census. The overall share of high-skill workers among Chinese manufacturing firms was approximately 12% in 2004 and there is substantial variation in the firm-level college worker ratio within an industry according to the Economy Census. We use the ratio of high-skill over low-skill workers in 2004 Economy Census as the measure of skill intensity (SI).

V Empirical Strategy

Suppose each city is a separate labor market. The market for high- and low-skill labor is purely local, with exogenously fixed local supplies that vary across cities and time.[18] To test whether firms invest in capital differently after a skill-mix shock, we introduce the regression in Equation (6). Consider a basic firm-level equation for the logged real value of capital K_{ict} in firm i of industry j in city c at time t as:

$$K_{ict} = \beta_i R_{ct} + \eta_i + \gamma_1 O_{it} + \gamma_2 C_{ct} + \gamma_3 I_{jt} + \epsilon_{ict} \quad (6)$$

where $R_{ct} = \log(\frac{H_{ct}}{L_{ct}})$ represents the city-level skill mix, and the capital, K_{ict} is interpreted broadly as production technology which can be measured by a firm's value of capital or R&D expenditure. We measure city level skill-mix, R_{ct}, using the logged ratio of workers with college or above education over workers with high school and below education. The η_i represents a firm's fixed but unobservable characteristics. To control for the effects of SOE reform in China, we add a time-specific ownership dummy (O_{it}).[19] The city economic indicators (C_{ct}) help absorb macro-economic shocks at the city level. We also

[18] The Chinese residency-permit system (hukou) largely restricts the inter-city labor mobility, which helps to justify our identification assumption.

[19] We include five ownership categories: SOEs; domestically private-owned enterprises or enterprises owned by shareholders; foreign invested enterprises; enterprises owned by investors from Hong Kong, Macau, or Taiwan; and collectively owned enterprises and enterprises with hybrid ownership.

add industry-specific year-fixed effects (I_{jt}) to disentangle any possible effects of China's joining the WTO on firms in different industries.[20] Finally, to cancel out firm fixed effects (η_i), we use a long-difference regression to test our model's prediction, where Δ represents the long difference operator.

$$\Delta K_{ict} = \beta_i \Delta R_{ct} + \gamma_1 \Delta O_i + \gamma_2 \Delta C_c + \gamma_3 \Delta I_j + \Delta \epsilon_{ict} \tag{7}$$

Our model predicts that the sign of β_i depends on the production technology a firm uses. From a firm's high level of SI_i, we can infer that this firm is more likely to use skill-biased capital. Therefore, we use a parametric approximation to estimate firm specific responses to changes in a city's skill mix, β_i:

$$\beta_i = \beta_0 + \beta_1 SI_i \tag{8}$$

We re-write Equation (7) as Equation (9) to test our model's prediction in the data.

$$\Delta K_{ict} = \beta_0 \Delta R_{ct} + \beta_1 \Delta R_{ct} \times SI_i + \gamma_1 \Delta O_i + \gamma_2 \Delta C_c + \gamma_3 \Delta I_j + \Delta \epsilon_{ict} \tag{9}$$

The coefficient of the interaction term between SI_i and change in R_{ct} shows if firms that use skill-biased capital invest more in capital after an influx of college-educated workers in a local labor market. The model's prediction is reflected in the positive coefficient of the interaction term, β_1.

The main challenge for estimating Equation (9) is that the change in a city's skill mix (ΔR_{ct}) can be related to unobserved shocks $\Delta \epsilon_{ict}$. We thus use an instrumental variable that is based on college enrollment expansion to isolate the exogenous shock in a city's skill mix. The instrumental variable, S_{ct}, uses a city's predicted share of college-educated workers in year t, e_{ct}, as specified in Equation (10).

More specifically, we calculate a city's college graduates compared to its population, e_{ct}, through dividing the cumulative college graduates in year t by a city's population in the year 2000 ($P_{c,2000}$). For any year after 2000, the cumulative college graduate population is the sum of the stock of college graduates in the 2000 Census ($Col_{c,2000}$) plus the predicted college enrollments from 1997 until year $t-4$. For any year before 2000, we can use the stock of college graduates in the 2000 Census ($Col_{c,2000}$) minus a city's predicted college enrollments from $t-4$ until year 1996.

One year's predicted college enrollment, $\hat{E}_{cj} = N_j \eta_c$, equals the national college enrollment in year j, N_j, multiplied by a city's share of the national college enrollment in 1998 (η_c).[21] Finally, equation (11) describes how we construct the instrument variable,

[20] Several trade models (e.g., Acemoglu, 2003 and Bloom et al., 2016) assert that exports from less developed countries to the U.S. or Europe lead to a decrease in skill premium in less-developed countries.

[21] The city-level college enrollment and graduation data in our study comes from the Statistical Yearbook of Regional Economy from 1999 to 2009. We use a 4-year lag to recover a city's college enrollment

S_{ct}, for city-level skill-mix, R_{ct}.

$$e_{ct} = \frac{Col_{c,2000} - \Sigma_{j=t-3}^{1996} \hat{E}_{cj} \cdot \mathbf{1}_{t \leq 1999} + \Sigma_{j=1997}^{t-4} \hat{E}_{cj} \cdot \mathbf{1}_{t \geq 2001}}{P_{c,2000}} \tag{10}$$

$$S_{ct} = \log(\frac{e_{ct}}{1 - e_{ct}}) \tag{11}$$

Figure A2 shows that a city's college enrollment share stays steady over time, which explains why our predicted college enrollment matches well with a city's actual college enrollment. Our instrument is different from a shift-share instrument because we do not assign future college graduates to cities where college-educated workers were located before the college expansion program. Nevertheless, we impose the assumption that a city's initial college enrollment share of the national college enrollment is randomly assigned after controlling for city observable characteristics, i.e. $Cov(\Delta\epsilon_{ict}, \eta_c|C_{ct}) = 0$.

To find out which city level controls (C_{ct}) we need to control for, we examine which city characteristics are likely to correlate with a city's pre-policy college enrollment share. According to Table 3, a city's type — whether it is a municipality that is directly overseen by the federal government, a provincial capital, or another type of prefecture-level city – significantly influences the a city's college enrollment numbers.[22] A city's urban population and GDP positively correlate with a city's enrollment share, but the city's migrant population and average wage do not correlate with a city's college enrollment share. Based on these findings, we conduct the following validity tests to examine our instrument.

In our firm-level long difference regressions, we add city type, region dummies and the base year level of urban population and GDP as controls to address the concern that local governments may impose industrial policies or provide support that targets provincial capitals, coastal cities, or cities with larger urban populations. Another concern is that cities with higher baseline enrollment shares have been more exposed to trade since China entered the WTO in 2001. Therefore, we add city-level export volume by destination country as a control.

We also test our instrument's validity by conducting a pre-trend test. As an illustration, we draw the average total capital and employment of firms in each year by cities that are predicted to have higher or lower changes in college enrollment in Figures A3 and A4. We divide cities into two groups based on the level of S_{ct} in 1998, so cities with top half value of $S_{c,1998}$ are predicted to have larger increases in college enrollment per capita. Note that the general downward trend in firm's average size over time can be

in 1998 and we verify that the college graduation rate in China is approximately 100 percent. We also use the number of colleges established as of 1998 to predict the enrollment share of each city in 1998, which generates similar results.

[22]To follow the higher education model of the Soviet Union, there was a major integration and reorganization through building and moving of all universities in 1952 which largely determined the location of the majority of current universities to be at capital cities.

explained by the composition change due to the specific sample selection criterion of the ASIF. From 1998 to 2008, the ASIF always used the nominal sales over CNY 5 million as the cutoff value to define a large manufacturing firm. As a result, the average size of firms that entered the ASIF in later years is smaller. To control for composition changes across different waves in the ASIF, we regress the annual logged value of capital, employment, revenue and 2-digit industry as well as city fixed effects for all firms. We then draw the capital and employment residuals from 1998 to 2008 in Figures A5 and A6 and find consistent results.

According to these figures, firms from low-expansion cities have slightly higher capital stock before 2003 but the difference reversed after 2003, with the timing matching when the first cohort of college graduates from the expansion program entered the labor market. We find a similar trend for firms' total employment.

In the pre-trend test regression, we add data from the 1995 Economy Census to supplement the firm-level observations in pre-policy periods, and then carry our main specification by using $S_{ct'}$ at future periods to replace the R_{ct} in Equation (9). For example, we can regress a firm's capital change from 1995 to 1999 on the change in S_{ct} from 2004 to 2008 using the same set of other control variables as that in Equation (9). We will discuss the empirical result of the pre-trend test in the next section.

Our policy-induced instrumental variable is similar to that in Fortin (2006). To the extent that past college enrollment is exogenous to current demand, two-stage least squares (2SLS) estimates should consistently estimate the supply shock. In Table 4, we run the following regression (Equation 12) at using data from the UHS to examine whether the instrumental variable (S_{ct}) has a strong first-stage result:

$$R_{ct} = \delta S_{ct} + \theta X'_{ct} + \varepsilon_{ct}. \tag{12}$$

The control variable list X_{ct} includes municipality, provincial capital dummies, and a city's time varying characteristics such as GDP and population. We also present the regression result using data from the Census in Table A2, which includes both rural and urban workers in the skill-mix measurement.

In Table 4, we show that a city's actual skill mix as measured in the UHS, R_{ct}, strongly correlates with the predicted skill mix, S_{ct}. This correlation does not weaken significantly after we control for the city characteristics. The coefficient of S_{ct} shows that a 10 percent increase in the predicted relative supply of college graduates predicts a 2.5 percent increase in a city's relative supply of college-educated workers.[23]

[23] We collect the placement reports of 116 universities (top-tier universities in China) in "Project 211" of the MOE in 2014 to estimate how likely students are to work in the city where they attended college relative to other cities. Of the 48 universities with city-level placement information, 46.5 percent of students work in the same city after graduation. For the other 28 universities with provincial-level placement information, we know that 62.6 percent of students choose to work in the same province after graduation. It appears that the ratio of students who choose to stay local after graduation in the

VI Results

In this section, we first verify our Proposition 1 by estimating the relative labor demand for college-educated workers using wage data from the UHS. We then present evidence to support Proposition 2, showing that after an influx in college-educated works, firms using skill-biased capital increase capital stock, R&D expenditure and employment compared to other firms. By using other sources of firm-level data, we find that confounding factors, such as China's joining WTO, SOE reform or rural-to-urban migration, are not the cause of the change.

VI.A Worker-level evidence

We use worker-level data to test how changes in skill mix affect the equilibrium wage in the labor market. Based on the UHS wage records, we estimate the relative demand curve at a city level to verify our wage prediction (summarized in Proposition 1). More specifically, we test if the outward shift in the relative demand for college-educated workers offsets the reduction in the supply of low-skilled workers using UHS data. The regression uses the dependent variable as the log of the relative wage of college-educated workers among workers aged 15 to 64. The key independent variable is the relative supply of college-educated workers in the same age group of that city, R_{ct}, which is also measured by the data from the UHS. The additional control variables, noted by X_{ct}, include city characteristics and year fixed effects. We again use a city's logged predicted relative supply of college-educated workers, S_{ct}, as the instrument for R_{ct}.

$$\log(\frac{w_{ct}^h}{w_{ct}^l}) = \theta_0 + \theta_1 R_{ct} + \theta_2 X_{ct} + \zeta_{ct} \tag{13}$$

According to Table 5, the point estimate of the slope of relative labor demand (the inverse elasticity of substitution between college-educated and high school-educated workers) ranges from -0.04 to 0.1 and not statistically different from 0 in all 2SLS specifications. Overall, our estimates for the inverse elasticity of substitution between college-educated and high school-educated workers are smaller in magnitude than previous estimates in Katz and Murphy (1992), Angrist (1995), Card and Lemieux (2001), and Fortin (2006) (which range from -0.2 to -0.7). One possible explanation for the difference in our estimate versus others is that the college worker ratio in China nearly doubled in the time frame we are examining while the observable change in the US was much smaller in magnitude. The smaller change in the market could limit the scale of endogenous technology adoption. Thus, it makes sense that our point estimate is consistent with what we hypothesized in Proposition 1.

placement reports is consistent with the observed significant first stage regression result.

VI.B Firm-level evidence

To test Proposition 2 (firms' have heterogeneous responses to changes in local labor market skill-mix), we define skill intensity (SI_i) using a firm's number of college-educated workers in the 2004 Economy Census divided by the number of high-school-educated workers. We use this proxy because our model predicts that firms using skill-biased capital hire a higher share of college-educated workers, verified by Table A1. In that table, we observe that firms with higher skill intensity are capital intensive and spend more in R&D.

With this proxy of production technology endowment, we use a firm-level long difference regression according to Equation (9) to examine how city-level skill mix shocks affect firms differently in Table 6. We measure a firm's logged real capital change in the period of 1998 to 2008 as the outcome variable. The coefficient of the interaction between city level skill mix shock ΔR_{ct} and firm skill intensity SI_i measures how much more capital a firm invests if its college over non-college educated workers ratio is one standard deviation higher. Suppose there is a 60% increase in the relative supply of a city's college-educated workers population (which is the average change across cities in our sample from 1998 to 2008), the point estimator for β_1 suggests that firms with one standard deviation higher skill intensity will accumulate 1.5 percent more in total capital.

While both OLS and IV estimates in Table 6 are significant and similar in magnitude, the overall magnitude of the capital adjustment appears small. One explanation for this result is that the accounting value of capital might be a noisy measure of a firm's production technology. We then turn to R&D as another measure of skill-biased capital. Table 7 uses the change in firms' R&D expenditures from 2001 to 2007 as a dependent variable to document firms' responses to changes in the skill mix of local labor markets. The ASIF has R&D records from 2001 to 2007. As most manufacturing firms in China are not associated with high-tech, it is not surprising that 59.3 percent of firms in the ASIF have zero R&D expenditure. To include all firms with zero expenditure in the regression, we add 1 to each firm's R&D expenditure before taking the natural log. We use this specification as our main empirical result (Panel A of Table 7). In addition, we run an alternative regression by restricting the sample to firms with non-zero expenditure (Panel B of Table 7).

We find that the OLS estimates for β_1 in columns (1-3) are smaller than the 2SLS estimates in columns (4-6), and the point estimators for β_1 are much larger in magnitude than the estimates in firms' capital investment in Table 6, suggesting that R&D expenditure can be a more accurate proxy for skill-biased capital than the value of capital in a firm's balance sheet. Quantitatively, a 60 percent increase in a city's relative supply of college-educated workers drives a firm to spend, on average, 8 percent more in R&D compared to firms that have one standard deviation lower skill intensity. As R&D expenditure is a directly observable indicator of technology (see Machin and Van Reenen, 1998), a firm's increase in R&D in response to an increasing share of college-educated workers provides additional evidence to support the theory of endogenous technology adoption.

To test our instrumental variable's validity, we use additional records on firms' real capital to run a pre-trend regression. We use the change in the city skill mix in future periods as the key independent variable. The results are presented in Table 8 and we find insignificant correlation between a firm's capital investment between 1995 to 1998 (or between 1995 to 1999) and the future influx of college-educated workers between 2005 and 2008 (or between 2004 to 2008). Unfortunately, as the R&D expenditure data is only available in the ASIF from 2001 to 2007, we cannot run a similar regression for firms' R&D expenditure for that time period.

We then continue to examine whether firms that use more skill-biased capital increase their total employment as the share of college-educated workers in the local labor market increases. According to Table 9, the point estimates suggest that when a city increases its relative supply of college-educated workers by 60 percent, firms that have one standard deviation higher skill intensity hire 2 percent more workers compared to other firms in the same city. This result is consistent with Proposition 2 as well.

To compare our results to that of Lewis (2011), we test whether firms that use more skill-biased capital adjust their capital intensity (measured by the value of capital per worker) after a change in local labor market skill mix. Lewis (2011) finds that firms in areas with larger increases in unskilled labor invest less in capital per worker because capital and skill are always complements. Our model predicts that the co-existence of different technologies leads to the constant capital intensity gap across firms that use skill- and labor-biased capital. This distinguishes our model from previous models, which focus on the average adjustment in capital per worker. In Table 10, we empirically verify that firms that use more skill-biased capital do not have different capital intensities as the coefficient of the interaction between city level skill mix shock ΔR_{ct} and firm skill intensity SI_i is not statistically different from zero.

Last, to summarize how the coefficient of the interaction term, β_1, varies across regions and industries in China, we separate firms by their geographic regions ("coastal" or "inland") and by type of industry (high-tech or low-tech) in Table 11.[24] As the coastal region is the economic hub for China, large manufacturing firms located there drive our main results. We also find that firms from high-tech industry respond more to local labor market skill-mix changes, both in capital investment and R&D expenditure. This helps explain the regional and industry-wide differences of Chinese manufacturing firms.

[24]We use 2013 NBS definition of high-tech industry to categorize whether each firm belongs to a high-tech industry. According to the NBS definition, there are 42 4-digit industries in the manufacturing sector that are considered as high-tech in China.

VI.C Robustness checks

To rule out confounding factors, we conduct robustness checks in Table 12 based on firm-level regressions (Equation 9). Cities with different college worker ratios might have faced different trade barriers before China joined the WTO in 2001, therefore firms' investments in capital and R&D could be responses to changes in international trade. By using the GAC data from 1998 to 2008, we aggregate each city's export volume by destination country (collapsed into two groups based on whether a destination country belongs to the WTO or not) and use this controlling variable to tease out the possible influence of change in trade access. We find that adding a city's export volume by destination country does not change the key coefficient of β_1 in all specifications, suggesting that city-specific trade barriers are unlikely to be a factor in explaining firms' responses in capital investment and R&D expenditure to changes in labor market skill mix.

Another variable we considered as a possible confounding factor was rural-to-urban migrant workers, which may influence how firms adopt technology. The UHS does not include migrants in its sample. To check for how and if changes in migrant workers could affect our data, we turn to Census data. We compare a citys college worker ratio (using UHS data) to changes in the migrant population (using Census data) and find that there is no correlation between the change in a citys college worker ratio and the proportional change in that citys migrant population (see Figure A7). As cross-validation, we also run a firm-level regression by including a city's extrapolated migrant population based on the 1990, 2000, and 2010 Census.[25] Table 12 shows that the point estimators for the key coefficients are similar to those in the baseline specification after adding controls for a city's migrant population.

One additional concern is that SOEs are different from non-SOE firms, though non-SOE firms cover 84 percent of firm-level observations in our ASIF sample. To demonstrate that our results are not driven by the SOEs alone, we run regressions on firms' capital, R&D and employment again and exclude SOE firms. As shown in Table 12, we again find consistent and similar estimates for β_1 across all three outcome variables.

One alternative explanation for our Proposition 1 is the Rybczynski theorem of the Heckscher-Ohlin trade model. It argues that changes in the relative supply of college graduates have no effect on city-specific relative wages as long as there are within city output adjustments which can fully absorb any endowment shock. To evaluate the possibility that a firm changes its output mix rather than production technology, we categorize a firm's main product using the 3-digit classification table published by the NBS in 2002 and track if firms in our ASIF sample have ever changed their main product over time.[26]

[25] As the only accurate counts of migrants are from Census years, we use a quadratic time trend to fill in the gap years.

[26] We use the established natural language processing method to map each firm's self-reported main product to the classification table published by the NBS.

We find 18 percent of the firms in our ASIF sample have changed their product types. By restricting our sample to firms with the same main product, we find larger (though less precise) estimates of β_1 in capital and R&D investment.

If there exists large measurement error in R_{ct}, the OLS estimates in Table 6 and Table 7 are biased towards 0. To evaluate the role of measurement error, we use Census data from 2000 to 2010 to construct the skill mix for 1998 and 2008 at a prefecture-level (including both urban and rural areas) as a robustness check (see Table A3). The point estimators for β_1 in Table 6 and Table A3 are well-aligned. We also regress the changes in firms' capital on the changes of city skill-mix in other periods (see Table A4 and find consistent 2SLS estimates.

VII Conclusion

Researchers have argued that the increasing college wage premiums in many countries are the outcome of SBTC. The difficulty facing the SBTC hypothesis has been the lack of explanation for why technical change tends to be skill-biased. We provide direct empirical evidence supporting models of endogenous technology adoption and show that firms actively respond to changes in the local skill ratio depending on technologies they use. Specifically, firms endowed with skill-biased production technology accumulate more capital and spend more on R&D when faced with an influx of college-educated workers. In conclusion, an education policy that alters the skill mix of a country can have profound effects in determining how firms adopt technology.

References

Acemoglu, Daron, "Why do new technologies complement skills? Directed technical change and wage inequality," *The Quarterly Journal of Economics*, 1998, *113* (4), 1055–1089.

_ , "Technical change, inequality, and the labor market," *Journal of Economic Literature*, 2002, *40* (1), 7–72.

_ , "Patterns of skill premia," *Review of Economic Studies*, 2003, *70* (2), 199–230.

_ , "Equilibrium bias of technology," *Econometrica*, 2007, *75* (5), 1371–1409.

Angrist, Joshua D, "The economic returns to schooling in the West Bank and Gaza Strip," *American Economic Review*, 1995, pp. 1065–1087.

Autor, David H, Frank Levy, and Richard J Murnane, "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

_ **, Lawrence F Katz, and Melissa S Kearney**, "Trends in US wage inequality: Revising the revisionists," *The Review of Economics and Statistics*, 2008, *90* (2), 300–323.

Barro, Robert and Jong-Wha Lee, "Sources of economic growth," *Carnegie-Rochester Conference Series on Public Policy*, June 1994, *40* (1), 1–46.

_ **, Francesco Caselli, and Jong-Wha Lee**, "Symposium on human capital and economic development: An Introduction," *Journal of Development Economics*, September 2013, *104*, 181–183.

Beaudry, Paul, Mark Doms, and Ethan Lewis, "Should the personal computer be considered a technological revolution? Evidence from US metropolitan areas," *Journal of Political Economy*, 2010, *118* (5), 988–1036.

Bekman, Eli, John Bound, and Stephen Machin, "Implications of skill-biased technological change: International evidence," *The Quarterly Journal of Economics*, 1998, *113* (4), 1245–1279.

Benhabib, Jess and Mark Spiegel, "The role of human capital in economic development evidence from aggregate cross-country data," *Journal of Monetary Economics*, October 1994, *34* (2), 143–173.

Bils, Mark and Peter Klenow, "Does schooling cause growth?," *American Economic Review*, December 2000, *90* (2), 1160–1183.

Bloom, Nicholas, Mirko Draca, and John Van Reenen, "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity," *Review of Economic Studies*, 2016, *83* (1), 87–117.

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang, "Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing," *Journal of Development Economics*, 2012, *97* (2), 339–351.

_ **,** _ **, Luhang Wang, and Yifan Zhang**, "WTO accession and performance of Chinese manufacturing firms," *American Economic Review*, September 2017, *107* (9), 2784–2820.

Card, David, "The causal effect of education on earnings," *Handbook of Labor Economics*, 1999, *3*, 1801–1863.

— **and Thomas Lemieux**, "Can falling supply explain the rising return to college for younger men? A cohort-based analysis," *The Quarterly Journal of Economics*, 2001, *116* (2), 705–746.

Carneiro, Pedro Manuel, Kai Liu, and Kjell G Salvanes, "The Supply of Skill and Endogenous Technical Change: Evidence From a College Expansion Reform," 2018.

Che, Yi and Lei Zhang, "Human Capital, Technology Adoption and Firm Performance: Impacts of China's Higher Education Expansion in the Late 1990s," *The Economic Journal*, September 2018, *128* (614), 2282–2320.

Chevalier, Arnaud, Colm Harmon, Ian Walker, and Yu Zhu, "Does education raise productivity, or just reflect it?," *The Economic Journal*, November 2004, *114* (499), 499–517.

Chow, Gregory C., "Capital formation and economic growth in China," *The Quarterly Journal of Economics*, August 1993, *108* (3), 809–842.

Ciccone, Antonio and Giovanni Peri, "Identifying human-capital externalities: Theory with applications," *Review of Economic Studies*, April 2006, *73* (2), 381–412.

Clemens, Michael A, Ethan G Lewis, and Hannah M Postel, "Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion," *American Economic Review*, 2018, *108* (6), 1468–87.

de la Fuente, Angel and Rafael Domnech, "Human capital in growth regressions: How much differences data quality make?," *Journal of the European Economic Association*, March 2006, *4* (1), 1–36.

de Silanes Nicola Gennaioli Rafael La Porta, Florencio Lopez and Andrei Shleifer, "Human capital and regional development," *The Quarterly Journal of Economics*, 2013, *128* (1), 105–164.

Duffy, John and Chris Papageorgiou, "A cross-country empirical investigation of the aggregate production function specification," *Journal of Economic Growth*, 2000, *5* (1), 87–120.

Dustmann, Christian and Albrecht Glitz, "How do industries and firms respond to changes in local labor supply?," *Journal of Labor Economics*, 2015, *33* (3), 711–750.

Feng, Shuaizhang, Yingyao Hu, and Robert Moffitt, "Long run trends in unemployment and labor force participation in urban China," *Journal of Comparative Economics*, 2017, *45* (2), 304–324.

Fortin, Nicole M, "Higher-education policies and the college wage premium: Cross-state evidence from the 1990s," *American Economic Review*, 2006, *96* (4), 959–987.

Goldin, Claudia and Kenneth Sokoloff, "The relative productivity hypothesis of industrialization: The American case, 1820 to 1850," *The Quarterly Journal of Economics*, 1984, *99* (3), 461–487.

_ **and Lawrence F Katz**, "The origins of technology-skill complementarity," *The Quarterly Journal of Economics*, 1998, *113* (3), 693–732.

Gregorio, Jos De and JongWha Lee, "Education and income inequality: New evidence from cross-country data," *Review of Income and Wealth*, September 2002, *48* (3), 395–416.

Hanlon, W Walker, "Necessity is the mother of invention: Input supplies and Directed Technical Change," *Econometrica*, 2015, *83* (1), 67–100.

Iranzo, Susana and Giovanni Peri, "Schooling externalities, technology, and productivity: Theory and evidence from US states," *The Review of Economics and Statistics*, 2009, *91* (2), 420–431.

Juhn, Chinhui, Dae Il Kim, and Francis Vella, "The expansion of college education in the United States: Is there evidence of declining cohort quality?," *Economic Inquiry*, April 2005, *43* (2), 303–315.

Katz, Lawrence F and Kevin M Murphy, "Changes in relative wages, 1963–1987: Supply and demand factors," *The Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Krueger, Alan B, "How computers have changed the wage structure: Evidence from microdata, 1984–1989," *The Quarterly Journal of Economics*, 1993, *108* (1), 33–60.

Krusell, Per, Lee E Ohanian, José-Víctor Ríos-Rull, and Giovanni L Violante, "Capital-skill complementarity and inequality: A macroeconomic analysis," *Econometrica*, 2000, *68* (5), 1029–1053.

Lewis, Ethan, "Immigration, skill mix, and capital skill complementarity," *The Quarterly Journal of Economics*, 2011, *126* (2), 1029–1069.

_ , "Immigration and Production Technology," *Annual Review of Economics*, 2013, *5* (1), 165–191.

Li, Hongbin, Yueyuan Ma, Lingsheng Meng, Xue Qiao, and Xinzheng Shi, "Skill complementarities and returns to higher education: Evidence from college enrollment expansion in China," *China Economic Review*, 2017, *46*, 10–26.

Li, Shi, John Whalley, and Chunbing Xing, "China's higher education expansion and unemployment of college graduates," *China Economic Review*, 2014, *30*, 567–582.

Lucas, Robert, "On the mechanics of economic development," *Journal of Monetary Economics*, June 1988, *22* (1), 3–42.

Machin, Stephen and John Van Reenen, "Technology and changes in skill structure: Evidence from seven OECD countries," *The Quarterly Journal of Economics*, 1998, *113* (4), 1215–1244.

Meng, Xin, Kailing Shen, and Sen Xue, "Economic reform, education expansion, and earnings inequality for urban males in China, 1988–2009," *Journal of Comparative Economics*, 2013, *41* (1), 227–244.

Moretti, Enrico, "Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data," *Journal of Econometrics*, 2004, *121* (1), 175–212.

_ , "Workers' education, spillovers, and productivity: Evidence from plant-level production functions," *American Economic Review*, June 2004, *94* (3), 656–690.

Romer, Paul M, "Endogenous technological change," *Journal of Political Economy*, 1990, *98* (5, Part 2), S71–S102.

Sato, Kazuo, "A two-level constant-elasticity-of-substitution production function," *The Review of Economic Studies*, 1967, *34* (2), 201–218.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing like china," *American Economic Review*, 2011, *101* (1), 196–233.

Stokey, Nancy L, "Free trade, factor returns, and factor accumulation," *Journal of Economic Growth*, 1996, *1* (4), 421–447.

Walker, Ian and Yu Zhu, "The college wage premium and the expansion of higher education in the UK," *Scandinavian Journal of Economics*, 2008, *110* (4), 695–709.

Xu, Chenggang, "The fundamental institutions of China's reforms and development," *Journal of Economic Literature*, 2011, *49* (4), 1076–1151.

Table 1: Summary statistics of the UHS worker sample

	(1) 1993-1999	(2) 2003-2009
Demographics		
Female	50.8%	50.8%
College or above	17.9%	29.5%
High school or below	82.1%	70.5%
Labor market outcomes		
Work in SOEs or government		
All	58.2%	37.5%
College or above	81.3%	61.2%
High school or below	53.2%	27.2%
Working experience (year)		
All	20.5	21.9
College or above	18.8	17.5
High school or below	20.8	23.8
Annual earnings (in 1998 CNY)		
All	5,913	12,774
College or above	8,722	22,008
High school or below	5,301	8,919
Observations	288,517	897,310

Note: The UHS worker sample include workers who have urban residence and age between 15 and 64 during the survey. The UHS has increased its survey sample since 2002.

Table 2: Summary statistics of the ASIF firm sample

Analysis sample 1998-2008	(1) Obs	(2) Mean	(3) S.D.
State-owned enterprise ratio	1,050,881	0.145	0.352
Real value-added (millions)	934,459	33.02	315.75
Real capital (millions)	1,050,881	34.89	423.20
R&D expenditure (millions)	855,937	1.73	51.59
Average number of employees	1,050,881	288.64	1157.79
Annual salary per employee	1,049,382	16,233	74,929

Note: All value variables are measured in 1998 CNY. The sample includes firms that with 2-digit industry code range from 13-42 according to the NBS industry classification from 1998 to 2008 ASIF data. We drop firms that did not enter the ASIF in 2004, as well as firms with missing, zero, and negative values for real capital stock and employment,and firms with fewer than eight employees.

Table 3: Determinants of a city's initial share of China's college enrollment in 1998

Dependent variable	Share of national college enrollment in 1998				
	(1)	(2)	(3)	(4)	(5)
Municipality	0.040***	0.034***	0.027***	0.027***	0.027***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Provincial capital	0.019***	0.018***	0.014***	0.014***	0.014***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
1994-1998 average population		0.003***	0.002**	0.002**	0.001**
		[0.0008]	[0.0007]	[0.0007]	[0.0007]
1994-1998 average GDP			0.003***	0.003***	0.004***
			[0.0008]	[0.0008]	[0.001]
1990 migrant population				0.0003	0.0003
				[0.0006]	[0.0006]
1994-1998 city average wage					-0.002
					[0.004]
Observations	141	126	126	126	126
R-squared	0.660	0.702	0.743	0.743	0.744

Note: The data source is China City Statistical Yearbook. The independent variables include population, GDP, migrant population, and city average wage, which are measured in a logarithm scale. Robust standard errors are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 4: Correlation between actual and predicted skill-mix based accumulated college graduates

Dependent variable	Relative supply of college educated workers $R_{ct} = log\frac{H_{ct}}{L_{ct}}$			
	(1)	(2)	(3)	(4)
Predicted relative supply: S_{ct}	0.247***	0.165***	0.145***	0.100**
	[0.043]	[0.037]	[0.042]	[0.044]
Year FE		Yes	Yes	Yes
Municipality, Capital & Region FE			Yes	Yes
Logged city GDP and population				Yes
F-stat	33.52	54.37	42.73	36.01
Observations	2,875	2,875	2,875	2,507
R-squared	0.107	0.338	0.348	0.339

Note: R_{ct} is logged city's ratio of college- to non-college-educated workers (age 15-64) in the UHS 1998-2009. S_{ct} is logged ratio of predicted college graduates share to the share without college education. The number of observations in column (4) is smaller due to missing GDP in City Statistical Yearbooks. The standard errors are clustered at cities in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 5: Relative labor demand for college-educated worker

Dependent variable	City college wage premium $\log \frac{w^h_{ct}}{w^l_{ct}}$					
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	-0.043*	-0.006	-0.041*	0.110	0.028	-0.057
	[0.022]	[0.119]	[0.022]	[0.225]	[0.026]	[0.311]
City population (log)	0.004	0.003	0.007	0.007	0.028	0.023
	[0.013]	[0.013]	[0.015]	[0.016]	[0.082]	[0.082]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE			Yes	Yes		
City FE					Yes	Yes
Observations	2,561	2,561	2,561	2,561	2,561	2,561
R-squared	0.155	-	0.157	-	0.569	-

Note: The wage and relative supply data is based on the UHS 1998-2009 and the city population is based on the city statistical yearbook. R_{ct} is instrumented by S_{ct} in columns (2, 4, 6). Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 6: The effect of a city's skill mix on firms' capital investment

Dependent variable	Change in logged value of real capital 1998-2008					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	0.055	0.056	0.016	0.046	0.044	-1.063
	[0.095]	[0.095]	[0.079]	[0.672]	[0.673]	[2.323]
Firm skill intensity X Change in R_{ct}		0.027***	0.027***		0.024***	0.025***
		[0.004]	[0.004]		[0.004]	[0.006]
Observations	13,576	13,576	13,277	13,576	13,576	13,277
R-squared	0.037	0.037	0.044	-	-	-
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: R_{ct} based on the UHS is instrumented by S_{ct} in columns (4-6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 7: The effect of a city's skill mix on firms' R&D expenditure

Dependent variable	Change in logged value of R&D expenditure 2001-2007					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Add 1 to firms' expenditure before taking the log					
Change in relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	0.076	0.079	0.084	0.263	0.260	-0.111
	[0.099]	[0.099]	[0.100]	[0.718]	[0.719]	[1.268]
Firm skill intensity X Change in R_{ct}		0.096^{***}	0.096^{***}		0.138^{***}	0.133^{***}
		[0.025]	[0.025]		[0.029]	[0.028]
Observations	30,373	30,373	29,946	30,373	30,373	29,946
R-squared	0.016	0.017	0.017	-	-	-
Panel B	Only keep firms with positive expenditure					
Change in relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	0.237	0.233	0.213	1.508^{*}	1.535^{*}	1.658
	[0.147]	[0.148]	[0.151]	[0.826]	[0.835]	[1.261]
Firm skill intensity X Change in R_{ct}		0.044	0.045^{*}		0.071^{***}	0.073^{***}
		[0.027]	[0.027]		[0.016]	[0.018]
Observations	2,838	2,838	2,807	2,838	2,838	2,807
R-squared	0.031	0.032	0.031	-	-	-
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: We measure R&D expenditure in two specifications: Panel A and B. R_{ct} based on the UHS is instrumented by S_{ct} in columns (4-6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 8: Pre-trend test: the correlation between city's future skill mix and firms' total capital

Dependent variable	Change in a firm's capital in past periods					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ logged value of real capital 1995-1998					
2005-2008 change in relative supply: $R_{ct'}$	0.061	0.061	-0.018	-0.054	-0.051	0.018
	[0.042]	[0.042]	[0.065]	[0.117]	[0.117]	[0.129]
Firm skill intensity X Change in $R_{ct'}$		0.006	0.006		0.021	0.021
		[0.012]	[0.011]		[0.026]	[0.027]
Observations	11,589	11,589	8,286	11,557	11,557	8,286
	Δ logged value of real capital 1995-1999					
2004-2008 change in relative supply: $R_{ct'}$	0.079*	0.079*	0.010	-0.041	-0.038	0.112
	[0.046]	[0.046]	[0.063]	[0.099]	[0.099]	[0.177]
Firm skill intensity X Change in $R_{ct'}$		0.007	0.007		0.018	0.019
		[0.012]	[0.011]		[0.020]	[0.021]
Observations	11,291	11,291	8,058	11,262	11,262	8,058
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: Future period's skill-mix, $R_{ct'}$, is instrumented by future period's $S_{ct'}$ in columns (4-6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 9: The effect of a city's skill mix on firms' employment

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Change in logged employment 1998-2008					
Change in relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	0.053	0.054	0.060	0.579	0.577	1.078
	[0.065]	[0.064]	[0.060]	[0.814]	[0.812]	[2.195]
Firm skill intensity X Change in R_{ct}		0.033***	0.032***		0.033***	0.032***
		[0.006]	[0.006]		[0.008]	[0.008]
Observations	13,576	13,576	13,277	13,576	13,576	13,277
R-squared	0.034	0.036	0.037	-	-	-
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: R_{ct} based on the UHS is instrumented by S_{ct} in columns (4-6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 10: The effect of a city's skill mix on firms' capital per worker

Dependent variable	Change in logged capital per worker 1998-2008					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in relative supply: $R_{ct} = \log \frac{H_{ct}}{L_{ct}}$	0.002	0.002	-0.044	-0.534	-0.533	-2.140
	[0.108]	[0.108]	[0.063]	[1.133]	[1.132]	[3.990]
Firm skill intensity X Change in R_{ct}		-0.006	-0.005		-0.009	-0.007
		[0.004]	[0.004]		[0.007]	[0.009]
Observations	13,576	13,576	13,277	13,576	13,576	13,277
R-squared	0.038	0.038	0.052	-	-	-
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: R_{ct} based on the UHS is instrumented by S_{ct} in columns (4-6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 11: Firms' responses to local skill mix shocks by region and industry

Dependent variable	Change in logged value of firm outcomes			
2SLS	By region		By industry	
	(1) Coastal	(2) Inland	(3) High-tech	(4) Low-tech
Panel A	Total capital			
Firm skill intensity X Change in R_{ct}	0.030***	-0.085	0.028***	0.019
	[0.007]	[0.224]	[0.007]	[0.015]
Observations	10,568	2,709	1,386	11,891
Panel B	Capital per worker			
Firm skill intensity X Change in R_{ct}	-0.004	-0.085	-0.001	-0.022
	[0.008]	[0.082]	[0.007]	[0.013]
Observations	10,568	2,709	1,386	11,891
Panel C	Employment			
Firm skill intensity X Change in R_{ct}	0.033***	-0.000	0.029***	0.041**
	[0.008]	[0.258]	[0.009]	[0.018]
Observations	10,568	2,709	1,386	11,891
Panel D	R&D expenditure			
Firm skill intensity X Change in R_{ct}	0.342**	0.120***	0.153***	0.104**
	[0.164]	[0.023]	[0.029]	[0.052]
Observations	23,356	6,590	2,909	27,037
Ownership dummies	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Note: Firm skill intensity is the standardized ratio of college- to non-college-educated workers at firm level in the 2004 Economy Census. The definition of high-tech industry is published by the NBS in 2013. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table 12: The effect of a city's skill-mix on firms' outcomes: robustness check

Dependent variable (changes in logged value)	Capital 1998-2008		R&D 2001-2007		Employment 1998-2008		Capital per worker 1998-2008	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
	Control for city's export volume by destination countries							
Firm skill intensity X Change in R_{ct}	0.028***	0.025***	0.097***	0.133***	0.033***	0.033***	-0.005	-0.008
	[0.004]	[0.005]	[0.025]	[0.027]	[0.006]	[0.008]	[0.004]	[0.007]
Observations	12,969	12,969	29,717	29,717	12,969	12,969	12,969	12,969
	Control for city's migrant population							
Firm skill intensity X Change in R_{ct}	0.027***	0.025***	0.096***	0.132***	0.032***	0.032***	-0.005	-0.006
	[0.004]	[0.007]	[0.029]	[0.024]	[0.006]	[0.008]	[0.004]	[0.009]
Observations	13,277	13,277	29,946	29,946	13,277	13,277	13,277	13,277
	Excluding State-owned Enterprises							
Firm skill intensity X Change in R_{ct}	0.025***	0.021***	0.095***	0.128***	0.030***	0.028***	-0.005	-0.007
	[0.004]	[0.007]	[0.024]	[0.026]	[0.006]	[0.009]	[0.004]	[0.012]
Observations	11,098	11,098	25,782	25,782	11,098	11,098	11,098	11,098
	Excluding firms that changed product category							
Firm skill intensity X Change in R_{ct}	0.059**	0.052	0.185*	0.268***	0.076***	0.063*	-0.017	-0.011
	[0.026]	[0.036]	[0.095]	[0.089]	[0.024]	[0.038]	[0.029]	[0.044]
Observations	7,681	7,681	18,033	18,033	7,681	7,681	7,681	7,681
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: R_{ct} and its interaction terms are instrumented by S_{ct} in columns (2, 4, 6). Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at the cities level are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

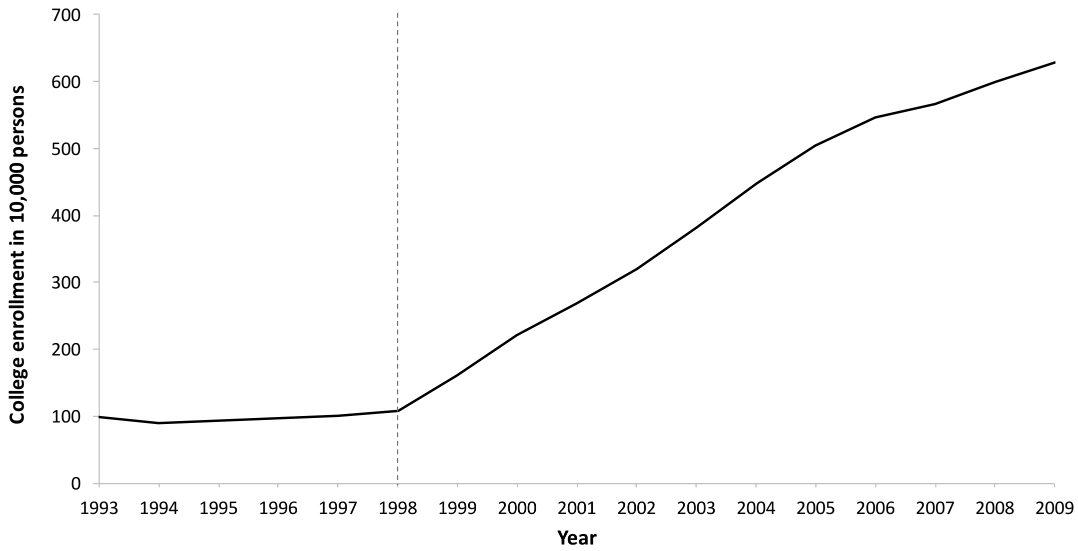

Figure 1: Trend of college enrollment in China from 1993 to 2009. The data is from the annual statistical yearbook published by the NBS.

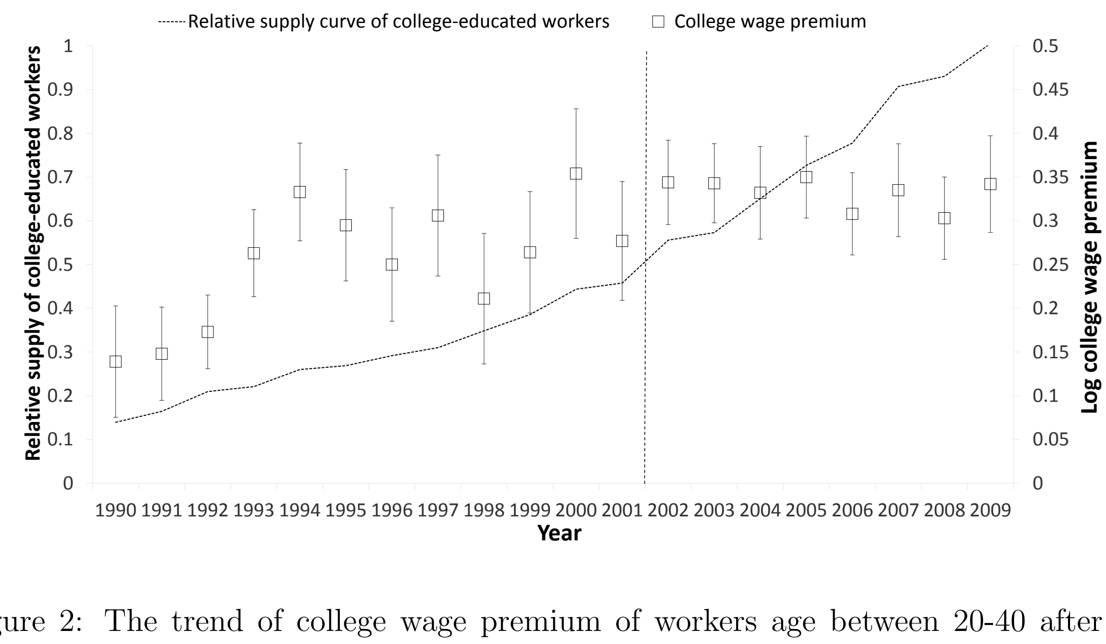

Figure 2: The trend of college wage premium of workers age between 20-40 after the increase in relative labor supply. We calculate the college wage premium using individuals' wage and education achievement data in the UHS.

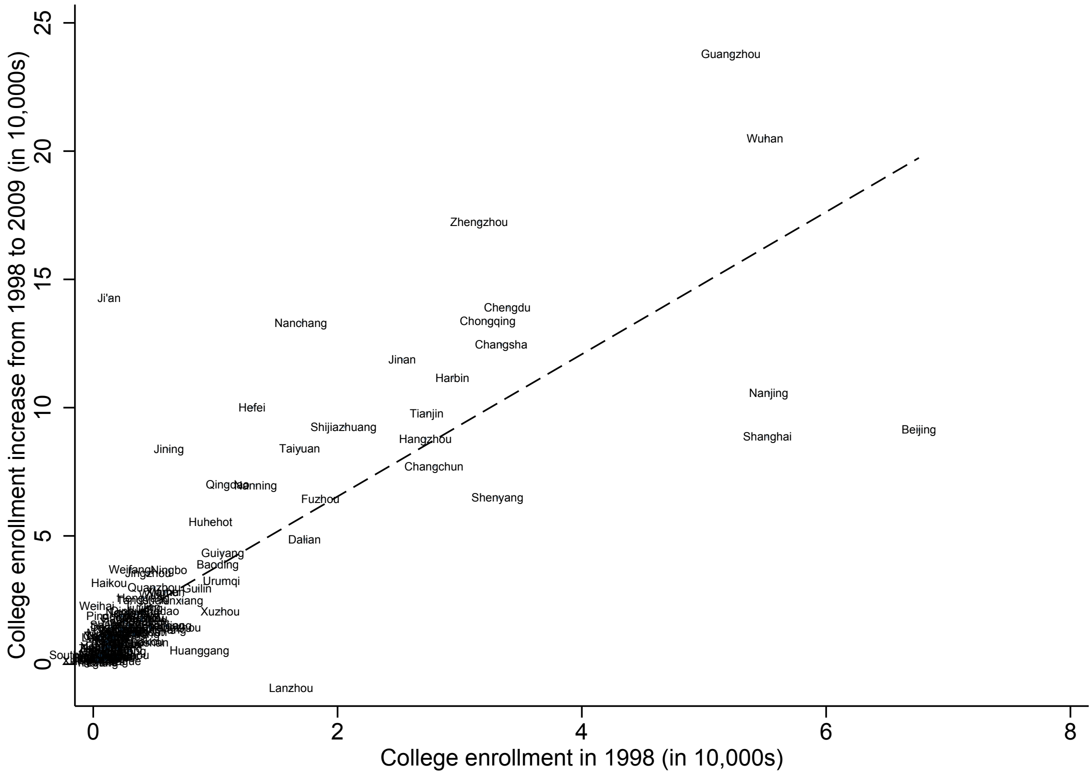

Figure 3: The increases of college enrollments in each city from 1998 to 2009 strongly relates to cities' college enrollments in 1998. The data is from the Statistical Yearbook of Regional Economy.

A Appendix

A.1 Proof for Proposition 1

Proposition 1: When firms can adjust capital freely and the range of parameters allows an interior solution for the equilibrium, the relative wage of high-skill workers compared to that of low-skill workers, $\ln(\frac{w_H}{w_L})$, only depends on exogenous production function parameters ($\mu, \alpha_1, \alpha_2, \rho^h$ and ρ^l) and capital rental price (r_h, r_l).

Proof. At the equilibrium with interior solution, each firm produces according to the first order conditions (Equations 14-19) of profit maximization problem in Equation (3-4):

$$\frac{\partial Y_1}{\partial K_h} = \alpha_1 y_1^{1-\mu} K_h^{\rho_1 - 1}(K_h^{\rho_1} + L_1^{\rho_1})^{\frac{\mu}{\rho_1}-1} = r_h \tag{14}$$

$$\frac{\partial Y_1}{\partial H_1} = (1-\alpha_1) y_1^{1-\mu} H_1^{\mu-1} = w_H \tag{15}$$

$$\frac{\partial Y_1}{\partial L_1} = \alpha_1 y_1^{1-\mu} L_1^{\rho_1 - 1}(K_h^{\rho_1} + L_1^{\rho_1})^{\frac{\mu}{\rho_1}-1} = w_L \tag{16}$$

$$\frac{\partial Y_2}{\partial K_l} = \alpha_2 y_2^{1-\mu} K_l^{\rho_2 - 1}(K_l^{\rho_2} + H_2^{\rho_2})^{\frac{\mu}{\rho_2}-1} = r_l \tag{17}$$

$$\frac{\partial Y_2}{\partial H_2} = \alpha_2 y_2^{1-\mu} H_2^{\rho_1 - 1}(K_l^{\rho_2} + H_2^{\rho_2})^{\frac{\mu}{\rho_2}-1} = w_H \tag{18}$$

$$\frac{\partial Y_2}{\partial L_2} = (1-\alpha_2) y_2^{1-\mu} L_2^{\mu-1} = w_L \tag{19}$$

As the production function has constant return to scale, we have the zero profit conditions in Equation (20-21).

$$Y_1 - w_L L_1 - w_H H_1 - r_h K_h = 0 \tag{20}$$

$$Y_2 - w_L L_2 - w_H H_2 - r_l K_l = 0 \tag{21}$$

We introduce the simplifications in Equations (22-27) to help solve the equilibrium wage of each type of worker.

$$
\begin{aligned}
(14)\ and\ (16): L_1 &= (\frac{w_L}{r_h})^{\frac{1}{\rho_1-1}} K_h && (22)\\
(14),(15)\ and\ (22): H_1 &= [\frac{\alpha_1 w_H}{(1-\alpha_1)r_h}]^{\frac{1}{\mu-1}}[1+(\frac{w_L}{r_h})^{\frac{\rho_1}{\rho_1-1}}]^{\frac{\mu-\rho_1}{(\mu-1)\rho_1}} K_h && (23)\\
(17)\ and\ (18): H_2 &= (\frac{w_H}{r_l})^{\frac{1}{\rho_2-1}} K_l && (24)\\
(17),(19)\ and\ (24): L_2 &= [\frac{\alpha_2 w_L}{(1-\alpha_2)r_l}]^{\frac{1}{\mu-1}}[1+(\frac{w_H}{r_l})^{\frac{\rho_2}{\rho_2-1}}]^{\frac{\mu-\rho_2}{(\mu-1)\rho_2}} K_l && (25)\\
(15)\ and\ (23): Y_1 &= (\frac{\alpha_1}{r_h})^{\frac{1}{\mu-1}}[1+(\frac{w_L}{r_h})^{\frac{\rho_1}{\rho_1-1}}]^{\frac{\mu-\rho_1}{(\mu-1)\rho_1}} K_h && (26)\\
(19)\ and\ (25): Y_2 &= (\frac{\alpha_2}{r_l})^{\frac{1}{\mu-1}}[1+(\frac{w_H}{r_l})^{\frac{\rho_2}{\rho_2-1}}]^{\frac{\mu-\rho_2}{(\mu-1)\rho_2}} K_l && (27)
\end{aligned}
$$

In summary, the first-order conditions for the equilibrium can be simplified as Equation (28-29)

$$
\begin{aligned}
(1-\alpha_1)^{\frac{1}{1-\mu}} w_H^{\frac{\mu}{1-\mu}} + r_1^{\frac{\mu}{\mu-1}} \alpha_1^{\frac{1}{1-\mu}}[1+(\frac{w_L}{r_h})^{\frac{\rho_1}{\rho_1-1}}]^{\frac{\mu(1-\rho_1)}{(1-\mu)\rho_1}} - 1 = 0 && (28)\\
(1-\alpha_2)^{\frac{1}{1-\mu}} w_L^{\frac{\mu}{1-\mu}} + r_2^{\frac{\mu}{\mu-1}} \alpha_2^{\frac{1}{1-\mu}}[1+(\frac{w_H}{r_l})^{\frac{\rho_2}{\rho_2-1}}]^{\frac{\mu(1-\rho_2)}{(1-\mu)\rho_2}} - 1 = 0 && (29)
\end{aligned}
$$

We further introduce two sufficient conditions (condition 1 and 2) so that there exists w_H and w_L satisfying both the first-order and the second-order condition for profit maximization.

Condition 1: A sufficient condition for there exist two w_H and w_L subject to equations (28-29) for every μ is that

$$
\begin{aligned}
g &< \frac{(1-\alpha_2)e(h-g)+g}{1-(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)} < min\{h, \frac{1}{1-\alpha_1}\} && (30)\\
e &< \frac{e+g}{1-(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)}) < min\{f, \frac{1}{1-\alpha_2}\} && (31)
\end{aligned}
$$

where

$$
\begin{aligned}
e &= (\alpha_1^{\frac{\rho_1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}} && (32)\\
f &= (\alpha_1^{\frac{\rho_1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}} && (33)\\
g &= (\alpha_2^{\frac{1}{\rho_2-1}} - r_2^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}} && (34)\\
h &= (\alpha_2^{\frac{\rho_2}{\rho_2-1}} - r_1^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}}. && (35)
\end{aligned}
$$

We derive this condition by finding two fixed points in Equation (28), $(0,(\alpha_1^{\frac{\rho_1}{\mu(\rho_1-1)}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}})$ and $(\frac{1}{1-\alpha_1},(\alpha_1^{\frac{\rho_1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}})$, that independent of the value of μ. Similarly, Equation (29) has two fixed points, $((\alpha_2^{\frac{\rho_2}{\mu(\rho_2-1)}} - r_2^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_1-1}{\rho_1}},0)$ and $((\alpha_2^{\frac{\rho_2}{\rho_2-1}} - r_1^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}},\frac{1}{1-\alpha_2})$.

Given that $\mu < \rho_1$ and $\mu < \rho_2$, we have

$$0 < (\alpha_1^{\frac{\rho_1}{\mu(\rho_1-1)}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}} < (\alpha_1^{\frac{1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}} \tag{36}$$

$$0 < (\alpha_2^{\frac{\rho_2}{\mu(\rho_2-1)}} - r_2^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}} < (\alpha_2^{\frac{1}{\rho_2-1}} - r_2^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}} \tag{37}$$

If we link these fixed points and define them as:

$$\begin{aligned}
A &= (0, (\alpha_1^{\frac{\rho_1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}}) = (0, e) &(38)\\
B &= (\frac{1}{1-\alpha_1}, (\alpha_1^{\frac{\rho_1}{\rho_1-1}} - r_1^{\frac{\rho_1}{\rho_1-1}})^{\frac{\rho_1-1}{\rho_1}}) = (\frac{1}{1-\alpha_1}, f) &(39)\\
C &= ((\alpha_2^{\frac{1}{\rho_2-1}} - r_2^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}}, 0) = (g, 0)) &(40)\\
D &= ((\alpha_2^{\frac{\rho_2}{\rho_2-1}} - r_1^{\frac{\rho_2}{\rho_2-1}})^{\frac{\rho_2-1}{\rho_2}}, \frac{1}{1-\alpha_2}) = (h, \frac{1}{1-\alpha_2}) &(41)
\end{aligned}$$

We further derive the point of intersection E as

$$E = (\frac{g-(1-\alpha_2)e(h-g)}{1+(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)}, \frac{e+g(f-e)(1-\alpha_1)}{1-(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)}) \tag{42}$$

Notice that w_H is continuous concave function of the w_L in Equation (28), but a continuous convex function of the w_L in equation (29). If the intersection point E is between fixed points A, and B, C and D, we can always find two sets of w_H and w_L that satisfy Equations (28-29) for every μ. The following condition guarantee the position of the intersection point E.

$$\begin{aligned}
g &< \frac{(1-\alpha_2)e(h-g)+g}{1-(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)} < min\{h, \frac{1}{1-\alpha_1}\} &(43)\\
e &< \frac{e+g}{1-(1-\alpha_1)(1-\alpha_2)(h-g)(f-e)}) < min\{f, \frac{1}{1-\alpha_2}\} &(44)
\end{aligned}$$

Figure A8 illustrates how we derive the sufficient condition using an example when $\alpha_1 = \alpha_2 = 0.4$, $r_1 = r_2 = 1$. If $\rho_1 = 0.3$, $\rho_2 = 0.5$, $\mu = 0.5$, the sufficient condition is satisfied and we can find two solutions for the Equations (28-29). However, if $\rho_1 = 0.3$, $\rho_2 = 0.3$, $\mu = 0.9$, the condition is not satisfied and there is no solution for the Equations (28-29).

Condition 2: The range of parameter generate interior solutions guarantees the existence of positive level of capital for each type of firms, K_h and K_l.

Under above conditions, we claim the relative wage of high- and low-skill workers $\ln(\frac{w_H}{w_L})$ does not change after the influx of high-skill workers in local labor markets in equilibrium. As we cannot analytically verify that at least one set of solution satisfy the second-order condition, we numerically verified that the Hessian matrix (based on second derivative of the profit function at the equilibrium) is always negative definite given above two conditions. The numerical computation codes are attached in the online appendix. □

A.2 Proof for Proposition 2

Proposition 2: When more high-skill workers enter the labor market, firms that use skill-biased capital hire more workers and invest more in capital. Correspondingly, firms use labor-biased capital employ fewer workers and divest in capital. However, the capital intensity measured by value of capital per worker remains constant among both types of firms.

Proof. In equilibrium with interior solution, labor markets for both types of workers clear.

$$H_1 + H_2 = H \tag{45}$$

$$L_1 + L_2 = L \tag{46}$$

By combining Equations (45-46) with Equations (22-25), we rewrite the labor market clearing conditions as

$$\begin{aligned} aK_h + bK_l &= H \\ cK_h + dK_l &= L \end{aligned}$$

where

$$\begin{aligned}
a &= [\frac{\alpha_1 w_H}{(1-\alpha_1)r_1}]^{\frac{1}{\mu-1}}[1+(\frac{w_L}{r_1})^{\frac{\rho_1}{\rho_1-1}}]^{\frac{\mu-\rho_1}{(\mu-1)\rho_1}} > 0 \\
b &= (\frac{w_H}{r_2})^{\frac{1}{\rho_2-1}} > 0 \\
c &= (\frac{w_L}{r_1})^{\frac{1}{\rho_1-1}} > 0 \\
d &= [\frac{\alpha_2 w_L}{(1-\alpha_2)r_2}]^{\frac{1}{\mu-1}}[1+(\frac{w_H}{r_2})^{\frac{\rho_2}{\rho_2-1}}]^{\frac{\mu-\rho_2}{(\mu-1)\rho_2}} > 0
\end{aligned}$$

thus we have

$$
\begin{aligned}
K_h &= \frac{dH - bL}{ad - bc} && (47)\\
K_l &= \frac{aL - cH}{ad - bc} && (48)\\
\frac{K_h}{H_1 + L_1} &= \frac{1}{a + c} && (49)\\
\frac{K_l}{H_2 + L_2} &= \frac{1}{b + d} && (50)
\end{aligned}
$$

Notice that

$$
ad - bc \propto ad \cdot K_h \cdot K_l - bc \cdot K_h \cdot K_l = H_1 \cdot L_2 - H_2 \cdot L_1 > 0 \quad (51)
$$

As $\frac{H_1}{L_1} > \frac{H_2}{L_2}$, if $\alpha_1 + \alpha_2 < 1$ (see discussion on Equation 5 in the main text). Therefore, we have following comparative statics

$$
\begin{aligned}
\frac{\partial K_h}{\partial H} &= \frac{d}{ad - bc} > 0 && (52)\\
\frac{\partial K_l}{\partial H} &= -\frac{c}{ad - bc} < 0 && (53)\\
\frac{\partial (H_1 + L_1)}{\partial H} &= (a + c)\frac{\partial K_h}{\partial H} > 0 && (54)
\end{aligned}
$$

Equations (52-53) indicate that firms that use skill-biased capital further invest in capital if there is an influx of high-skill workers in the local labor market, and firms that use labor-biased capital reduce capital stock after more college-educated workers enter the related labor markets. These adjustments in K_1 and K_2 also help explain the constant college wage premium after the influx of college-educated workers observed in Figure 2. According to Equation (49-50), the capital per worker does not change after the skill-mix shock in this model, which we can empirically test as well. In addition, Equations (54) shows that the total employment of firms that use skill-biased capital will increase as well. □

Table A1: Correlation between a firm's skill intensity and other outcomes in 2004

Dependent variable (in logged value)	Capital (1)	Capital per worker (2)	Employment (3)	R&D expenditure (4)
Firm skill intensity in 2004	0.019**	0.057***	-0.038***	0.082***
	[0.009]	[0.013]	[0.006]	[0.014]
Ownership dummies	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	197,164	197,164	197,164	197,164
R-squared	0.082	0.052	0.088	0.055

Note: Firm skill intensity is the standardized ratio of college- to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table A2: Correlation between actual and predicted skill-mix based accumulated college graduates: in Census data

Dependent variable	Relative supply of college educated workers $R_{ct} = log\frac{H_{ct}}{L_{ct}}$			
	(1)	(2)	(3)	(4)
Predicted relative supply: S_{ct}	0.684***	0.568***	0.269**	0.264***
	[0.128]	[0.124]	[0.111]	[0.097]
Year FE		Yes	Yes	Yes
Municipality, Capital & Region FE			Yes	Yes
Logged city GDP and population				Yes
F-stat	28.29	280.18	223.70	382.58
Observations	704	704	704	623
R-squared	0.320	0.443	0.596	0.822

Note: R_{ct} is logged city's ratio of college- to non-college-educated workers (age 15-64) in Census 2000, 2005 and 2010. S_{ct} is logged ratio of predicted college graduates share to the share without college education. The number of observations in column (4) is smaller due to missing GDP in City Statistical Yearbooks. The standard errors are clustered at cities in brackets. ***p<0.01, **p<0.05, *p<0.1

Table A3: The effect of a city's skill mix (measured in the Census) on firms' capital investment

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Change in logged value of real capital 1998-2008					
Change in city skill mix (R_{ct})	0.822***	0.829***	0.625***	1.256	1.276	0.557
	[0.167]	[0.168]	[0.159]	[1.432]	[1.438]	[3.773]
Firm skill intensity X Change in R_{ct}		0.026***	0.028***		0.026***	0.025**
		[0.003]	[0.003]		[0.008]	[0.012]
Observations	13,301	13,301	13,013	13,301	13,301	13,013
Dependent variable	Change in logged capital per worker 1998-2008					
Change in city skill mix (R_{ct})	0.320	0.319	0.003	-0.407	-0.415	-4.687
	[0.214]	[0.214]	[0.208]	[1.784]	[1.789]	[10.498]
Firm skill intensity X Change in R_{ct}		-0.006	-0.004		-0.011	-0.021
		[0.004]	[0.004]		[0.008]	[0.031]
Observations	13,301	13,301	13,013	13,301	13,301	13,013
Dependent variable	Change in logged employment 1998-2008					
Change in city skill mix (R_{ct})	0.502***	0.510***	0.623***	1.663	1.691	5.244
	[0.133]	[0.133]	[0.153]	[1.256]	[1.264]	[9.298]
Firm skill intensity X Change in R_{ct}		0.032***	0.032***		0.038***	0.046
		[0.005]	[0.005]		[0.010]	[0.029]
Observations	13,301	13,301	13,013	13,301	13,301	13,013
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)			Yes			Yes

Note: R_{ct} based on population Census is instrumented by S_{ct} in columns (4-6). Firm skill intensity is defined as the standardized ratio of college-educated to non-college-educated workers in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

Table A4: Different periods of long difference effect on firms' capital and employment

2SLS: Dependent variable	Change in logged value of firm outcomes					
	(1) 2003-1998	(2) 2004-1998	(3) 2005-1998	(4) 2006-1998	(5) 2007-1998	(6) 2008-1998
Panel A	Total capital					
Firm skill intensity X Change in R_{ct}	0.030**	0.027**	0.023***	0.021***	0.021***	0.025***
	[0.013]	[0.011]	[0.008]	[0.007]	[0.008]	[0.006]
Panel B	Capital per worker					
Firm skill intensity X Change in R_{ct}	0.024*	0.020	-0.004	-0.005	-0.008	-0.007
	[0.013]	[0.012]	[0.008]	[0.007]	[0.005]	[0.009]
Panel C	Employment					
Firm skill intensity X Change in R_{ct}	0.005	0.007	0.027***	0.026***	0.029***	0.032***
	[0.008]	[0.008]	[0.010]	[0.009]	[0.009]	[0.008]
Change in city skill mix (R_{ct})	Yes	Yes	Yes	Yes	Yes	Yes
Firm ownership & 2-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality, Capital & Region FE	Yes	Yes	Yes	Yes	Yes	Yes
1998 city GDP, population (in log)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,360	21,745	19,202	17,307	15,529	13,227

Note: R_{ct} based on the UHS is instrumented by S_{ct} in all columns. Firm skill intensity is the standardized ratio of college-educated to non-college-educated workers at firm level in the 2004 Economy Census. Clustered standard errors at cities are shown in brackets. ***p<0.01, **p<0.05, *p<0.1

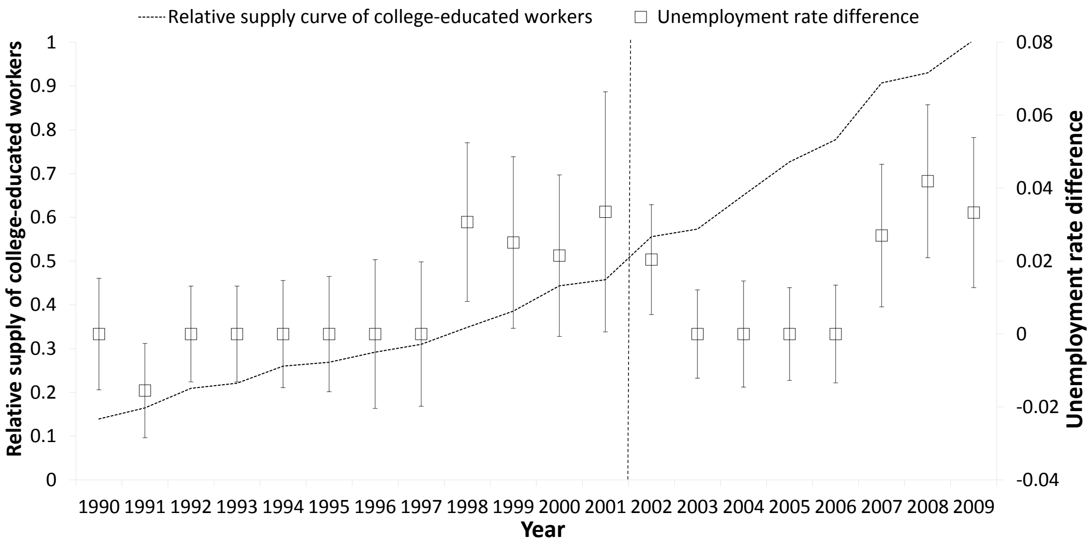

Figure A1: The trend of unemployment rate premium of workers age between 20-40 after the increase in relative labor supply. We calculate the college wage premium using individuals' wage and education achievement data in the UHS.

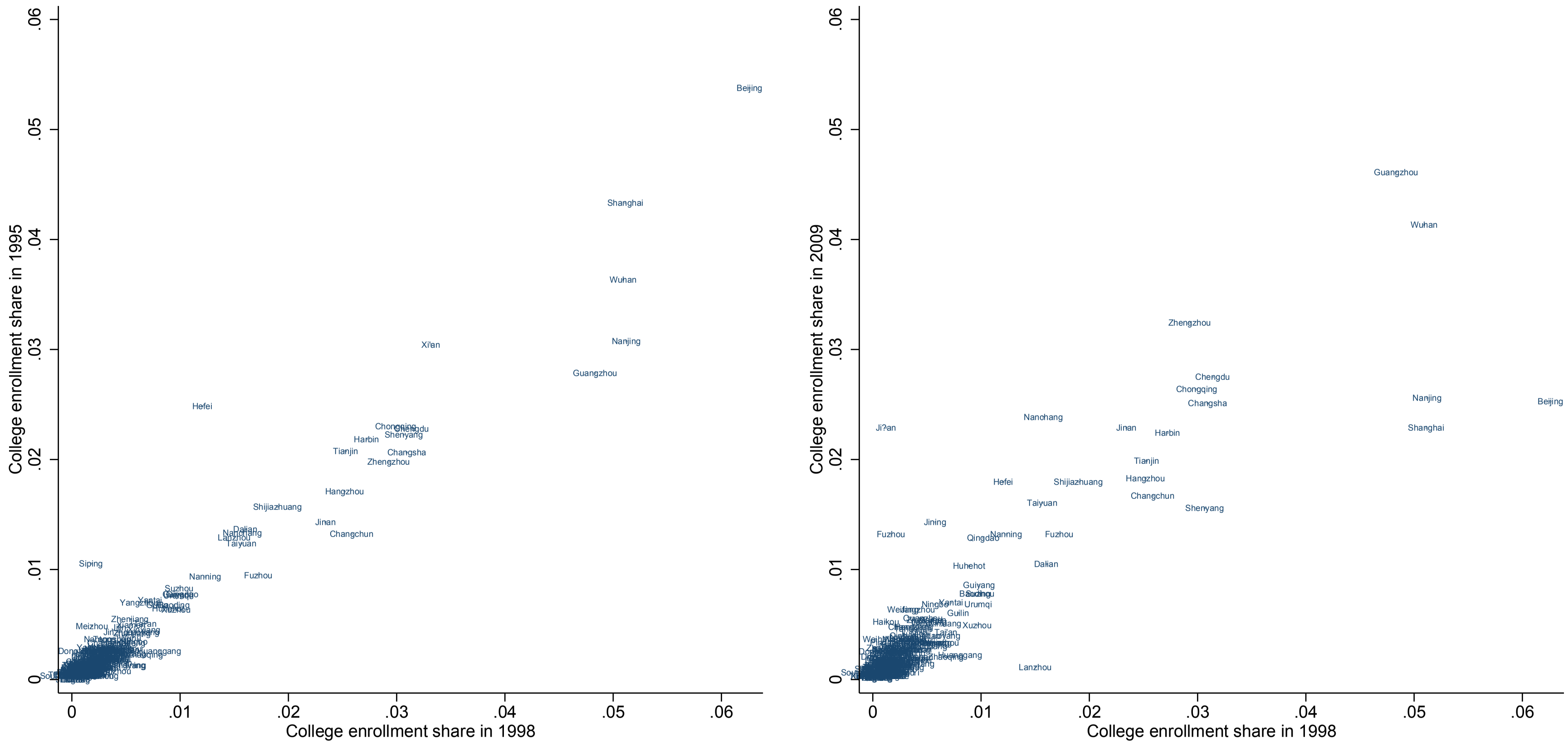

Figure A2: There is a strong correlation in a city's college enrollment share over time (1995 is the earliest year with city-level enrollment). The data is from the Statistical Yearbook of Regional Economy.

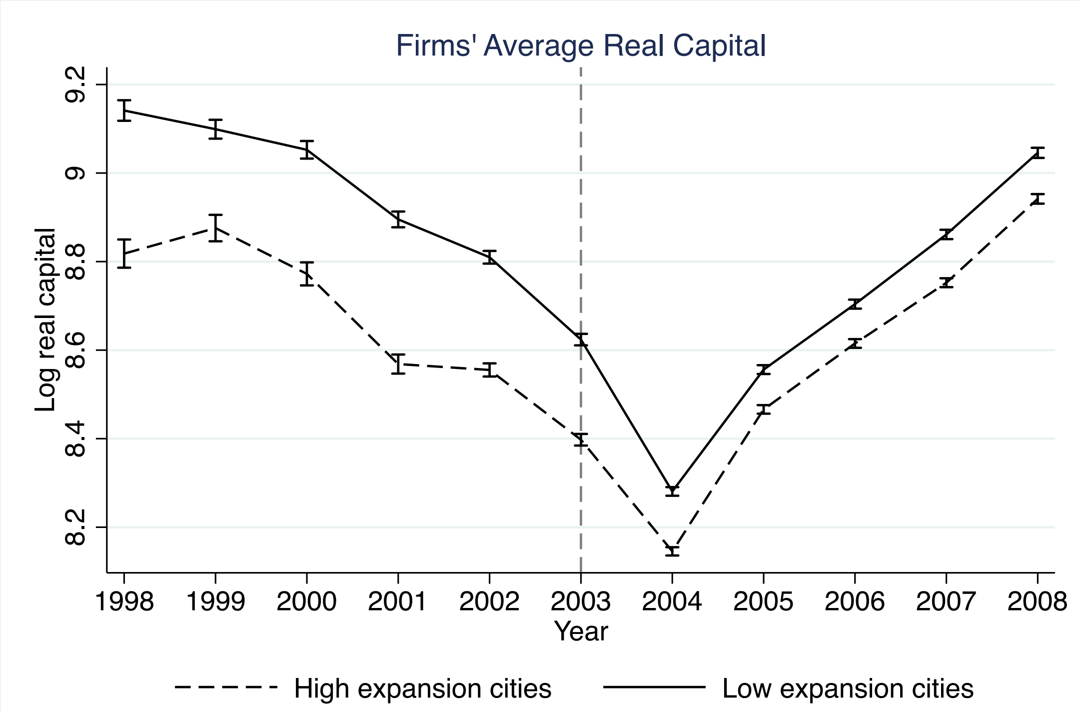

Figure A3: The trend of firms' logged capital in original value across two types of cities from 1998 to 2008. The data is from the ASIF.

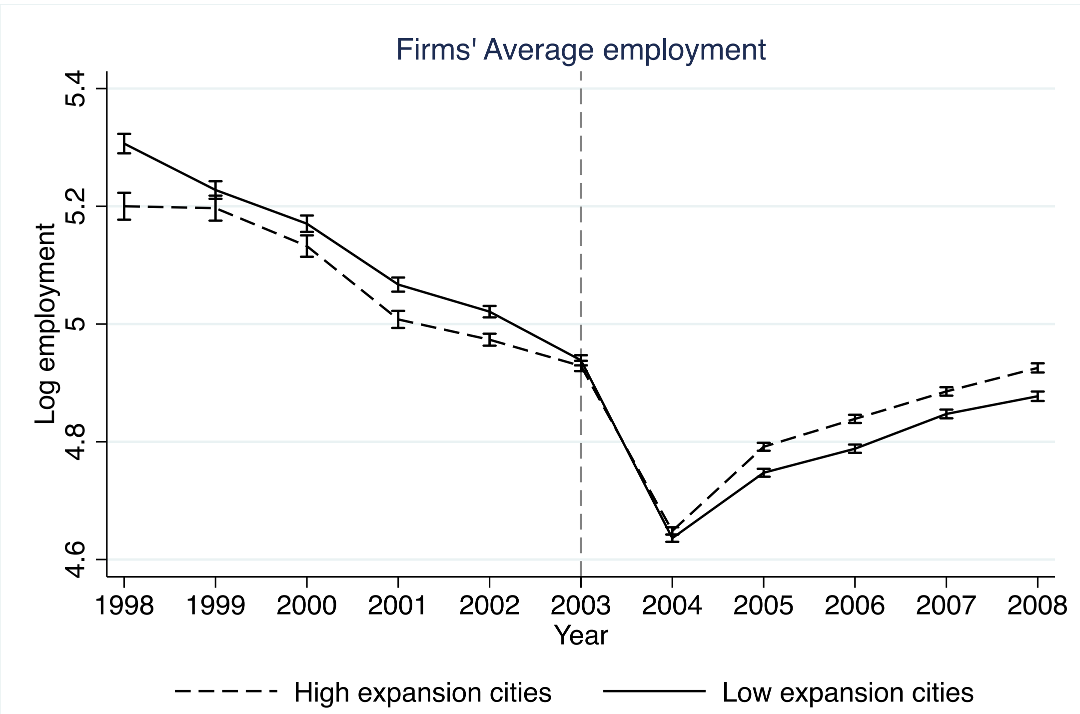

Figure A4: The trend of firms' logged employment in original value across two types of cities from 1998 to 2008. The data is from the ASIF.

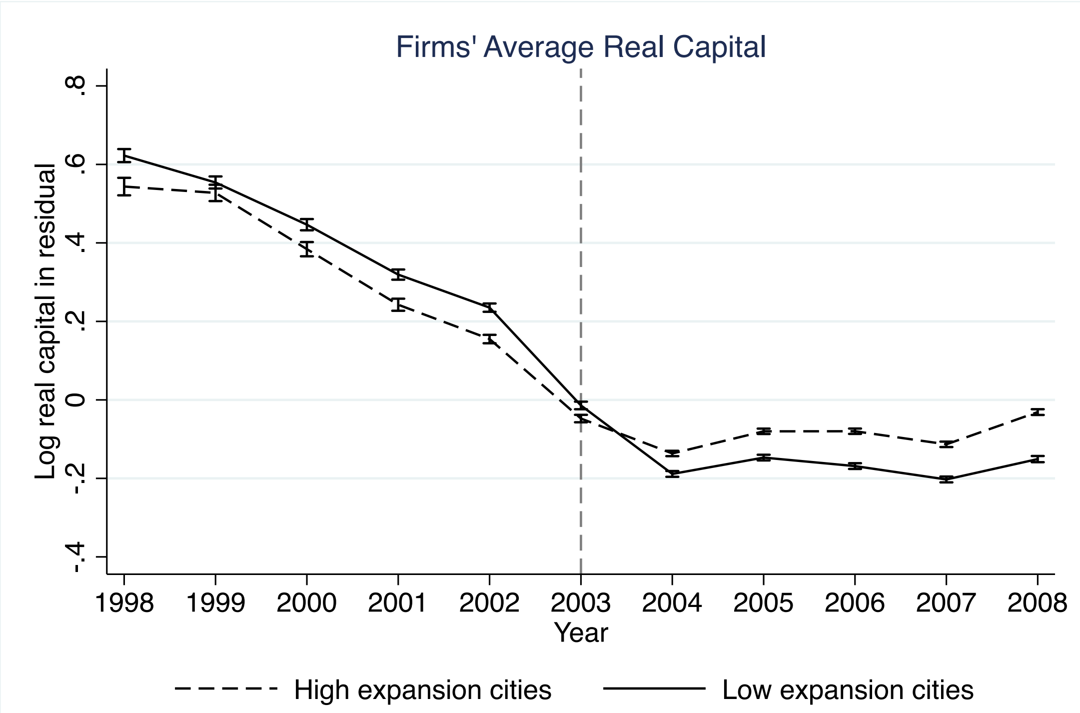

Figure A5: The trend of firms' logged capital in residual across two types of cities from 1998 to 2008. The data is from the ASIF.

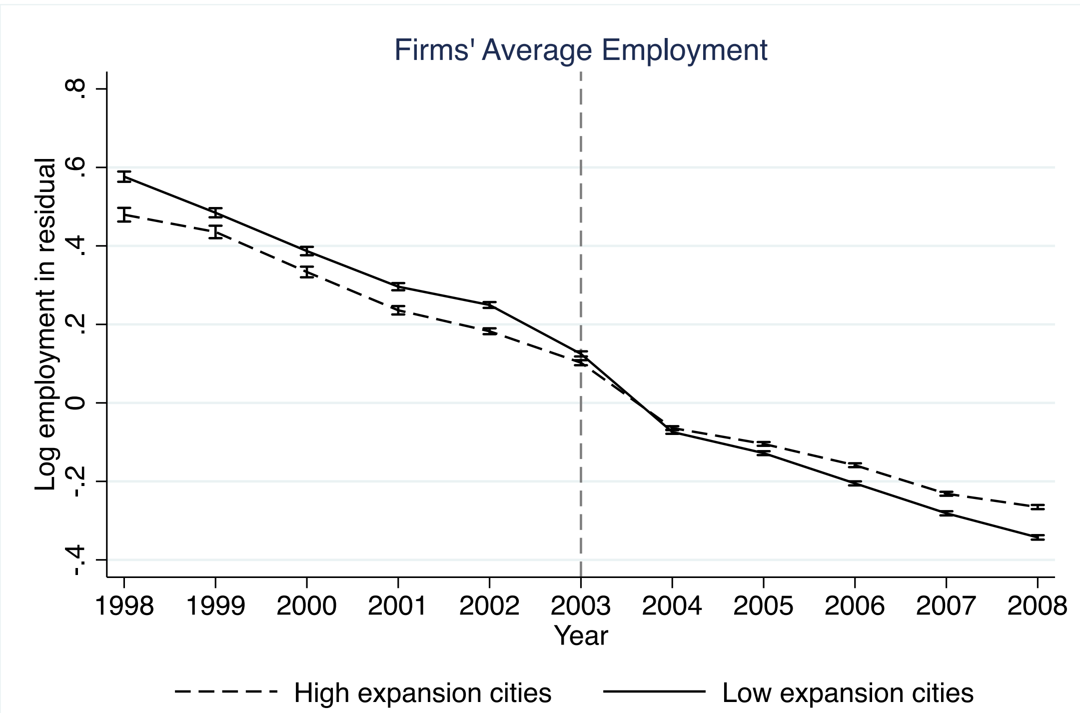

Figure A6: The trend of firms' logged employment in residual across two types of cities from 1998 to 2008. The data is from the ASIF.

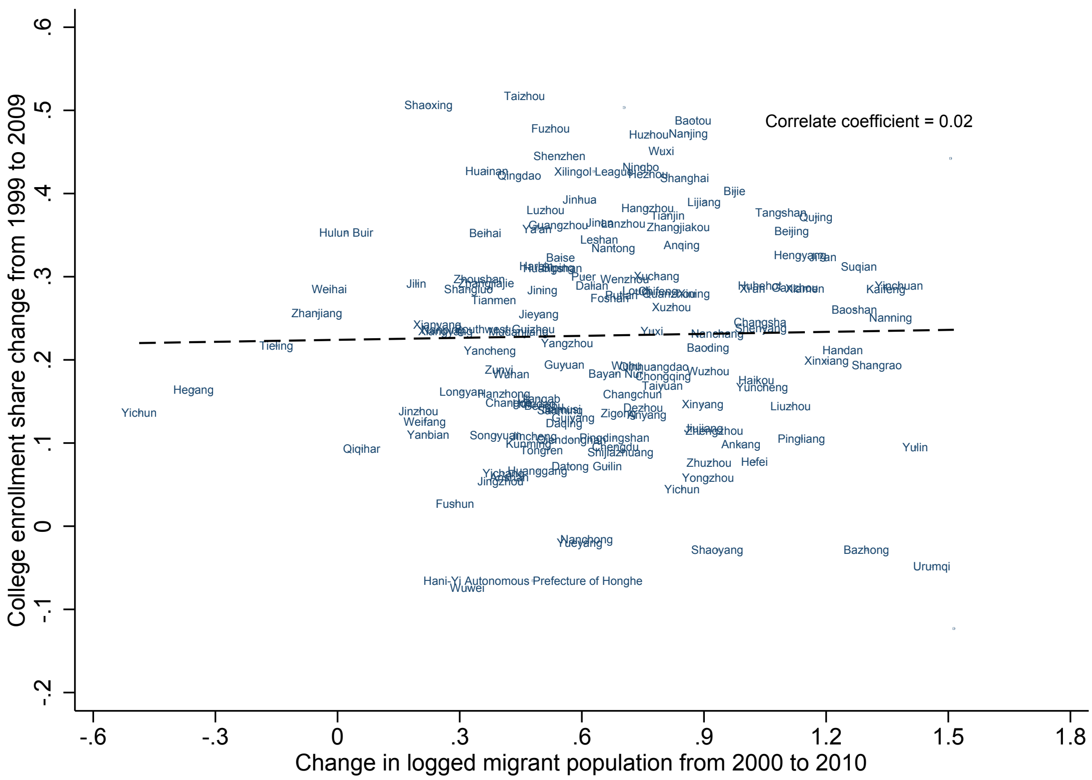

Figure A7: Correlation between the change in a city's college enrollment share and the proportional change in the city's migrant population. The data is from the UHS and Census.

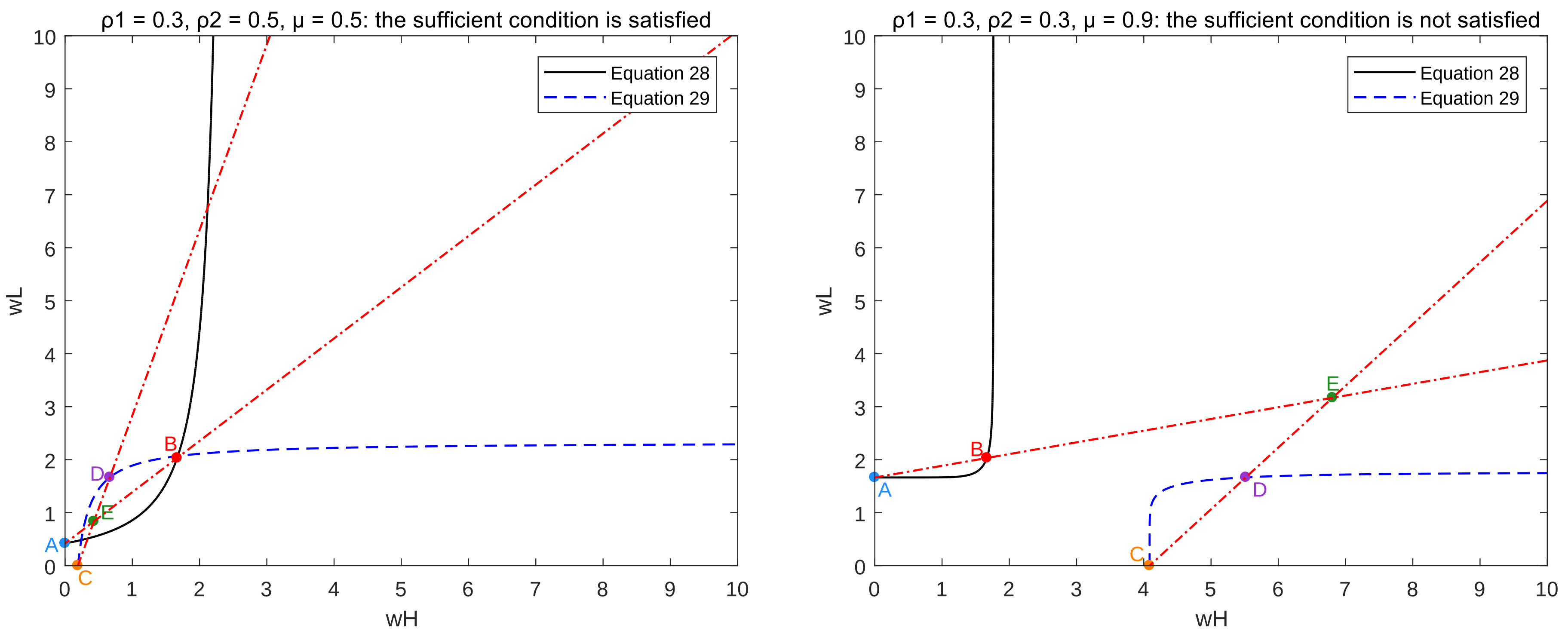

Figure A8: Illustrating the sufficient condition for model solutions.