ABSTRACT

Title of dissertation:	HIGHER EDUCATION, HUMAN CAPITAL SPILLOVERS AND ECONOMIC GROWTH
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Many theorists suggest that the concentration of human capital in a region helps improve productivity for firms and individuals by creating social learning chances for workers. Such human capital spillovers can generate innovations and new ideas which are the driving forces for sustainable long-term growth. My dissertation provides systematic empirical evidence for human capital spillovers using micro-level data from China.

In chapter 1, I provide motivation, a discussion of identification challenges, a literature review on human capital spillovers, a description of the data used in my dissertation, a description of the Chinese economy, and a preview of my identification strategies and findings.

In chapter 2, I investigate the effect of aggregate human capital on productivity in an indirect way. I compare the wages of otherwise similar individuals that live in cities with different level of college share. The resulting estimates indicate that workers working in cities with higher human capital do have higher wages than

otherwise similar workers in cities with lower human capital. Interestingly, I find that both skilled and unskilled workers benefit from the increase in human capital, but unskilled workers benefit more than skilled workers. This is may be due to imperfect substitution between skilled and unskilled workers.

In chapter 3, I take a constant-composition approach, which in theory separates imperfect substitution effect from spillovers by holding the skill composition in the workforce constant, to further investigate the existence and magnitude of human capital spillovers. The results show that the relationship between workers' wages and city-level human capital remains positive and statistically significant. The estimates from individual wage data indicate that a one percentage point increase in the share of college-educated workers in the population is associated with a 1.4 to 3.6 percent increase in wages.

In chapter 4, I take a direct approach to estimate the impact of aggregate human capital on productivity. Specifically, I apply a first differenced instrumental variable model to a balanced firm panel data to study the impact of an increase in the share of college-educated workers on firms' total factor productivity (TFP). I find that one percentage point increase in college share in a city increases firms' TFP by 0.8 to 2.1 percent. Private firms are more responsive to overall human capital than state firms, and the human capital spillovers are stronger in denser and larger cities. Chapter 5 concludes.

HUMAN CAPITAL EXTERNALITIES:
EVIDENCES FROM CHINA

by

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Chapter 1: Introduction

1.1   Motivation

Economic growth is one of the most important topics in economics. In his seminal model Solow (1956) provides the following important insight: in the long run, economic growth must come from technological progress instead of capital accumulation. In the Solow model, the technological progress is exogenously given. Though it is known that human capital plays a central role in the process of generating new ideas and innovation, human capital is not considered in the growth models until Romer (1990) who explicitly puts human capital as one of the key factors affecting the technological change. Romer (1990) argues that cities with higher human capital grow faster. Romer's core insight is that ideas are non-rival, one person's use of the oral rehydration therapy (Romer's favorite example) would not reduce such therapy available to other people to use to save lives of children with diarrhea.

As a result, the non-rivalry of human capital leads to human capital spillovers. That is, the presence of skilled workers makes other workers more productive because workers can learn from each other through social interactions among them. Ellison and Glaeser (1997) and Jovanovic and Rob (1989) build their growth models by assuming that individuals augment their human capital through pairwise

meetings with more skilled neighbors at which they exchange ideas.[1] Lucas (1988) suggests that human capital spillovers may help explain the long-run differences in the economic performance of countries.

Whether human capital spillovers can be regarded as a major driver of macroeconomic performance is ultimately a quantitative question(Chang et al., 2016). My dissertation is an attempt to provide systematic empirical evidence for the existence of human capital spillovers using data from China.

In the literature, most of the evidence on the human capital spillovers is based on models that regress workers' wage or firms' output on measures of the aggregate stock of human capital which is either average years of schooling or the percent of individuals with a college degree in a city, controlling individual human capital or firm human capital. The identification comes from the comparison of wages or outputs for otherwise similar individuals or firms in cities with different aggregate human capital.

1.2   Identification Challenges

The issue of omitted relevant variables is probably the most important empirical challenge facing researchers in the area of human capital spillovers. In a simple OLS estimation, the presence of unobservable factors that are correlated with ag-

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[1]Human capital spillovers could also arise when firms find it profitable to invest in new technologies only when there is a sufficient supply of trained workers to allow for normal turnover, that is, more educated workers in the economy increases the willingness of firms to invest in productivity improving technologies (Acemoglu and Angrist, 2001). In addition, high human capital may have non-monetary benefits as well, such as increasing civil participation and reducing crime (Lochner and Moretti, 2004).

gregate human capital, workers' wages and firms' productivity will likely bias the estimates of human capital spillovers.

Cities differ from each other in many ways, such as institution, infrastructure, industry structure, amenities, geographic location, natural resources, and population composition. Most of these characteristics are not observable to econometricians. Cities with advantages in these factors could lead to higher productivities for both firms and workers. As a consequence, firms would be able to pay higher wages which could attract a very skilled workforce to these cities. Software developers tend to move to Silicon Valley in the U.S., Chinese college graduates tend to go to big cities in China such as Beijing and Shanghai. In such case, it is better wages that cause an increase in human capital, not the other way around.

Moreover, workers could sort themselves into cities with different aggregate human capital based on their unobservable ability. It is possible that workers with higher unobservable ability move to cities with higher aggregate human capital. Comparing wages of workers with identical observable characteristics but different unobservable ability living in cities with different aggregate human capital could lead to an upward biased estimate of spillovers. The opposite may also be true that workers with lower unobservable ability may move to cities with higher human capital as these cities often have a thicker labor market and these workers may find jobs that they may not find in cities with lower human capital. In this case, the spillovers would bias downward.

Similarly, firms tend to choose places where they could have a good match between their cost function and city characteristics. Firms that in nature are more

productive and require a more educated workforce would choose to locate in cities with more educated workers. For example, software development companies tend to locate in Silicon Valley where a well-educated workforce is available. On the contrary, firms that are less productive and need less educated workers would locate in cities with lower human capital.

In reality, it is common for us to observe that wages for workers are higher in cities with a well-educated labor force than cities with a less-educated labor force and more productive firms are located in cities with higher aggregate human capital. Therefore, it is very crucial to address this endogeneity issue caused by omitted variables to obtain credible estimates for human capital spillovers.

1.3   Literature Review

In this literature, the way to deal with such endogeneity is context-specific and relies on the relevant data. Rauch (1993) is among the first to empirically estimate human capital spillovers. He uses 1980 census data of the U.S. and assumes average schooling is historically predetermined. So, the endogenity problem is ignored in his study. Rauch finds a significant effect of the increase in average years of education in a city on individual wages controlling for individual education and other characteristics.

Acemoglu and Angrist (2001) instrument for the average schooling with the state variation in compulsory attendance laws and child labor laws and they find their estimate of human capital externalities close to zero, while they have positive

and significant spillovers in their OLS estimation. This may be due to the fact that their instruments only identify the exogenous variation of education in the lower tail of its distribution, while the benefits of the spillover are in the form of technological progress and higher productivity which is more likely to come from higher education.

Moretti (2004b) uses the share of college-educated workers as a measure of the average human capital and he instruments for the college share with the (lagged) demographic structure and the presence of land-grant universities in a city. He finds that one percentage point increase in college share raises the wages of workers by about 0.4 to 1.9 percent. Using plant-level data of ten years apart, Moretti (2004c) finds one point increase in college share is associated with a 0.5-0.6 percentage point increase in output. In his research, Moretti (2004c) takes an instrumental variable approach and uses the fraction of large plant openings among all the plant openings in a city excluding the relevant 3-digit industry as an instrument for college share in other industries, and he finds the spillovers effect using plant-level data is similar to what he obtained from individual-level data. Ciccone and Peri (2006) apply the constant-composition approach to U.S. census data between 1970 and 1990 but their estimation yields no evidence of significant average-schooling externalities.

Liu (2007) uses a cross-sectional data from 1995 China Household Income Project to estimate the external returns to education. Similar to Acemoglu and Angrist (2001), Liu uses the compulsory education law in China to deal with the endogenous average schooling of cities. Since the information on the timing of the compulsory education law across cities is not available, Liu assigns each city

into one of three categories based on their ranking in the administrative hierarchy[2] assuming cities with higher ranking complied with the law quicker. Liu finds a one-year increase in city average education could increase individual earnings by between 11 and 13%. Using a panel of Chinese manufacturing firms from 1995 to 1999, Liu (2014) finds a positive and statistically significant relationship between firm productivity and city-level human capital. His main results are derived from a firm fixed effects model. The city-level average schooling in his study is computed with individual data from the urban household survey of the same period. One drawback of this measure of human capital is that this survey only covers urban households and may not provide an accurate description of city level average human capital.

Liang et al. (2016) estimate external returns to education using China Urban Household Survey data 1993, 1995 and 1997 with city fixed effect which controls for city-level unobservable factors that correlate with both the city-level average schooling and wages of workers at the same time. They use the number of college students in the city as an instrument for college share. Their fixed-effects estimates show a one-year increase in city average education could increase individual earnings between 7.3% and 8.9% and their IV estimate indicates a 7.6% increase in wages. Liang et al. (2016) also uses China Health and Nutrition Survey data (a panel conducted in 1989 to 2006 in every two to four years) for the estimation and they find a one year increase in average education of a city rises average wage by 8% to

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[2]At the top of the city hierarchy is the city of Beijing-the nation's capital. Provincial capitals consist of the city centers at the second level, followed by prefecture-level cities, county-level cities, and rural towns

9% using individual fixed effects and city fixed effects respectively.

1.4   Data Used in the Dissertation

It is not until recent decades that micro-level data in China become increasingly available to researchers. I conduct the empirical investigations of human capital spillovers using both individual-level and firm-level data from China.

To study human capital spillovers from workers' perspective, I use two data sets from two different household surveys. The first one is the China Household Income Project (CHIP). Five waves of the CHIP surveys have been conducted in 1989, 1996, 2003, 2008 and 2014 collecting household and individual information on income, expenditure and other social demographic variables in great details for the year of 1988, 1995, 2002, 2007 and 2013. They are called CHIP1988, CHIP1995, CHIP2002, CHIP2007, and CHIP2013 officially. These surveys were carried out as part of a collaborative research project on incomes and inequality in China organized by Chinese and international researchers, with assistance from the National Bureau of Statistics. Many studies using this data set have been published since the emergence of this data[3].

Another individual-level data is from China Urban Household Survey conducted by NBS from 2002 to 2009 to monitor the performance of the Chinese economy at the household level. Both of the two individual-level data sets contain rich information of individuals ranging from their demographic information to their employment and income information. Most importantly, these two data sets reveal the

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[3]For more detailed information, please visit http://ciid.bnu.edu.cn/chip/index.asp?lang=EN

national standard code of cities that individuals resided at the time of the surveys which allows me to study human capital spillovers at the city level. To my best knowledge, the two data sets are the only micro data in China that permit general researchers to access geographic location of individuals at the city level.

A panel data of manufacturing firms from China's Annual Survey of Industrial Enterprises (ASIE) is used to study the effect of aggregate human capital on firm productivity. This survey is conducted by the National Bureau of Statistics annually since 1998. It covers a large number of questions such as products produced, total assets, investment, salary expense, insurance, sales, employment, taxes and so forth. In total, there are more than 100 variables in the data set are available, making the ASIE the most comprehensive and detailed database of domestic and foreign firms operating in China (He et al., 2018). In my study, I use firm data from 2001 and 2011 to match to the college share derived from the population census of 2000 and 2010. Along with other city-level information from China's city yearbook, I have been able to estimate the effect of city-level human capital on firms' total factor productivity.

1.5   Why China?

Close-to-double-digit growth in the last four decades gains China the praise of growth miracle, as well as draws great research interests from all over the world. One of the important questions is to identify the sources of China's economic growth. another question is whether such substantial growth is sustainable.

Researchers generally believe that China's economic growth is largely labor-intensive, and relies on high fixed capital investment (Chow, 1993; Amsden et al., 1996; Arayama and Miyoshi, 2004). If this is the whole story, China's growth pattern faces a limit as its population age and the level of capital investment has reached high.

Alternatively, endogenous growth theory shows that a high social human capital sustains economic growth by continuously generating new ideas and productivity-enhancing technological innovations (Romer, 1990). As a consequence, more outputs can result from the same inputs. In this sense, human capital is input and productivity-enhancing rather than just an input.

China's rapid economic growth and its major educational expansion since 1999 (college enrollment in China increase fivefold between 1997 and 2007) provide a great opportunity to empirically investigate the role of human capital in economic development at the micro level.

Figure .1 shows the new college enrollment in China from 1958 to 2012 has increased dramatically. The number of new college enrollments before 1977 is missing and presumably very low because universities in China were paralyzed and disrupted during the Great Cultural Revolution (1967 - 1977) and other political movements. Only a small number of individuals who were supposed to go to college before 1977 (theoretical college entering age is 18 years old) actually went to college and the college share for them is below 5%. The years between 1977 and 1998 saw an increasing expansion in higher education, new college enrollments increased from 0.27 million in 1977 to 1.08 million in 1998. In 1999 the Chinese government made a

strategic decision to expand higher education and the number of new students admitted to college increased by more than 40% in 1999 and the expansion continued in subsequent years. By the year 2012, new college enrollments reached 6.85 million and the total enrollments became 25.36 million which made China the country with the largest college student population.

Similar to China, in the past decades, we have observed many other countries expand their education system in a dramatic way as well. Between 1990 and 2010, the number of students in tertiary education per 100,000 people has tripled in Brazil, India, and Russia(Carnoy et al., 2013). Therefore, Finding empirical evidence of human capital spillovers from higher education could also provide important insights for development policies in other emerging markets.

1.6   Identification Strategies and Findings

In my dissertation, I first investigate the existence and magnitude of human capital spillovers using wage data of individual workers. If human capital spillovers exist, we expect to observe that individuals will have higher wages in cities with higher human capital than their counterparts in cities with lower human capital assuming firms award workers according to their marginal productivity. Then I study human capital spillovers using firm-level data. If aggregate human capital indeed increases productivity as my first investigation shows, we should observe that firms in cities with more well-educated labor force will have higher productivity than firms in cities with less-educated labor force after controlling firm-level and city-level

factors that affect firm productivity and college share. The estimations from these two perspectives as a whole provide a complete picture for human capital spillovers.

In both cases, the endogeneity of college share is the central issue that deserves special attention. I implemented several different approaches to provide identifications to the estimation of human capital spillovers.

For the human capital spillovers estimation with individual wage data from China Household Income Project in 1988, 1995, 2002, 2007 and 2013, I use a simulated college share as the instrument for the observed college share. The idea is that workers could sort themselves into different cities according to their own unobservable characteristics and unobservable city factors which lead to biases in our estimation. If workers didn't move across cities, then the human capital spillovers can be identified. Using population census data from 2005, I simulate the counterfactual college share for cities in the years of study by assuming no movement of workers has happened across cities over time. Together with the city fixed effects, which weep away any city-level permanent factors that may be correlated with both wages and college share, I find that one percentage point increase in college share will increase wages for workers by 1.4 percent.

If there exists the imperfect substitution between skilled and unskilled workers, the wage model may not be able to provide a good estimate for human capital spillovers (Moretti, 2004b; Ciccone and Peri, 2006). To mitigate this concern, I implement the constant-composition approach proposed by Ciccone and Peri (2006) with a repeated cross section data from China Urban Household Survey. In this approach, human capital spillover effect is obtained by regressing the weighted city-

level average wages on average schooling. The weighted city-level average wages are calculated by multiplying city-year-education group specific average wage with the relative size of each group in a base year. The intuition is that holding the relative size of each skill group constant separates complementarity from spillovers. Through this approach, I find that one percentage point increase in college share increase wages by 3.6 percent.

To provide a direct estimate of the effect of aggregate human capital on productivity, I compare the TFP of otherwise similar firms that locate in cities with different college share. I use both fixed effects and instrumental variable approaches to establish a causal relationship between firm productivity and college share. The panel feature of this firm data allows me to eliminate any unobservable firm-level and city-level factors affecting both firm productivity and college share that would bias my estimation of human capital spillovers. The instrument that I implement is from an unexpected historical event of academic departments relocation across cities in China in the 1950s. Specifically, I use the net number of departments that moved into a city in the 1950s as the instrument for the changes in college share in 2000s. The idea is that this historical event that relocated higher education resources such as faculties, students, libraries and equipments has a significant impact on the availability of higher education for the cities where departments have moved and this impact lasts a very long time, because the moved-in departments serve as skilled labor force generators which keep producing new college graduates for these cities. This relocation has occurred largely due to political concerns of the Chinese government in the 1950s and it has little to do with the factors that affect firm pro-

ductivity in the 2000s. I show that indeed the net number of relocated departments is not correlated with infrastructure investment and per capita GDP in the 2000s. The resulting estimates of human capital spillovers range from 0.8 percentage point to 2.3 percentage point.

Though my instruments are not flawless and the identification in the estimation of human capital spillovers remains a challenge, different approaches in my study arrive at similar estimates for human capital spillovers. I believe my study provides a plausible addition to the empirical literature of human capital spillovers.

Chapter 2: Human Capital Spillovers: Evidence from Chinese Household Survey Data

In this chapter, I investigate the existence and measure the magnitude of human capital spillovers from the perspective of individual workers. Applying an augmented Mincerian equation to the population census of 2005 in China and a repeated cross-sectional data from China Household Income Project, I find that one percentage point increase in the share college educated workers in a cities is associated with a 1.4 percent increase in wages of workers.

2.1 Empirical Model For Wage Data of Individual Workers

The theory of human capital spillovers suggests that the presence of more skilled workers makes all workers more productive. That is, if human capital spillovers exists, we expect to observe that workers living in cities with higher human capital would have higher wages than similar workers who live in cities with lower human capital.

Empirically, the human capital spillovers are estimated by regressing wages for individuals on aggregate human capital, which is either measured as average years of schooling or share of college-educated workers in the labor force, and other

characteristics of individual workers and cities in the following equation:

$$\log(w_{ijt}) = \theta S_{jt} + \alpha S_{ijt} + \beta Z_{ij} + d_j + d_t + v_{jt} + \varepsilon_{ijt} \tag{2.1}$$

where $\log(w_{ijt})$ is the log wage of the individual i in city j at year t, S_{jt} is the schooling level of the city j at year t, S_{ijt} is the individual's education level, Z_{ij} represents other wage determinants of the individual, d_j is the city fixed effect, d_t id the year fixed effect, v_{jt} is the time-variant city variables that could affect individuals' wages, and ε_{ijt} is the idiosyncratic error term. The parameter of interest is θ. If there exist human capital spillovers, we anticipate θ is positive.

Though this augmented Mincerian equation is widely adopted in the literature of human capital spillovers (Rauch, 1993; Acemoglu and Angrist, 2001; Moretti, 2004b; Liu, 2007; Liang et al., 2016), some concerns have been raised. For instance, Moretti (2004b) argues that the existence of imperfect substitution between skilled and unskilled workers can contaminate the spillover effects found in the Mincerian model.

Moretti (2004b) assumes there is a Cobb-Douglas production technology employing unskilled workers (N_0), skilled workers (N_1) and capital (K) to produce output y (the θs are productivity shifters affected by aggregate human capital):

$$y = (\theta_0 N_0)^{\alpha_0} (\theta_1 N_1)^{\alpha_1} K^{1-\alpha_0-\alpha_1} \tag{2.2}$$

The share of more educated workers $\frac{N_1}{N1+N_0}$ represented by S affects output y through

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its influence on the productivity shifters:

$$\log(\theta_j) = \phi_j + \gamma(\frac{N_1}{N1 + N_0})$$

where j=0, 1 represent unskilled and skilled workers respectively, and γ represents the spillover effect.

In a competitive economy, wage is equal to marginal social product. Log-transforming the partial derivatives of Equation 2.2 with respect to N_1 and N_0 yields:

- $\log w_1 = ln(\alpha_1) + \alpha_1 \log(\theta_1) + (1 - \alpha_1 - \alpha_0)\log(K/N) + (\alpha_1 - 1)\log(S) + \alpha_0 \log(\theta_0(1 - S))$

- $\log w_0 = ln(\alpha_0) + \alpha_0 \log(\theta_0) + (1 - \alpha_1 - \alpha_0)\log(K/N) + (\alpha_0 - 1)\log(1 - S) + \alpha_1 \log(\theta_1 S)$

Then, to understand how wages for skilled and unskilled workers change differently as S changes, we take derivatives of the two equations above with respect to S:

$$\frac{d \log(w_1)}{dS} = \frac{\alpha_1 - 1}{S} - \frac{\alpha_0}{1 - S} + (\alpha_1 + \alpha_0)\gamma, \qquad (2.3)$$

$$\frac{d \log(w_0)}{dS} = \frac{1 - \alpha_0}{1 - S} + \frac{\alpha_1}{S} + (\alpha_1 + \alpha_0)\gamma, \qquad (2.4)$$

where

- $(\alpha_1 + \alpha_0)\gamma$ represents the spillover, and it is nonnegative which means both skilled and unskilled benefit from the spillover.

- $\frac{\alpha_1 - 1}{S} - \frac{\alpha_0}{1-S}$ is the imperfect substitution effect for skilled workers and it is negative. Combing with the spillover, wages of skilled workers may or may not increase and it depends on the relative strength of the imperfect substitution effect and the spillover effect.

- $\frac{1-\alpha_0}{1-S} + \frac{\alpha_1}{S}$ represents the imperfect substitution effect for unskilled workers and it is positive. Combining with the spillover, wages of unskilled workers will unambiguously increase with respect to college share increase.

The external return to education is defined as the difference between social return and private return. Social return is the derivative of average wage with respect to s, and private returns is $\log w_1 - \log w_0 = \beta$:

$$\text{external returns} = \text{social returns} - \text{private returns} = \frac{d \log(\bar{w})}{dS} - \beta \qquad (2.5)$$

where $\log(\bar{w})$ is the weighted average of log wages of the two groups, $\log(\bar{w}) = S \log(w_1) + (1 - S) \log(w_0)$(Moretti, 2004b). Equation 2.5 can be expressed as :

$$\frac{d \log(\bar{w})}{dS} - \beta = [S]\frac{d \log(w_1)}{dS} + [1 - S]\frac{d \log(w_0)}{dS} = S\frac{d\beta}{dS} + \frac{d \log(w_0)}{dS} \qquad (2.6)$$

The first term in Equation 2.6 is negative because the increase of the supply of skilled workers drives down the private return to education. The second term is positive because of the imperfect substitution between skilled and unskilled workers.

Using the expressions for $\frac{d \log(w_1)}{dS}$ and $\frac{d \log(w_0)}{dS}$ in Equation 2.3 and Equation 2.4,

Equation 2.6 can be expressed as:

$$\frac{d \log(\bar{w})}{dS} - \beta = \frac{(1-S)\alpha_1 - S\alpha_0}{S(1-S)} + (\alpha_1 + \alpha_0)\gamma \qquad (2.7)$$

From Equation 2.7, we observe that the external return has two parts: the imperfect substitution effect (first term) and the spillover effect (second term). When $\gamma = 0$, the first term can still be positive. This means that in the augmented Mincerian approach the spillover effect is not separable from imperfect substitution effect. That is, the θ from Equation 2.1 overstates the spillover effect. Nevertheless, this approach provide a way to detect the existence of spillover effects by estimating Equation 2.1 for skilled workers. Based on Equation 2.3, if the resulting estimate of θ for skilled workers is positive, we can claim that the spillover effect indeed exists and it is large enough to offset the negative supply effect of skilled workers. In addition, the augmented Mincerian equation predicts that unskilled workers benefit more from the increase in overall human capital than skilled workers since both the imperfect substitution effect and the spillover effect are in their favor.

In the empirical section, I will using the augmented Mincerian equation to estimate the external effects of human capital and investigate Moretti (2004b)'s suggestion by testing these predictions.

2.2   Data

The main data I use in this study is the repeated cross sectional data from the China Household Income Project (CHIP 1988, 1995, 2002, 2007 and 2013) and the

20% of the 2005 population census of 1% sample in China.

The CHIP surveys are conducted by collaboration between the National Bureau of Statistics, domestic and international researchers aiming to study the income and inequality dynamics in China over time. It contains very detailed information on income, employment and other social economic characteristics at both the individual and the household levels. A probabilistic sampling and stratified multistage approach has been adopted in the surveys to ensure the representativeness of the data. CHIP data covers 65 cities and these cities appear in the survey at least two years which allows me to implement city fixed effects models.

The 2005 population census data is a single cross section data. Unlike other population census data in which income information is often not surveyed, this 2005 population census contains information on annual income of individuals. In addition, it has the largest sample size among all the individual-level micro data available in China. After excluding individuals with missing information on key variables such as income and education, I end up with 312462 observations age between 16 and 60 years old.[1] The large sample size not only gives a good estimate of the city-level human capital to estimate human capital spillovers using the population census itself, it also provides the instrument for the estimation using CHIP data. I will explain this in detail in the identification section.

In this study, I use the share of college educated workers in each city as the measure of the city-level human capital. An accurate computation of college share is crucial for properly estimating the human capital spillovers. In the literature,

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[1]The minimum age for working is 16, and the retirement age is 60 in China.

aggregate human capital is often measured at metropolitan areas, while in China cities, based on which aggregated data is assembled, often contains both metropolitan areas and massive rural areas. For this reason, when it comes to the study of urban China, researchers often choose to use population with urban household registration status to approximate the urban population. CHIP have two separate data collections, one from rural areas and one from urban areas based on the definitions given by National Bureau of Statistics. For the same reason, I use the CHIP data collected in urban areas.

Table .1 reports the summary statistics for the 2005 inter-census data and the CHIP data. All 345 cities in China are covered in the 2005 population census. There are 65 cities appearing at least once in the repeated cross sectional CHIP data, and wages are measured on a monthly basis.

2.3   Identification Strategies

The fundamental problem of the estimation of human capital spillovers with the augmented Mincerian equation is the omission of relevant variables that could affect both individual wages and city-level human capital. There are many unobservable factors of workers and cities can impact wages and at the same time affect college share.

The first source of bias comes from time-invariant city specific omitted variables. Cities are different from each other in many aspects like geographic location, industrial structure, technology, institution and amenities. City fixed effects using

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multiple years of data can control for any permanent city-specific omitted variables that can lead to bias in analysis using a simple cross-sectional data. I include city fixed effects in all my specifications using multiple years data.

The second source of bias is from time-variant unobservable shocks to cities that are correlated with both wages and college share. For instance, the establishment of a special economic zone in a city can attract both firms to invest more in productivity improving technologies and highly educated workers to move to that city. Positive demand shocks like this will lead to spurious correlation between college share and wages which biases the true effect of college share on wages. Note that if variation in college share across cities is driven by unobserved supply factors, OLS estimation is biased downward (Moretti, 2004b).

Individual level unobservable factors, like ability, is another omitted variable that could also lead to biased estimates of external returns to higher education. Individuals observed in cities with high college share may be better workers in general than workers with the same observable characteristics in cities with low college share. If a city with high college share rewards unobservable ability more than a city with low college share, workers with similar observable characteristics may decide to move to different cities based on their unobservables. For instance, a lawyer in Beijing working for a foreign company is very likely different along some unobservable dimensions from a layer in Datong of Shanxi. Therefore, the unobservable individual ability could bias our estimates of external return to higher education. Though I don't have a panel data to directly control for the individual unobservable ability, I take the advantage of the restrictive household registration

system in China to investigate if the effect college share on wages for people who never move is different from the overall effect.

To control for these omitted variable biases and spurious correlations, I use instrumental variables that can predict college share but are not correlated with unobservable factors. Each instrument variable corresponds to a specific data set.

2.3.1 Instrumental variable for the estimation using inter-census 2005 data

For the inter-census 2005, which is a cross-sectional data set, I use the presence of elite universities in each city as the instrumental variable for college share. This is inspired by Fan et al. (2015), but instead of looking at the number of universities with special status at province level, I focus on the presence of elite universities at the city level. Focusing on finer geographic units allows better identification of human capital spillover since the main mechanism behind human capital spillovers is the interactions among workers, which is more likely to occur at the city level rather than the province level. In addition, narrowing down to city-level human capital permits province fixed effects which further improve the estimates for human capital spillover effects. In 1995, the Central Government of China and the Ministry of Education initiated the "211" project aiming at establishing about 100 high quality universities in 21st century in China by providing extensive finance and policy support to the selected universities. Whether a university can be listed on the "211" project is determined by its accumulated and existing good reputation.

Most "211" universities have a history of over 100 years, and no universities with less than 50 years of history were nominated (Fan et al., 2015). Thus, factors from 100 years ago that influence the accumulated quality and reputation of a university potentially should have limited impact on workers' wages in 2005, if any. But the presence of the "211" universities has a big effect on the supply of college educated workers since it makes universities more accessible to local high school students.

2.3.2   Instrumental variable for the estimation using the pooled cross-sectional CHIP data

Though the extremely restrictive household registration system in China has reduced population mobility and mitigated the concern for endogenous formation of college share, we may still worry about the issue of endogeneity for college share for workers of the latter years, since they are more likely to make migration decisions in response to labor demands as the household registration system becomes less restrictive over time.

To estimate the causal impacts of college share on wages with the pooled cross sectional China Household Income Project (CHIP) data, I derive counterfactual college share for each city in each year from the inter-census 2005 data and use this derived college share as an instrument for the endogenous college share observed in the CHIP data. Specifically, I consider workers age between 28 and 48 years old in each of these survey years as people on the labor market. Then I find the same cohort in the 2005 census data and use educational and geographic information

of this cohort to simulate the counterfactual college share. For instance, to obtain counterfactual college share in 2013, I use individuals age between 20 and 40 in 2005 (who would be 28 and 48 in 2013). People in this cohort may migrate across cities from 2005 to 2013, but my simulation process assumes no migration, consequently, the resulting counterfactual college share should be exogenous. The same procedure is applied to simulate college share for other years.

Table .6 illustrates the process of deriving the counterfactual college share from the inter-census 2005 data. The first column of Table .6 shows the years covered by CHIP survey and the second column indicates the idea that workers age between 28 and 48 years in each year form the local labor markets. The third column of Table .6 shows the ages of these cohorts in 2005. The fourth column of Table .6 reports the averages of the counterfactual college share derived from the external data source in each survey year. It is clear that workers in early CHIP years worked in an environment with less human capital around them (smaller college share) than workers in later years. The last column of Table .6 shows the college entering year (birth year plus 18) for individuals in each survey year. Note that all these numbers are calculated using urban population only.

A concern is that the large wage increase in later years may merely reflect the decrease of the supply of college educated workers due to the implementation of one-child policy initiated in 1979 in China (cohorts born after 1979 form the labor market in the later years of my study) rather than productivity improvement from the increase of college share. Figure .2 shows the distribution of college and non-college educated workers at national level and we see that for younger age

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groups the supply of college educated workers does not go down, instead, it increases significantly, though the overall population of the younger age groups fall partially due to one-child policy[2].

Though the simulation process of the counterfactual college share is intuitive when we simulate college share forward from 2005 for later years, and anything that could lead to endogenous formation of college share at city-level is assumed away, there may be a concern about the simulation of college share backward from 2005 to 1988. Because for early years, the simulated college share may reflect the accumulated changes in college share up to 2005 due to the migration and it not necessarily represents the exogenous college share we would like to have. However, this is less of a concern thanks to the highly restrictive household registration system (Hukou) in China which made migration out of someone's Hukou registration place extremely difficult, especially in the early years (the Hukou registration system becomes less restrictive over time).

Table .7 shows the migration rate (across county, province and cross city) for the years of CHIP where the city level college share is obtained by backward simulation using inter-census 2005. The migration rates computed with both the inter-census 2005 data and the census 2000 data demonstrate that workers from these concerned age groups have very limited migration behavior, for instance, only about 1.1 percent of population whose ages are between 45 to 65 years old in 2005 (they were 28 to 48 years old back in 1988) have reported they lived out of the current province. And across province migration is less likely to happen than across

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[2]Fertility rate normally decreases as well when the economic situation improves

county migration. The highest migration rate comes from the cross county migration of the age group between 31 and 51 years old in 2005 (they correspond to labor force age between the 28 and 48 years old in 2002), which is about 9 percent. Since the geographic unit of study is city and in China city is above county in the administrative hierarchy, we would expect migration rate across city is lower than that.

Though the inter-census 2005 data doesn't have information relevant to across city migration, the census 2000 data does have such information and I found the migration rate across city is indeed very small as expected. Figure .7 and Figure .8 provide intuitive visualizations for the migration in China both across county and across province for different ages in 2000 and 2005. The transparent bars represent total population in each age and the green bars denote the number of people who migrated from other places to their current residential places. And the red line is the migration rate. Clearly, the old age groups (the groups that we worry about the appropriateness of the backward simulated of college share) have very low migration rate. Therefore, it should be relatively safe to assign the backward simulated college share to early CHIP years as the college share that workers in these years would have exposed to.

Note that variations in the simulated counterfactual college share across cities come from the differences in demographic structures of each place which should be orthogonal to factors that correlate with worker productivity. Figure .6 shows that the overall college share is almost identical in the urban cores of Qinghai and Tianjin for population between 20 and 65 years old in 2005. However, by examining

the simulated college shares, drawn from the 2005 data, we can see that actual college shares are likely to be very different across the years from 1988 to 2013. For example, although the simulated college share in 1988 is similar for both cities, the simulated college share in 2013 is very different. The difference can be seen in the 2005 data and comes from the fact that the distribution of college share across ages is very different in the two places. For example, Quinghai has a high college share for workers between the ages of 35 and 45 whereas Tianjin has a low college share in this age group.

Thus, the simulated college share is a good instrument for real college share (calculated from the data directly) because it assumes away endogenous changes in college share and it is generated based on predetermined and exogenous demographic structure across cities. Combining with city fixed effect which sweeps away permanent city-specific factors that may correlate with worker productivity and college share at the same time, the estimation using the simulated college share as IV should deliver unbiased estimates for external returns to higher education.

2.4 Results

Figure .5 shows the correlation between the fraction of college educated workers in the population between 16 and 60 years old and the regression-adjusted average wages for 315 prefecture cities (urban parts) in China using data from 20% sample of 1% inter-census 2005[3]. It is evident that after controlling for individual

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[3]Conditioning on individual age, gender and education, the regression-adjusted average wages are obtained.

characteristics, wages are still higher in cities with higher college share. Yet, the causality between the average wage and college share canot be simply drawn from this correlation. There are many other factors at the city-level that may affect college share and wages at the same time. In this empirical section, I will start with the augmented Mincerian equation to estimate the external returns to education and shed some light on the presence of human capital spillover using different data sets and different specifications. Then I use the constant-composition approach to estimate potential human capital spillover effects.

2.4.1 Empirical Results from the 2005 Population Census

First, I start with the cross sectional data of inter-census 2005. Table .2 reports estimates of Equation 2.1. The coefficients on age, age squared and years of education have expected signs and significance across specifications. Female workers make about 20% less than male workers and the estimates on age and its squared term (to proxy experience) are consistent with theoretical expectations. The private returns to one year of schooling is about 9.6%. All standard errors in this paper are clustered at city level. The OLS result in column (1) of Table .2 shows that a one percentage point increase in college share in a city is associated with about 2.02% increase in average wages controlling for gender, age squared and years of education. Similar to Rauch (1993), the estimate of external return to college education is driven by variations in college share across cities. When the province fixed effects are included in column (2), the external return to education reduces to 1.73% where

the variations in college share are from cities within the provinces. Though both OLS and province fixed effects models provide positive and significant estimates for the external return to college share, there still may exist city-specific unobservables that affect both wages and college share at the same time which can confound the results. To address the issue of omitted variables, I use the presence of 211universities as the instrumental variable for college share as previously discussed. The first stage in column (3) of Table .2 shows that the presence of 211 universities in cities is a strong predictor for the college share in 2005. The resulting external effect of college share on wages is 1.96%. Results are similar when I use alternative instrumental variables such as the number of 211 universities, the presence of 985 universities or the lagged college share in 2000.[4].

Table .3 provides some robustness checks for the estimates in Table .2. All regressions are 2SLS estimations using the presence of 211 universities as the instrument. The resulting estimates for external return to college share range from a low of 1.04% to a high of 1.86%. Column (1) in Table .3 includes sector dummies to control for heterogeneity across sectors and the resulting external effect of college share is about 0.1% less than that in column (3) of Table .2. Column (2) of Table .3 only looks at manufacturing sector and the result is slightly lower which might be due to the fact that manufacturing sector is labor intensive but not human capital intensive. Column (3) and column (4) of Table .3 show the results from two separate regressions, one includes the interaction between college share and the dummy for

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[4]All 985 universities are 211 universities as well, but not every 211 universities are 985 universities. In general, 985 universities are more privileged than 211 universities.

male and the other includes the interaction between college share and the dummy for female. Interestingly, the external effect of college share for female is larger than male. Private returns to education may not be linear in years of education which could bias the estimate of external returns to education (Moretti, 2004b). In column (5) of Table .3, instead of using years of education, I use dummies for each education level in the regression. The result is similar with the benchmark result in column (3) of Table .2. Column (6) of Table .3 uses a different measure for college share, it is the college share in the city outside the industry an individual belongs to. The coefficient on this college share investigate if a worker is more productive when the human capital he or she is exposed to is higher in other industries of the city. This is an attempt to estimate potential spillovers across industries. The result from this specification is much lower than the benchmark result where the overall external effect of college share is estimated. This is not surprising given the fact that workers have less opportunity to interact with others from other industries. Nevertheless, the presence of external returns to education across industries may also indicate the presence of spillover effects within a city. Even though we do do not have an individual level panel data to control for unobservable ability that may drive people's mobility decisions, one unique characteristic of Chinese population, low migration rate due to the restrictive household registration system, provides an opportunity to investigate the effect of college share on wages of these who have never relocated. The estimating result in column (7) of Table .3 implies that a one percentage point increase in college share is associated with 1.7% increase in wages for people who never leave their household registration places.

Though we see positive and significant external returns to education in various specifications using inter-census 2005 data, the estimates are likely biased since variations in college share may be determined by factors changing over time, which are not captured in the single cross-sectional estimations. In next subsection, I use pooled cross sectional data to estimate the external returns to education.

2.4.2   Empirical results from CHIP data

In this section, I estimate a FE model with the pooled cross-sectional data from China Household Income project covering 1988, 1995, 2002, 2007 and 2013. Table .4 shows the estimates of Equation 2.1 with year fixed effects and city fixed effects. In this fixed effects model, the permanent factors affecting both wages and college share such as city-specific amenities, culture and climate are controlled for. The identification comes from the variation of college share within a city over time. The endogenous college share is instrumented with the simulated college share based on inter-census 2005. This is a valid instrument under the assumption that individuals do not move to other cities after 2005 and they all are native residents of their cities (none of them migrated from other cities before 2005). Notice that the OLS estimate of external return to college share is about 0.47%, much smaller than the 2SLS result of 1.42%, this is likely a reflection of measurement errors in college share using sample of CHIP data itself. The first stage result shows that the simulated college share predicts actual college share very well. The resulted estimate of the external effect of college share on wages of 1.42% is in the range of estimates from

the estimates using inter-census 2005 data.

As predicted by the theory (Moretti, 2004b), the external returns estimated from the augmented Mincerian equation may not necessarily represent the productivity-enhancing spillover, it may merely reflect the imperfect substitution effects where the decrease in wages of college educated workers is more than offset by the increase in wages of non-college educated workers. Nevertheless, the augmented Mincerian equation still provides a way to test the existence of spillover by estimating the external returns to education for college educated workers only.

If the spillover is absent, wages of college educated workers would decrease as the share of college educated workers increases because of the supply effect. That is, when there is no spillover, the external return to education for college educated workers would be negative. But if we observe positive and significant external turn to education for the college educated workers, it indicates that spillover indeed exists and large enough to offset the negative supply effect of more skilled workers on their wages. Column (3) and (4) in Table .4 shows the estimation results for skilled (college educated) and unskilled (below college educated) workers separately. The significant and positive coefficient on college share in column (3) implies the presence of productivity-enhancing externality. And consistent with the theoretical prediction, the coefficient on college share for unskilled workers is larger than that for skilled workers since unskilled workers benefit from both the imperfect substitution effect and the spillover effect, though the difference between the two estimates is not statistically significant.

To investigate the robustness of the results, I drop observations in different year

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and the results are largely unchanged see Table .5, except for the year 1988. When I exclude 1988 from the analysis, the result is still positive but becomes insignificant. This is not surprising, since the identification of human capital spillover using CHIP data relies on the college share variations induced by college expansions in China since 1977[5] and observations in CHIP 1988 serves as the contrast before expansions (people who were 28 to 48 years old in 1988 potentially went to college between 1958 to 1978). Taking away CHIP 1988 from the analysis leaves less variations in college share and weakens the results.

It might be thought that using college share simulated from 2000 census will lead to more robust estimates because it should mitigate the migration concern for backward simulation. However, this is not the case since some of the individuals in CHIP 2013 (they were between 28 and 48 years old in 2013, they were 15 and 35 in 2000) has not had the opportunities to go to college yet, and the college share simulated from them will be very inaccurate. Moving the labor market "window" to older cohorts (33 to 35 years old in each CHIP year) doesn't improve the results because the biggest variation of college share was induced by the college expansion in 1999, and any simulation for college share from 2000 will fail to capture this variation and lead to insignificant estimates. These results are not reported but available upon request.

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[5]The enrollment of higher education has started to expand since the end of Cultural Revolution in 1977. New enrollment has increased from 0.27 million in 1977 to 1.08 million in 1998. And this expansion has been accelerated in 1999 and thereafter in a drastic way, the new enrollment reached 5.04 million in 2005 and 6.85 million in 2012, see Figure .1.

2.4.3   Discussion

Economists have long suspected that social returns to education exceed private returns to education. The consequent human capital spillover is believed to be the main engine driving economic growth in cities. In this chapter, I apply various empirical strategies to the most recent data available from China to estimate the external returns to higher education and to identify human capital spillover. The biggest challenge in estimating the causal effect of college share at city level on worker productivity is the issue of endogenous formation of college share. I use the presence of elite universities in each city, the simulated college share from a base year as the instrumental variables for college share in the augmented Mincerian model, and I have found statistically significant external returns to higher education and these results are robust to different specifications.

Though Moretti (2004b)'s theoretical work suggests that the coefficient on college share may not necessarily indicate human capital spillovers because of the imperfect substitution between unskilled and skilled workers, the strong evidences of human capital spillovers can not be ignored. His theory predicts that if there is no human capital spillovers at all, we would observe negative coefficient on the variable of college share when we use only the the sample of skilled workers because the increase in college educated workers would drive down wages for them. However, the resulting positive and statistically significant estimate from the CHIP data shows that not only there exist human capital spillovers, and such spillovers are big enough to more than offset the negative effect of the increasing supply of educated workers.

One of the important implications from these findings is that, the presence of strong human capital spillover in Chinese cities provides justifications for the college expansion policy since 1999 in China. The dramatic increase in the supply of college educated workers does not necessarily decrease wages for skilled workers due to the productivity - enhancing nature of human capital. That is, individuals' productivity can be improved if they are working with other productive workers because of the social learning process happening among them.

Another implication is that policies attracting high skilled workers should be encouraged. Investments in physical capital can drive economic growth in the short term, but to ensure a long-term and sustainable growth in the long term, it is very necessary to accumulate a high stock of human capital as skilled workers can generate more innovations and new ideas to keep the economy grow.

Chapter 3:   Human Capital Externalities: Constant-composition Approach

In this chapter, I take the constant-composition approach proposed by Ciccone and Peri (2006) as an alternative for estimating human capital externalities as it is expected to address the imperfect substitution issue raised from the augmented Mincerian approach.

3.1   Empirical Framework of the Constant-composition Approach

In this approach, skilled workers have a positive spillover effect SPL on output Y which is equal to the difference between marginal social product $\partial Y/\partial S$ and the wage premium $w_1 - w_0$,

$$SPL = \partial Y/\partial S - (w_1 - w_0) \tag{3.1}$$

Assuming output equals labor income:

$$Y = w_0(1 - S) + w_1 S \tag{3.2}$$

Differentiating both sides of Equation 3.2 with respect to S yields $\partial Y/\partial S = (1 - S)\partial w_0/\partial S + (S)\partial w_1/\partial S + w_1 - w_0$. Combine with Equation 3.1, and solve for SPL:

$$SPL = (1 - S)(\partial w_0/\partial S) + S(\partial w_1/\partial S) \tag{3.3}$$

Dividing both sides by Y yields:

$$\theta = \frac{SPL}{Y} = (1-b)\frac{\partial w_0/\partial S}{w_0} + b\frac{\partial w_1/\partial S}{w_1} = (1-b)\frac{\partial \log(w_0)}{\partial S} + b\frac{\partial \log(w_1)}{\partial S} = \frac{\partial}{\partial S}\log([1 - \bar{S}w_U] + [\bar{S}w_S]) \tag{3.4}$$

where θ represents spillover measured by percentage change in output and $b = Sw_1/Y$ denotes the share of skilled workers in earnings. $\bar{S}$ represents the value that held constant.

Thus, the spillover effect can be identified as the earnings-weighted average percentage change in wages (the third equality), or, the log-change in the average wage holding skill-composition constant (the fourth equality, upper bars denote values that are held constant). Ciccone and Peri (2006) refer this as the constant-composition approach to identify human capital spillovers.

The constant-composition approach can be used at city, region or country level over any period in two steps: 1) obtaining wages w_x and labor shares l_x by skill type x in each local labor market at the beginning and the end of the relevant period to calculate the log-change in the average wages holding skill-composition constant $ln(\Sigma_x \bar{l}_x \tilde{w}_x) - ln(\Sigma_x \bar{l}_x \bar{w}_x)$, where upper bars denote values of beginning period, tildes denote values of ending period. 2) regressing the log-change in constant-composition

average wages on the (exogenous) change in the supply of human capital and other determinants of wages.

In the first step, I obtain the average wages by running the following regression to eliminate gender, marital status effects from individual wages:

$$\log w_{ict} = \log w_{ct}(s) + \lambda X_{ict} + v_{ict} \tag{3.5}$$

where w_{ic} denotes annual wage for individual i at city c in time t; s is individual schooling level; X represents dummies for gender and marital status, v stands for other factors affecting wages. The intercept, $\log w_{ct}(s)$, corresponds to the log-wage of married males with education level s at city c in time t. Equation 3.5 is estimated by ordinary least square method.

With the city-time specific average wages of workers by levels of education handy, we can construct the necessary average wages using $ln(\Sigma_x \bar{l}_x \tilde{w}_x) - ln(\Sigma_x \bar{l}_x \bar{w}_x)$ to estimate human capital spillovers with the constant-composition approach. Specifically, the constant-composition average wage in year τ is defined as $w_{c\tau} = \Sigma_s w_{c\tau}(s) l_{c\tau}(s)$, where $w_{c\tau}(s)$ is the average wage at city c in year τ for schooling level s and $l_{c\tau}(s)$ is the share of workers with schooling s in city c in year τ. Holding skill composition constant, the constant-composition average wage in year t using year τ education labor force composition is $w_{ct}^{\tau} = \Sigma_s w_{ct}(s) l_{c\tau}(s)$.

Now the spillover effect θ in cities between year τ and year t can be estimated by regressing the log-change in average wages holding labor composition constant

on the change in average human capital and other controls:

$$\Delta \log w^{\tau}_{ct-\tau} = Controls + \theta \Delta S_{ct-\tau} + \varepsilon_c \qquad (3.6)$$

where $\Delta \log w^{\tau}_{ct-\tau} = \log w^{\tau}_{ct} - \log w_{c\tau}$

3.2 China's Urban Household Survey

The main data that I use in the constant composition approach comes from two waves of China's Urban Household Survey in 2002 and 2009, respectively. I choose these two specific years for two reasons. First,They are the most recent urban household survey data available to researchers. Second, these two waves are close to the ten-year apart population censuses (2000 and 2010) which provide good estimates for the city-level human capital.

The urban household surveys are conducted by National Bureau of Statistics to monitoring the economy's situation from individual household perspective. The individual and household level data are aggregated at county, city, province and even country level to serve as building blocks of important economic indices such as CPIs and average wages.

As I have mentioned in the previous chapter that properly defining the metropolitan area of a city is crucial for the estimation of human capital externalities. Fortunately, the Urban Household Survey data reveals the national standard codes for city district or county that each individual lives. A typical Chinese city often consists of several city districts, which are close to each other geographically and

economically, and some counties, which are often distant from city districts and much less developed.

Therefore, I define the unit of study to be the "urban core" which is the cluster of city districts of a prefectural city. College shares are computed using the aggregate census 2000 and census 2010 at urban core level. City-level average wages are computed at urban core level using Urban Household Survey data in 2002 and 2009.

Table .8 reports the summary statistics for the key variables used in this study from China's Urban Household Survey.

3.3 Instrumental variable for the estimation using Urban Household Survey data

Inspired by Moretti (2004b) and Ciccone and Peri (2006), I use age structure to predict the changes in average human capital between two census years (2000 and 2010). China has experienced a continuous increase in college participation in the past decades. Statistics from UNESCO shows that the Gross Tertiary Enrollment Ratio [1] in China was only 3.01% in 1990, and it raised to 7.71% in 2000, it increased at a fast pace because of the college expansion in 1999, it became 19.34% in 2005, reached 23.95% in 2010 [2].

Thus, the younger cohorts entering the labor force are better educated than

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[1] According to the education index of United Nations, Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown.

[2] This number was already 70.71% for the U.S. in 1990.

their older counterparts, and the relative population shares of different cohorts differ across cities which will lead to different college shares in later period across cities. If two cities are the same in every aspect except that one city has larger share of young and old workers than the other, the city with larger share of young and old is expected to experience a bigger increase in college share. Such an increase in college share is arguably due to exogenous and predetermined age structure of the city which should not affect wages or productivities of workers in later time except through its influence on the changes in college shares. To alleviate the concern that young people in 2000 can perfectly foresee the prosperity of cities ten years later and relocate to cities with fastest economic growth which can make age structure correlated with wages directly, instead of using age structure in 2000, I use the share of young people and the share of old people in 1990 (lagged age structure) to forecast the changes in college share between 2000 and 2010.

3.4 Empirical Results from Constant-composition Approach

To implement the constant-composition approach, I first obtain regression-adjusted wages for each city in each year at each education level (below high school, high school and college education) by estimating Equation 3.5. Then constant-composition average wages are calculated using the formula $w_{c2000} = \Sigma_s w_{c2000}(s) l_{c2000}(s)$, where I sum up the products of the regression-adjusted wages in each year and the share for each skill group in the base year of 2000 in the population for each city. The next step is to compute the change in log average wages (holding skill compo-

sition constant) and the change in college share over the period of study (2000 and 2010). Now, the human capital spillover can be readily estimated by regressing the change in log constant-composition average wages on the change in college share over time (Equation 3.6).

To estimate the spillover, I use age structure of cities in 1990 to instrument for the change in college share between 2000 and 2010. Table .9 shows the strong first stage. The coefficients of the changes in college share regression combined with the sample values of the explanatory variables reveal that cities with a larger share of young population (age 16 to 25) and/ or a larger share of old population (age 61 to 70) in 1990 experienced a greater increase in college share. This is because young people entering the labor market had an education above the labor force average and old people leaving the labor market had education below the average in the period of time (Moretti, 2004b; Ciccone and Peri, 2006).

Table .10 shows the estimates of human capital spillover from higher education (the benchmark estimates). The column (1) and (2) are from OLS estimation, column (3) and (4) are from 2SLS estimation using age structure as instrumental variables. Column (2) and (4) include log change in employment and dummies for macro regions (east, north east, middle and west regions) as controls. Comparing column (1) and column (2) (or column (3) and column (4)), we see that including more controls increases the spillover effects. And the estimates of spillover from 2SLS are larger than the estimates from OLS which indicates the supply heterogeneity dominates the demand heterogeneity[3]. Column (4) indicates that a one percentage

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[3]See Moretti (2004b) for more details on the discussion about the relationship between supply

point increase in the share of college educated workers will raise average wage by 3.59 percent.

Due to skill-biased technological progress, only the increase of college educated workers can contribute to the growth of productivity by creating new skills and new technologies through interactions among workers while the increase in other education levels has no direct impact on the overall productivity increase (Moretti, 2004b).

In Table .11, I test this prediction by regressing average wages holding labor force composition constant on the change in college share, high school share, and primary school share separately. Column (1) in Table .11 is taken from Table .10 directly, column (2) and column (3) correspond to the regression results of the change in the share of high school educated workers and the change in the share of primary school educated workers on overall wage growth respectively. The estimation results confirm the prediction. It shows that the change in college share has positive and significant effect on wage growth while the change in high school share and primary school share has either a negative effect or an insignificant effect on wage growth.

Finally, due to the nature of sharing of skills and knowledge, it is predicted that areas with higher population density have lower costs of communication which makes human capital spillover more likely to happen in these areas (Rosenthal and Strange, 2008; Moretti, 2004b). In order to test this prediction I split the observations of urban cores into high-density ones (with population density greater than and equal to 3000 people / sq. km) and low-density ones (with population density smaller than

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and demand heterogeneity and comparison of OLS and IV results.

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3000 people / sq. km)[4]. The estimation results in Table .12 reveal that the spillover effects are very strong in high-density urban cores that one percent increase in college share will bring an increase of 6.676 percent in wage growth, but insignificant in low-density urban cores. This is consistent with both the theoretical prediction and our life experience. In denser cities, people have more opportunities to interact with each other and share information because of reduced communication costs. Denser cities with higher human capital facilitate the exchange of ideas and creation of new thoughts which are the powerful engine for the development of both individuals and cities as a whole.

3.5 Discussion of the Results from the Constant-composition Approach

Since the augmented Mincerian equation may suffer from the imperfect substitution between skilled ad unskilled workers, I take an alternative approach of the constant-composition approach (Ciccone and Peri, 2006) to estimate the human capital spillovers. I use the lagged age structure in 1990 as the instrument for the change in college share between 2000 and 2010, I find that one percentage point increase in the share of college educated workers raises average wages by 3.59 percent and it is statistically significant. I also find that it is the increase in college share, instead of the increase in any other education levels, that is responsible for wage growth. This is consistent with the fact that technological progress nowadays

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[4]3000 people per square km is the mean of population density in these urban cores

is skill biased, high skilled workers will lead to higher productivity. Furthermore, my empirical results also show that human capital spillover is larger in cities with higher population density. This can be explained by the fact that in denser cities workers have better chances to meet each other and learn from each other. That is, the concentration of population facilitates the exchange of ideas and makes denser cities more productive.

Chapter 4: Human Capital Externalities: Evidence from China's Annual Enterprise Survey

4.1   Empirical Framework

In this section, I will set up the econometric model for the empirical estimation of human capital externalities. If human capital spillovers exist, firms located in cities with higher human capital level, (in our case, the share of college-educated workers,) will have higher productivity. Therefore, we employ the following version of Mincerian equation to estimate human capital spillovers.

$$\ln TFP_{ijct} = \gamma CS_{ct} + \alpha X_{ijct} + \beta Z_{ct} + \epsilon_i + \epsilon_j + \epsilon_c + \epsilon_{ct} + \epsilon_{jt} + \epsilon_{ijct} \qquad (4.1)$$

The left-hand side is the log form of total factor productivity (TFP) which is a function of aggregate human capital - the share of college-educated workers in this study, firm characteristics X_{ijct}, and city characteristics Z_{ct}. ϵs are the unobservable factors that could affect the productivity of a firm at the firm level, the industry level, the city level, and over time. γ captures the external effect of city-level human capital on the firm productivity, which is the so-called human capital spillovers. With the firm-level panel data, we can weep out all the effects of the permanent

unobservable factors specific to firm, city and industry. Notice that college share is at the city-year level, so running a model like the one above will not be feasible as the key coefficient of interest γ will be completely absorbed by the city-year dummy.

Instead, I will estimate the model below where the city-year dummy is replaced by the provincial fixed effect ϵ_{pt}, If we believe most of the city-specific time-varying shocks are actually at the province-year level, ϵ_{pt} helps mitigate the problem caused by omitting ϵ_{ct}(Moretti, 2004c; Liu, 2014).

$$\ln TFP_{ijct} = \gamma CS_{ct} + \alpha X_{ijct} + \beta Z_{ct} + \epsilon_i + \epsilon_j + \epsilon_c + \epsilon_{pt} + \epsilon_{jt} + \epsilon_{ijct} \qquad (4.2)$$

Though the firm fixed effects and province-year fixed effects help reduce the biases of omitted variables by large, we cannot completely rule out the possibility that other unobservable and time-varying factors may play a role in the estimates of human capital spillovers. A firm with higher productivity may choose to locate in a city with higher college share for reasons independent of human capital spillovers (Moretti, 2004c). I will further deal with this issue with an instrumental variable approach.

4.2   Data

The data being used in the paper consist of three parts: the firm-level records from China's Annual Survey of Industrial Enterprises (ASIE), the college shares at the city level from population census and the city characteristics from the City Statistical Yearbook. All the data are from surveys conducted by the National

Bureau of Statistics (NBS) of China.

4.2.1 China's Annual Survey of Industrial Enterprises

China's Annual Survey of Industrial Enterprises starting from 1998 up to present is by far by far the most comprehensive and largest firm survey conducted by the National Bureau of Statistics. It covers all industrial firms with sales above 5 million RMB (so-called above-scale firms), and both state-owned and not-state firms are included. The industry includes mining, manufacturing, and public utilities, for the analysis in my dissertation I only use the data of manufacturing firms.

Specifically, the ASIE is a nationwide mandatory census covering firms that account for around 95% of total Chinese industrial output and 98% of total Chinese industrial exports throughout the country's 31 provinces, autonomous regions, and province-equivalent municipalities (Beijing, Shanghai, Tianjin, and Chongqing). The sample size of this data has increased from 121,928 in 1998 to 283,144 in 2013. Together, the substantial geographic coverage and the large sample size of this ASIE firm data makes it ideal for the study of human capital externalities as it allows me to disaggregate the data by city.

The firm-level information contained in the ASIE database is very rich and detailed. For instance, it includes total output values, value added, total sales, employment, total assets, fixed capital stock, ownership, industry classification, main products, foreign direct investment, along with other information like firm name, address, year of founding, investment, tax paid, salary expense, and so forth. With

these variables, I am able to construct the key variables of total factor productivity (TFP) and firm-level human capital.

4.2.2 Construction of total factor productivity

The dependent variable in this study is the total factor productivity (TFP), which is constructed in the following way (Brandt et al., 2012, 2017; De Loecker and Warzynski, 2012):

$$\ln TFP_{ijct} = \ln q_{ijct} - \alpha_L \ln l_{ijct} - \alpha_K \ln k_{ijct}, \tag{4.3}$$

The ln TFP is obtained by taking the difference between the log of real value-added and the weighted average of production inputs where the weights are the estimated industry-specific input elasticity. The elasticities are estimated from a Cobb-Douglas production function for each manufacturing industry. The value-added, and capital are deflated using 1998 as the base year.

4.2.3 Human capital measurements

One of the key variables in the human capital spillovers studies is the city-level human capital measure. In my study, it is mainly measured as the share of college-educated population in each city (college share thereafter). As the variable of the interest, it is crucial to get it measured as accurately as possible, and population census serves this purpose extremely well as population census includes every individual in China. Specifically, college share is calculated as the proportion of

the population with a bachelor degree and above among the total population who are more than 15 years old[1] for each prefectural city, where a prefectural city is an administrative entity right below a province and there are 334 perpetual cities in China. Additionally, I also construct the ratio between college enrollment and total population as an alternative measure for the city-level human capital, and the estimated spillover effects change very little.

I match the variable of college share, which is derived from population census in 2000 and 2010, to the firm-level data in 2001 and 2011. The matching results in a balanced panel of 19276 firms observed in each year.

Note that there is one year gap between the firm data and the population census data as there lack some input variables in the firm data to calculate TFP for firms in 2010, but the one year gap should not affect the results much as the city-level college share is unlikely to change a lot in one single year. As a matter of fact, in literature, the lagged city-specific human capital measures are often used as a way to break the possibility of reverse causality of firm productivities and city-level education attainments (Moretti, 2004c; Liu, 2014). To check the robustness of the results, I also combine college share in 2000 and 2010 with firm data in later years like 2003 and 2013, the findings remain largely unchanged.

4.2.4   Other important variables

While the ASIE data contains the total number of employees, it does not report the number of workers for each education level. To account for firm-specific

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[1]In China, the minimum work age is 16 years old

human capital, I compute the ratio of firm average wage to industry average wage. The underlying assumption is that average wages are good proxies for firms' human capital (Liu, 2014). The ratio approach helps normalize firm-level educational proxies by eliminating changes in the average wage resulting from industry-wide factors other than changes in the average educational attainment of firm employees. For instance, firms in some industries face a surge in demand for its products and the average wage would increase in each firm without any changes in the average education level in each firm, therefore, changes in the human capital of each firm would be better reflected by the ratio of the firm average wage to the industry average wage (Liu, 2014).

Following Liu (2014), I construct the Herfindahl-Hirschman Index (HHI) to take into account the impact of the market structure of each industry on the productivity of firms in the respective industry. HHI is calculated as the sum of the market share of each firm in the city and industry it operates. HHI varies between 0 and 1. Larger HHI means that the market is more concentrated. I expect that human capital spillover effects decrease as the market concentration increases since a monopolistic power discourages learning among firms and workers.

Other city-level variables, such as share of employment in industrial sector, the volume of cargo (ten thousand tons), green land per capita (km sq), college enrollment rate, population density, are drawn from the City Statistics Yearbook of China.

Table .13 provides the summary statistics for the variables used in this study. In the following section, I will introduce several strategies to identify the human

capital externalities if they exist.

4.3   Identification Strategies

I use two main strategies to deal with the endogeneity issue of identifying human capital externalities. The first one is the fixed effect models which are permitted by the panel feature of the firm data. The second one is an instrumental variable approach where I use a historical event and a city amenity separately as instruments for endogenous college share.

4.3.1   Fixed Effect Models

First and foremost, using the balanced panel of 19,276 firms observed in 2001 and 2011, I am able to include firm-fixed effects to control for any permanent characters of firm, industry, and city that do not change over time but influence both the firm productivity and the city-level college share. In addition, along with year fixed effects, I add firm-specific year dummies, industrial-specific year dummies, and provincial-specific year dummies, as well as provincial-industrial year dummies to control for potential time-varying shocks that are unobservable to me.

To some extent, these fixed effects above would greatly reduce the biases of the estimation of γ, if I assume the idiosyncratic error is uncorrelated with any of the explanatory variables. But in practice, admittedly, some observable city-level time variant shocks could still correlated with the variable of college share.

Therefore, in addition to these fixed effects, I add other observable city char-

acteristics to mitigate this concern. For example, a rapid economy like China has gone through substantial improvement in its infrastructure in the past, and it is very likely that it is the upgraded transportation system that improves firm productivity, rather than the human capital externalities. Attributing the increases in productivity solely to human capital externalities is inadequate. I use the volume of cargo, which is measured in ten thousand tons per year in a city including all cargo by road, plane, and water, as the proxy for the city infrastructure.

Another concern is that the structure of the city economy could also affect firm productivity. It could be the case that it is the changes in the structure of the economy that improve firms' productivities as well as attract more college-educated workers. For example, Shenzhen China started as a labor-intensive economy in the 1980s, but now it is one of the leading cities in technology and innovation in China. Failing to take the structure of the economy into consideration, we will have biased estimates for human capital externalities. So I include the share of employment of industrial sector (v.s. agricultural sector and service sector) in the total employment of a city to approximate the city economic structure.

The competitiveness of the market environment in which firms conduct business could also affect firms' productivities. So the market share of each firm at the two-digit industrial level is included in the model, as well as the Herfindahl-Hirschman Index (HHI)(Liu, 2014).

In the fixed-effect models, any time-invariant shocks at the firm level, industry level, province level, which could bias the estimates of human capital externalities γ, are well controlled for. With the inclusion of industrial-specific and provincial-

specific year dummies, and some city and firm characteristics, the fixed-effects models should provide a good estimate for human capital externalities.

4.3.2   Academic Departments Relocation As An Instrument

While firm-level fixed effects can take away a large number of permanent factors affecting both the city-level college share as productivities as firm fixed effects absorb permanent factors at the firm, city, and industrial levels, and the industrial and province-specific year dummies can help alleviate the industry-wide shocks and the provincial level business-cycle conditions can help achieve a more consistent estimate of human capital spillovers, it is still possible that some city-specific time-varying unobservable shocks can bias the estimates. So alternatively, I estimate human capital with a first-differenced instrumental variable model.

The first instrumental variable that I use is the number of academic departments relocated in early 1950s (Glaeser and Lu, 2018). During the massive relocation movement, some cities saw their local education institutions diminished drastically in the early years of Communism, while other cities saw their educational institutions increase. The changes in the higher education resources have a long-term impact on the local human capital development that lasts decades. It turns out that the changes in the net number of departments received is a strong predictor for the changes in college share. But the relocation of academic departments was rather unexpected and the net number of departments received by each city in the 1950s was not correlated with local city characteristics, so it should not affect changes in

firms' productivity in 2000s.

To understand why the relocation of academic departments is a valid instrument and it should satisfy the exclusion restriction, it is important to see how and why the massive relocation movement took place. First of all, like other communist countries, the Chinese communist government quickly adopted the Soviet Union university system, which was highly specialized to serve the economic development, once it got the power. The way it achieved this goal was to transform the comprehensive universities into single-disciplinary colleges of science or liberal arts, or multi-disciplinary universities of science and technology by uprooting departments from their home universities, regrouping them, and then relocating them across universities in different cities. As a consequence, 502 departments were moved out of their home universities, 282 of which were relocated to other cities, and 623 departments were moved into other universities, 333 of which were from a different city (Glaeser and Lu, 2018).[2]

Secondly, this movement was very political and the new regime took this relocation of academic departments as an opportunity to eliminate the influence of previous regime and western culture in higher education, and to spread the communist ideology as much as possible. For instance, National Central University, which was one of the flagship higher education institutes of the Republic of China, was split into 11 colleges in 1952, and these colleges were spread across many different cities. All Christian universities were nationalized, renamed and reorganized. See

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[2]The number of departments got split was greater than the ones merged, that is why we observe more moved-in than move-out.

Glaeser and Lu (2018) for more details about the academic relocation movement in China in the early 1950s.

Thus, this unexpected historical event of academic department relocation, which happened a half-century ago should have no influence on firm's productivities in later 2000s, except through its impacts on the local resources of higher education as the presence of higher education institutes has a long-term effect on the local human capital (Card, 1993).

Another instrumental variable is the green land per capita in each city which measures the city-level amenity. Since better amenities attract more college-educated workers, the city-level college share will increase as a result, but there is little reason to believe that better amenities can affect firm productivity other than through their effects on college share.

4.4   Results from Fixed Effect Models

4.4.1   Baseline Results

Column 1 of Table .14 provides the estimated result when each firm is treated as if they were independent observations and only city effects and year effects are included. It shows that a one percentage point increase in college-educated workers is associated with a 1.6 percentage increase in firms' productivity. In column 2, I consider the panel feature of the firm data so that the identification of the human capital spillovers comes from the changes in college share at the city level and the changes of productivity of the same firms over time. The inclusion of the firm effects

saturates permanent factors at city and industry level. Compared to column 1, the resulting coefficient of the college share decreases slightly.

Though the firm effects have sufficiently controlled the time-invariant unobservable factors that may affect both college share and firm productivity, there could still exist some time-variant variables that could potentially bias the estimates. To further purge the results, I add industry-year effects in column 3 to take into account the possible industry-wide changes that could take place at industry level that attract more college-educated workers and improve firms' productivity. For instance, the introduction of a new technology in the automobile industry demands more workers with higher education and the technology itself makes firms more productive. Without the industry-year effect, we could falsely claim human spillover effects when they do not exist. The estimate in column 3 of Table .14 is about half of the effects found in column 1 and column 2, which clearly indicates the importance of considering technological changes over time.

Analogically, in column 4 of Table .14, I include province-year effects to control for time-variant geographic factors that may bias the estimates of the human capital spillovers. The resulting estimate 1.65 is close to column 1 and 2 which implies that time-variant factors at provincial level have almost no effects on firm productivities. Column 5 of Table .14 provides the estimate from the most parsimonious model where firm-industry-province year effects are included. The resulting estimate is close to that in column 3.

Other coefficients in Table .14 behave largely as we expect. Firm-specific human capital has significant and positive effects on firm productivity, and its mag-

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nitude changes very little across different models. A firm with a larger market share in the industry has higher productivity. The more concentrated the industry a firm belonging to is, the less productive a firm is since the competition decreases (higher HHI means higher concentration and less competition). The employment share of the industrial sector (other two sectors are the agricultural sector and the service sector) does not have a consistent impact on firms' productivity across models. The log of cargo volume has positive but insignificant impacts on firms' productivity.

4.4.2   Robustness Checks

To probe the robustness of the results in Table .14, I present the results from a number of alternative models in Table .15 and Table .16. One concern is that firms located in larger cities are more productive since larger cities allow for more subcontracting and specializing (Moretti, 2004c). In row 1 of Table .15, I include city population density in addition to the baseline model in column 5 of Table .14. The resulting coefficient of college share is slightly larger than the model without population density[3].

Another concern is that college share may simply pick up agglomeration effects rather than human capital externalities. That is, firms could be more productive if they located in cities where the overall level of physical capital is higher (Moretti, 2004c). The way I address this concern is to add different measures of overall physical capital to the baseline model to test if human capital spillovers disappear.

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[3]The coefficient in each row of Table .15 represents the coefficient of college share from a separate regression

In row 2 of Table .15, I add the average of physical capital per firm excluding firms'
own physical capital, and the coefficient remains largely unchanged. The result is
similar in row 3 when I measure overall physical capital by the average physical
capital per worker outside firm. I conduct the same exercise in row 4 and 5 where
the average capital is measured outside of the 4-digit industry that a firm belongs
to in each city. The resulting estimates of human capital spillovers are very robust.

In the models of row 6 and 7 of Table .15, I introduce the foreign direct
investment (FDI) to the baseline model as the additional control as it is likely that
firms with a larger share of their capitals controlled by foreign investments would
be more productive. In row 6, the FDI share is weighted by its capital share in the
4-digit industry the firm belongs to, and in row 7 the FDI share is weighted by its
employment in the same industry. The resulting estimates indicate that the human
capital externalities are not impacted by the inclusion of FDIs.

4.4.3   Alternative specification

To further check the robustness of my results, I replace college share with
the ratio of college enrollment to population above 15 years old as an alternative
measure for city-level human capital. The results in Table .16 largely mirror that
in Table .14. The coefficients in the model with city effects (column 1) are close
to that in the model with firm effects (column 2); adding industry-year fixed effect
greatly reduces the estimates but they are still statistically significant. The most
conservative model of column 5 of Table .16 indicates that one percentage point

increase in the ratio of college enrollment to population is associated with 0.009 percent increase in firm productivity.

4.5   Instrumental Variable Approach

4.5.1   Results from Instrumental Variable Model

The number of academic department relocated in 1952 and the green land per capita are the two instrumental variables I use. To a large extent, the academic department relocation movement is unexpected and it has a long-lasting impact on the local human capital as it changed the higher educational resources at the city level. Therefore, it is expected that the net number of moved-in departments should be correlated with changes in college share in the 2000s. Since this movement is a historical event that happened a half century ago and it should have no direct impacts on firms' productivity in the 2000s.

The green land per capita serves as a proxy for local amenities which are valued by more skilled workers. Therefore, more green land could help retain local college-educated workers and attract others from outside. There seem to be no compelling reasons to believe that amenities such as green land would have a direct impact on firm productivity.

Column 1 of Table .17 provides the estimate of the simple first-differenced model. The result indicates that one percentage point increase in college share is associated with a 1.7 percentage point increase in firms' productivity. Column 2 and 3 of the upper panel of Table .17 shows that both the academic department

relocation event and the green land per capita are good predictors of the changes in college share. One more net academic department a city received is associated with a 0.1 percentage point increase in the change of college share between 2000 and 2010. One more square meter green land per capita is associated with 0.02 percentage point increase in the changes of college share in the 2000s.

The magnitudes of the first stages are small, but these numbers are reasonable given the fact that the relocation of academic departments took place decades age and local amenities such as green land per capita is just one of many factors affecting workers' choice of work locations. Take the department relocation as an example, the average population size of Chinese cities in 2010 is about 3.2 million according to the 2010 population census, so the coefficient of 0.001 means that 3200 more workers on average have become college educated over the time period of 2000 and 2010 because of the historical event in the 1950s. The resulting estimates indicate that one percentage point increase in changes of college share leads to 2.1 to 2.3 percentage point increase in firm productivity.

4.5.2   Validation of the Instrumental Variables

Though the significant first stages show that academic department relocation and green land are strongly and positively associated with changes in college share, the estimated results could still be invalid if the relocation is correlated with other local factors that could affect firms' productivity. For instance, the relocation may favor some cities over others. Certain cities could receive more departments than it

could lose if the central government preferred to concentrate resources to a few cities that were already in a faster growth track, like cities with more existing universities or better infrastructure. Or, if cities that gained more departments during the relocation movement happened to receive more investments in a later period, the estimated human capital spillovers would still be questionable.

Glaeser and Lu (2018) show that the net number of relocated departments is not correlated with either number of universities at that time or the average infrastructure investment in the time period of the 1950s and 1960s. Figure1-3 copied from Glaeser and Lu (2018) provide some visual evidence that while the number of moved-in departments and the number of departments moved-out concentrate in certain cities, the net number of departments relocated does not reflect such concentration.

More importantly, other city characteristics that may influence firms' productivity should not be correlated with the instrument. Any linkage between the academic department relocation and current city characteristics will cast doubt on the validity of the instrument and the resulting estimates of human capital externalities.

Table .18 shows that for the year 2000, cities with more infrastructure investment per capita and higher GDP per capita indeed gained more departments during the relocation movement but they also lost more departments. Overall, the net number of department moved-in is not correlated with the infrastructure investment and economic performance. Similar conclusions are reached when I use the infrastructure investment and GDP data from 2010 and the difference between 2000

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and 2010, see Table .19 and Table .20 for details.

4.6   Heterogeneity of human capital spillovers

The story of human capital externalities builds upon the assumption that through formal and informal interaction among them, workers learn from each other, consequently, knowledge and skills are no longer limited to individuals who originally acquire them, instead, knowledge and skills are widely spread out which benefit many other people (Marshall, 1890; Lucas, 1988). An increase in firms' productivity is one of the results of such social learning.

This social learning process brings benefits but also involves costs. Therefore, anything that increases the benefits and decreases the costs of social learning is expected to improve the intensity of human capital externalities. This is the place where further evidence comes from.

First, if social learning is the main mechanism of human capital externalities, firms located cities with larger and denser population would gain more from overall human capital since in larger and denser cities people have more chances to meet each other which lowers the cost of learning, as Rosenthal and Strange (2008) finds that human capital spillovers attenuate sharply with distance.

I investigate this prediction by dividing the cities into small cities and large cities according to the sizes of the population. The cutoff is 5.7 million population which is the median size of the cities considered. Besides the total population, the population density is another important aspect to determine the intensity of human

capital spillovers. I use the median density of 570 people per square kilometers as the threshold for denser cities and less dense cities.

The resulting estimates of human capital spillovers in the first two columns of Table .21 shows that firms in larger cities are far more sensitive to human capital spillovers than firms in small cities. In large cities, one percentage point increase in college share is associated with a 2.65 percent increase in firm productivity, whereas in small cities, the effect is much smaller and statistically not significant. The results do not change much when I divide the sample by city population density in column (3) and (4). Other coefficients are similar to the main estimation.

One concern of the above analysis is that a Chinese prefectural city often includes both an urban area where major economic activities take place and a massive rural area where fewer population and firms present, simply classifying cities by "raw" number of population size and population density may misplace some cities and lead to incorrect results. For this reason, I regroup cities into small and large cities, less dense and denser cities based on population size of population density of the "metropolitan" area of a city instead of the whole city. Then I reestimate the FDIV model and the results are presented in Table .22. The pattern of human capital externalities is the same in this new classification of cities compared to the previous classification: the intensity of human capital externalities is much higher in larger and denser cities. But the results from the new classification of cities are stronger.

Second, according to the assumption of human capital externalities if the benefits of social learning are greater the intensity of human capital externalities will

also be higher since workers will have more incentives to implement what they learn from others. This argument can be tested by separately applying the FDIV model to state firms and private firms. Compared to state firms, private firms are more likely to operate on profit-maximizing principles and competing in product and factors markets where wages are more tightly linked to individual productivities, and workers have more incentives to engage in some form of social learning Liu (2014). Table .23 confirms our prediction that firms with private ownership (both domestic and foreign) are more responsive to the overall human capital level than firms with state ownership.

4.7   Discussion

In this chapter, I match a firm-level panel data from China's Annual Survey of Industrial Enterprises (ASIE) to population census data in China to estimate human capital externalities suggested by classic literature (Marshall, 1890; Lucas, 1988). In both the fixed effects model and the first-differenced instrumental variable model, I find strong and positive relationships between firms' productivity measured as Total Factor Productivity (TFP) and overall human capital in a city measured as the share of college-educated workers in the population above 15-year-old. The most robust fixed effects model shows that one percentage point increase in college share is associated with 0.85 percentage point increase in TFP. Using the historical event of academic department relocation and city amenities as exogenous shocks to local higher educational resources, I am able to estimate that one percentage point

increase in college share leads to 2.1 to 2.3 percentage increase in firms' TFP.

The key assumption of human capital externalities suggests that there exists a social learning process as the main mechanism that facilitates such externalities. Though I don't have direct evidence to show this is the case for sure, I provide supplementary evidence to support this mechanism. If social learning is one of the main mechanisms of human capital externalities, we expect firms in cities with larger and denser population and firms providing more incentives for workers to engage in social learning would be more responsive to human capital. Since in bigger cities workers have more chances to learn and in firms rewarding efforts more properly (private firms) workers have more incentives to exert their efforts in social learning. My empirical results are perfectly consistent with such predictions.

Chapter 5:   Conclusion and Discussion

A large body of theoretical literature in both macroeconomics and urban economics has suggested that aggregate human capital has a positive effect on productivity for workers and firms (Marshall, 1890; Lucas, 1988; Romer, 1990). Lucas (1988) suggests that human capital spillovers may be large enough to explain long-term income differences between rich and poor countries. In his most foundational paper of "Endogenous Technological Change", Romer (1990) incorporates human capital as one of the key factors affecting productivity of firms in his new growth model, and he argues that human capital is responsible for the long-term economic growth as human capital can keep generating new ideas and innovations that continuously improve productivity.

The goal of my dissertation is to provide some systematic empirical evidence for the existence and magnitude of human capital spillovers using individual-level and firm-level data from China.

As the second largest economy in the world, China has experienced a spectacular economic growth, and at the same time, the level of schooling of its population has also increased dramatically. It is interesting and important for both researchers and policymakers to know if human capital spillovers have played a role in its eco-

nomic growth. The magnitude of human capital spillovers is a useful tool for evaluating the efficiency of public funding in education as almost all levels of education are subsidized by governments which is true not only in China but also in many other countries. Moreover, the magnitude of spillovers from higher education is crucial for local development policies as well. Local governments often face a variety of policy options to develop local economies. They need to choose to invest in infrastructure to attract new businesses, to change environmental regulations to make development easier or to invest in higher education to create an educated workforce. Understanding the role of human capital spillovers in productivity improvement is very important when local governments want to strike a balance between these options and try to have an optimal development policy (Moretti, 2004a).

In Chapter 2 of my dissertation, I first investigate the impact of aggregate human capital on productivity by comparing wages for otherwise similar workers who live in cities with different shares of college graduates in the labor market using CHIP (China Household Income Project) data. If aggregate human capital spillovers truly present, we would observe wages for workers in cities with higher college share are higher than in cities with lower college share after controlling for individual characteristics and cities characteristics. The biggest obstacle in identifying such human capital spillovers is the presence of unobservable factors at both the individual level and the city level, such as individuals' unobservable ability, workers' preference for amenities, cities' natural endowment and institutions. Workers may sort to different cities based on these unobservable factors. The simple OLS may just capture the effect of these unobservables rather than human capital spillovers. To overcome

this identification issue, I implement an instrumental variable approach using the simulated college share as the instrument for the observed college share assuming workers did not migrate over time across cities. I find that one percentage point increase in college share is associated with a 1.4 percent increase in wages.

To facilitate our understanding of the magnitude of the estimated spillover effects, consider that the average annual increase in college share over the period of 1988 to 2013 is about 0.96 percentage points. According to the 2SLS estimate of 1.4 percent in Table 4 Column 2, the 0.96 percentage point increase in the share of college educated workers would be associated with an increase in wages by about 1.36 percent. For an average worker in China in 2002 making 12000 RMB (about 1700 US dollars) yearly, this translates into about 157 RMB (roughly 22 US dollars) each year.[1]. The employed population in 2002 was 732.8 million in China according to China Labor Statistical Yearbook. The national spillovers can be as large as 114.8 billion RMB (roughly 16.4 billion US dollars). The annual investment in higher education of the government was 58.9 billions RMB (about 8.4 billion US dollars)[2]. That is, the national human capital spillovers can be two times higher than the investment in higher education made by the government.

There is a caveat in this Mincerian approach where the individual wage is regressed on aggregate human capital and other covariates. We may find a positive coefficient on college share even if there are no human capital spillovers when skilled workers and unskilled workers are imperfect substitutes. To mitigate this

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[1]The approximated effect found by Moretti (2004b) is 62 dollars

[2]China Educational Statistical Yearbook shows that there were 9534600 students enrolled in higher education institutes in China in 2002 and the investment was 6178 RMB per student

concern, I run separate estimations for skilled and unskilled workers. If there is no spillovers, the coefficient of college share for skilled workers will be negative as supply and demand rules suggest. However, we find that the coefficient of college share is significantly positive for skilled workers. This provides one piece of evidence that human capital spillovers not only exist but large enough to offset the negative imperfect substitution effect.

In addition, in Chapter 3, I implement the constant-composition approach (Ciccone and Peri, 2006) which makes it possible to separate human capital spillovers from the imperfect substitution effect by holding the skill composition of workforce in the city constant. In this approach, I instrument for the change in college share in the 2000s with the age structure in 1990 and I find that one percentage point increase in college share increases wages by 3.6 percent.

We can interpret the coefficients in Table 10 at the similar fashion. For instance, Column 4 in Table 10 implies that one percentage point increase in college share was responsible for an increase in wages of about 3.59 percent. The average annual increase in the percentage of college share is about 2.4 percentage points between 2000 and 2010. This increase indicates that a typical worker in year 2002 gains 1037 RMB (148 US dollars). Such effect is larger the one found in Chapter Two. This is due to higher college share increase in the period of 2000 to 2010 and higher estimate of spillover effects from the Constant-composition Approach.

In Chapter 4, I directly estimate the impact of college share on productivity by regressing firm total factor productivity (TFP) on city-level college share and other covariates. In the most parsimonious model where I include not only the

firm fixed effects and the year fixed effects, also the industry-year effect and the province-industry-year, I find that one percentage point increase in college share leads to 0.85 percent increase in firm TFP. Furthermore, I take a first-differenced instrumental variable approach where I use the net number of academic department moved-in during the department relocation in the 1950s across Chinese cities. This politics-driven and unexpected event has a long-term influence on the composition of the local labor force as it is shown in the first stage of the 2SLS estimation, but it should not have any impacts on firm productivity in the 2000s other than through its impact on college share changes. The estimates show that one percentage point increase in college share increases firm TFP by 2.3 percent. The result is similar when I use green land per capita as the instrument. The yearly increase in college share between 2000 and 2010 is about 2.4 percentage points. Therefore, the actual spillover effect is about 5.5 percent which means 1.3 million RMB (0.19 million dollars) gain for an average Chinese firm.

Though I have implemented a variety of identification strategies to overcome the endogeniety issue of omitted variables, I can not completely rule out that some unobservable factors still play a role in my estimated human capital spillovers. However, the fact that all my estimates across data and model specifications are all significantly positive and they are very close to one another provides credibility to my estimates of human capital spillovers.

My dissertation has focused on identifying human capital externalities and estimating the magnitude of them, future work can be extended toward exploring the micro-mechanisms through which human capital takes place. For instance, how

overall human capital affects location choices of firms and industry formations of a region.

Appendix : Tables and Figures

Table .1: Summary Statistics

	(1) Inter-census 2005	(2) CHIP
age	37.3	38.6
	(9.5)	(5.7)
gender	0.42	0.50
years of education	11.8	11.11
	(304)	(3.08)
log wage	6.83^a	6.13^a
	(0.70)	(1.38)
share of college graduates	0.23	0.20^b
	(0.07)	(0.07)
Cities	345	65
Individuals	312,462	29,557

Notes: Standard deviations are in parentheses for continuous variables.

a: Log of monthly wages

b: Interpolated from inter-census 2005

Table .2: The effect of changes in college share on individual wages: Inter-census 2005

	(1) OLS	(2) Province FE	(3) IV
First stage			
presence of 211 universities			0.089***
			(0.009)
Second stage			
College share	2.021***	1.731***	1.960***
	(0.378)	(0.286)	(0.243)
gender	-0.200***	-0.206***	-0.206***
	(0.00769)	(0.00764)	(0.00774)
age	0.0254***	0.0381***	0.0384***
	(0.00536)	(0.00307)	(0.00285)
age2	-0.000266***	-0.000427***	-0.000431***
	(7.04e-05)	(3.55e-05)	(3.22e-05)
education year	0.0962***	0.0966***	0.0957***
	(0.00419)	(0.00344)	(0.00390)
Constant	4.707***	4.689***	4.597***
	(0.130)	(0.177)	(0.110)
Observations	312,462	312,462	312,462
R-squared	0.293	0.391	0.390
Province Dummy	NO	YES	YES

Notes: Dependent variable is individual log wages. Data: inter-census 2005 of China

Standard errors in parentheses are clustered at prefecture city level.

*** p<0.01, ** p<0.05, * p<0.1

Table .3: Robustness check: Inter-census 2005

	(1) sector dummies	(2) manufacturing only	(3) male	(4) female	(5) non linear edu	(6) CS in other industry	(7) stayer only
college share	1.866***	1.682***	1.124***	1.644***	1.778***	1.039***	1.701***
	(0.254)	(0.300)	(0.336)	(0.262)	(0.253)	(0.306)	(0.239)
gender	-0.189***	-0.239***	0.103	-0.607***	-0.188***	-0.203***	-0.185***
	(0.00811)	(0.0110)	(0.0766)	(0.0621)	(0.00847)	(0.00754)	(0.00899)
age	0.0343***	0.0250***	0.0324***	0.0331***	0.0345***	0.0364***	0.0350***
	(0.00272)	(0.00469)	(0.00204)	(0.00267)	(0.00260)	(0.00261)	(0.00274)
age2	-0.000380***	-0.000306***	-0.000354***	-0.000363***	-0.000385***	-0.000399***	-0.000377***
	(3.00e-05)	(5.29e-05)	(2.24e-05)	(3.08e-05)	(2.90e-05)	(2.94e-05)	(3.10e-05)
education year	0.0809***	0.0880***	0.0865***	0.0855***		0.104***	0.0765***
	(0.00510)	(0.00698)	(0.00535)	(0.00522)		(0.00381)	(0.00435)
Constant	4.385***	5.015***	4.719***	4.988***	4.744***	4.821***	4.424***
	(0.113)	(0.172)	(0.128)	(0.0911)	(0.109)	(0.224)	(0.107)
Observations	312,462	63,597	312,462	312,462	312,462	312,462	239,220
R-squared	0.429	0.386	0.414	0.416	0.437	0.378	0.411
Province Dummy	YES	YES	YES	YES	YES	YES	YES

Notes: Dependent variable is individual log wages. Data: inter-census 2005 of China

All regressions are 2SLS using presence of 211 universities as instrumental variables

(1) Include dummies for industry

(2) Use observations in manufacturing industry only

(3) College share is interacted with dummy for male

(4) College share is interacted with dummy for female

(5) Returns to education vary by education level

(6) College share is from other industries in the city where an individual belongs to.

(7) Use observations that stay at their birth places.

Standard errors in parentheses are clustered at prefecture city level.

*** p<0.01, ** p<0.05, * p<0.1

Table .4: The effect of changes in college share on individual wages: pooled cross sectional data

VARIABLES	(1) OLS	(2) 2SLS	(3) Skilled	(4) Unskilled
First stage				
Interpolated college share		0.783***	0.787***	0.707***
		(0.285)	(0.329)	(0.259)
Second stage				
College share	0.469***	1.417***	0.917**	1.240**
	(0.157)	(0.364)	(0.391)	(0.483)
education year	0.0541***	0.0518***	0.0339***	0.0337***
	(0.00247)	(0.00248)	(0.00536)	(0.00272)
age	0.0830***	0.0792***	0.0435***	0.0855***
	(0.00817)	(0.00899)	(0.0149)	(0.0117)
age2	-0.000923***	-0.000874***	-0.000384**	-0.000937***
	(0.000108)	(0.000117)	(0.000194)	(0.000152)
gender	-0.215***	-0.217***	-.168***	-.231***
	(0.0133)	(0.0130)	(0.0143)	(0.0163)
Observations	29,403	29,403	7,905	21,498
R-squared	0.803	0.801	0.805	0.777
Number of city	65	65	65	65
Year Dummy	YES	YES	YES	YES
City Dummy	YES	YES	YES	YES

Notes: Dependent variable is individual log wages.
Column (1) and (2) use all observations, column (3) and (4) use skilled and unskilled observations respectively.
Data: pooled cross sectional data
Standard errors in parentheses are clustered at prefecture city level.
*** p<0.01, ** p<0.05, * p<0.1

Table .5: Robustness check: The effect of changes in college share on individual wages

VARIABLES	(1) all	(2) drop 1988	(3) drop 1995	(4) drop 2002	(5) drop 2007	(6) drop 2013
College Share	1.110***	0.199	1.289***	1.264***	1.109***	1.692**
	(0.387)	(0.482)	(0.385)	(0.426)	(0.395)	(0.841)
edu_yr	0.0548***	0.0673***	0.0580***	0.0435***	0.0538***	0.0517***
	(0.00237)	(0.00266)	(0.00293)	(0.00269)	(0.00244)	(0.00249)
age	0.0845***	0.0885***	0.0775***	0.0673***	0.0943***	0.0864***
	(0.00811)	(0.0115)	(0.0102)	(0.00878)	(0.00840)	(0.00827)
age2	-0.000941***	-0.00103***	-0.000863***	-0.000720***	-0.00104***	-0.000950***
	(0.000107)	(0.000151)	(0.000131)	(0.000121)	(0.000110)	(0.000107)
1.gender	-0.214***	-0.269***	-0.230***	-0.185***	-0.201***	-0.197***
	(0.0132)	(0.0161)	(0.0143)	(0.0139)	(0.0141)	(0.0125)
Constant	1.936***	3.624***	2.040***	2.357***	1.708***	1.811***
	(0.181)	(0.223)	(0.217)	(0.190)	(0.192)	(0.232)
Observations	29,403	21,060	22,812	22,188	25,918	25,634
R-squared	0.803	0.501	0.825	0.854	0.807	0.765
Number of city	65	65	65	65	65	65
Year Dummy	YES	YES	YES	YES	YES	YES
City Dummy	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is individual log wages.
Results are from the reduced form regressions.
Data: pooled cross sectional data from China Household Income Project.
Standard errors in parentheses are clustered at prefecture city level.
*** p<0.01, ** p<0.05, * p<0.1

Table .6: College share simulated for CHIP data from inter-census 2005

CHIP survey year	labor force age	labor force age in 2005	college share	college enter year
1988	28 - 48	45 - 65	0.136	1958 - 1978
1995	28 - 48	38 - 58	0.175	1965 - 1985
2002	28 - 48	31 - 51	0.232	1972 - 1992
2007	28 - 48	26 - 46	0.281	1977 - 1997
2013	28 - 48	20 - 40	0.347	1983 - 2003

Notes: Population with urban household registration are used.

Table .7: Migration Rate of Different Cohorts

CHIP survey year	labor force age	2005			2000			
		labor force age in 2005[a]	migration rate across county[b]	migration rate across province[c]	labor force age in 2000[a]	migration rate across county[b]	migration rate across province[c]	migration rate across city[d]
1988	28 - 48	45 - 65	0.046	0.011	40 - 60	0.055	0.009	0.0101
1995	28 - 48	38 - 58	0.061	0.018	33 - 53	0.068	0.016	0.0111
2002	28 - 48	31 - 51	0.090	0.032				

Notes:

a: Numbers in this column are the 2005 or 2000 corresponding ages of workers between 28 to 48 in each CHIP survey year.

b: Migration rate across county corresponds to the share of people whose Hukou registration counties differ from their residential counties in 2005 or 2000.

c: Migration rate across province corresponds to the share of people whose long-term residential provinces five years ago differ from their residential provinces in 2005 or 2000.

d: Migration rate across county corresponds to the share of people whose Hukou registration cities differ from their residential city in 2000.

Figure .1: College Enrollment in China, 1977-2012
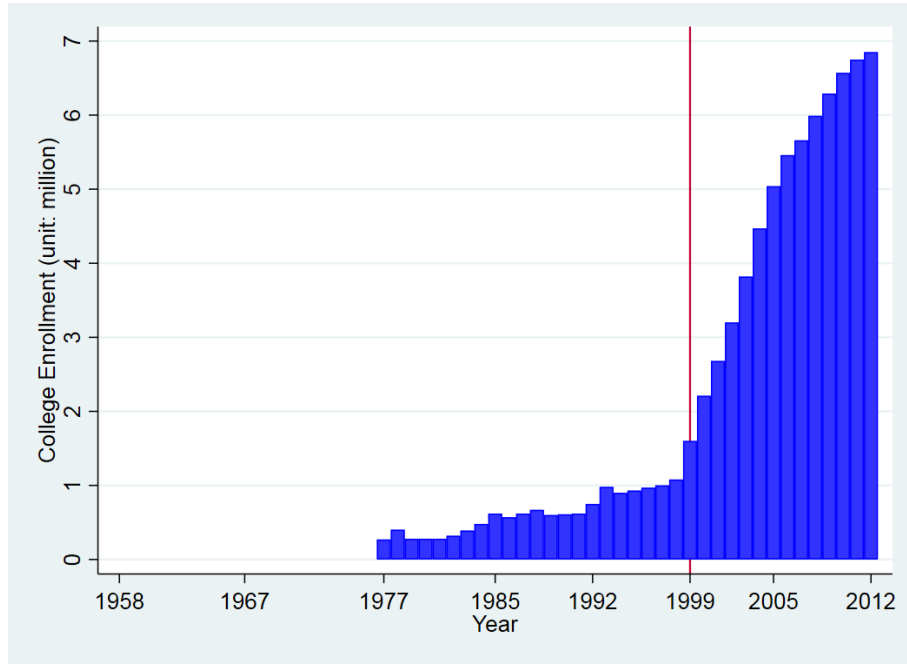
Data source: Ministry of Education of the People's Republic of China

Figure .2: Distribution of college and non-college educated workers (whole population)
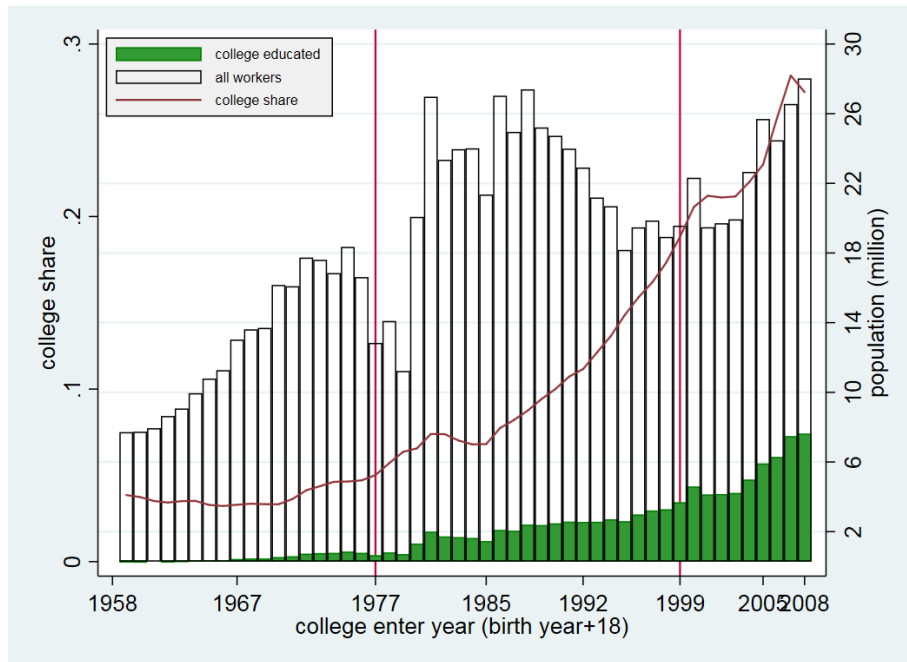
Data source: 2010 Population Census of China.

Figure .3: College Enrollment in China, 1977-2012
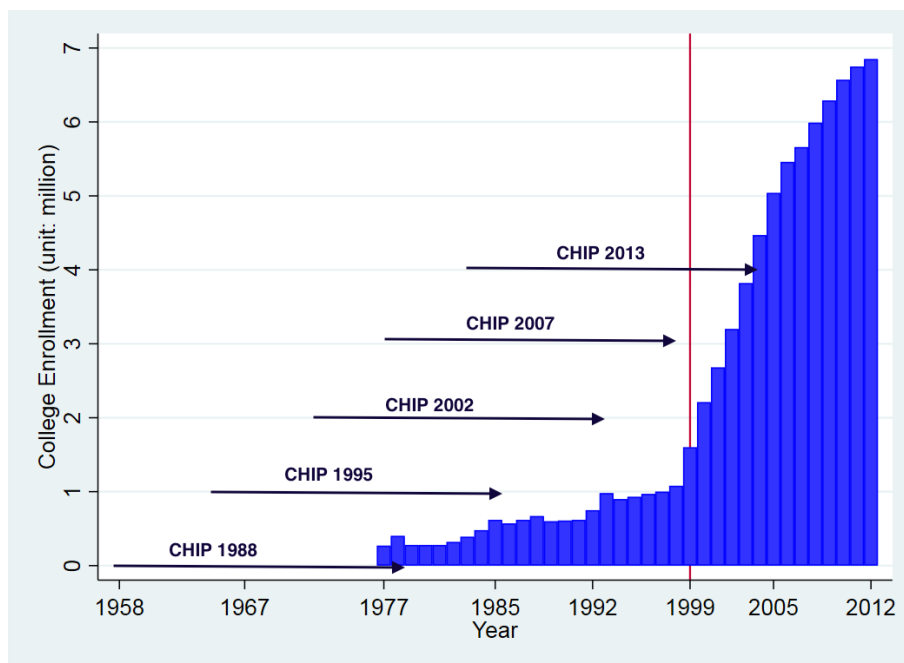
Data source: Ministry of Education of the People's Republic of China

Table .8: Summary Statistics of the Urban Household Survey

	(1) UHS
age	39.1
	(5.7)
gender	0.48
years of education	12.62
	(2.71)
log wage	9.68[a]
	(0.84)
share of college graduates	0.13[b]
	(0.08)
Cities	134
Individuals	45,835
year covered	2002, 2009

Notes: Standard deviations are in parentheses for continuous variables.
a: Log of annual wages
b: College share is computed using population census data of 2000 and 2010

Figure .4: Skilled Labor Share and Skill Premium, 1992-2009
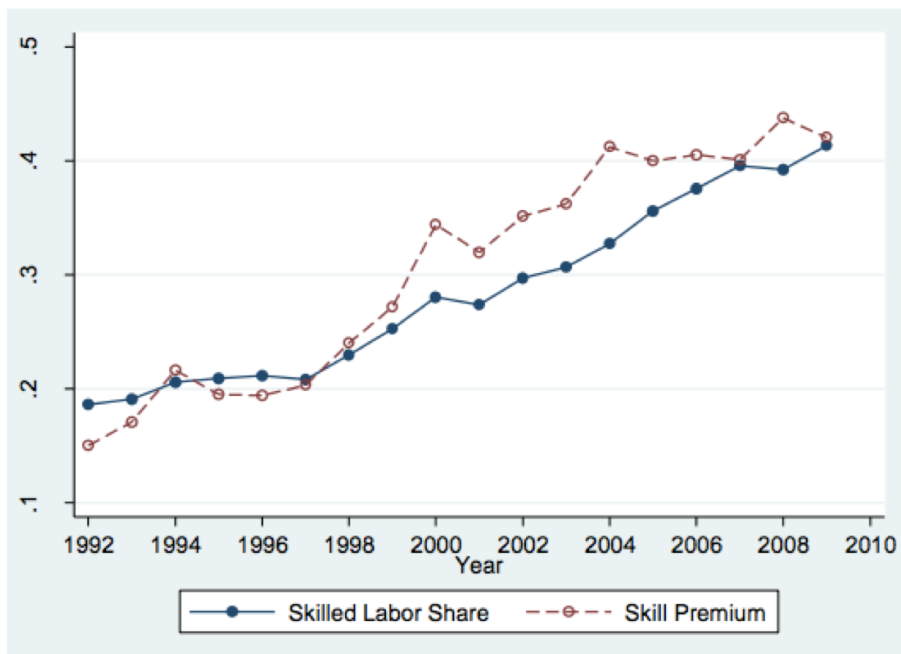
Source: Li, Li and Ma (2016).
Note: Skilled labor is defined as people (aged between 16 and 60) with college degree or above (15 years education or more). Skill labor share is defined as share of skilled workers among all employed workers in urban China. People who are not in the labor force or remain unemployed are not included. College premiums are calculated based on Mincer-style OLS regression, controlling for gender, experience, experience square, ownership (state-owned firm, collective-owned firm or private-owned firm), province and industry dummies.

Figure .5: Correlation between average wage and college share across cities
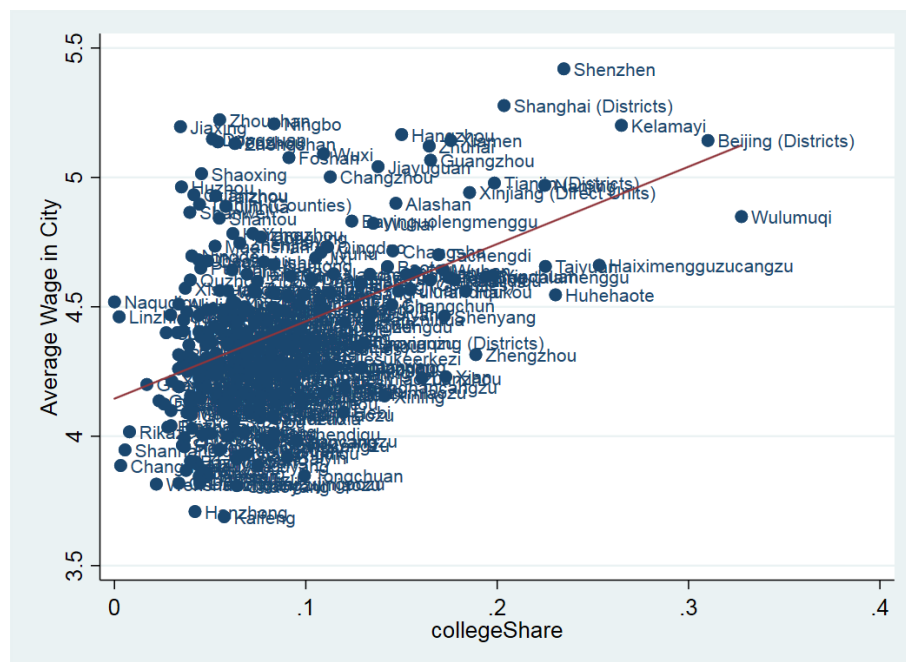
Note: Regression adjusted average wage in a city is obtained by conditioning on individual age gender and education. Source: 20% sample of inter-census 2005.

Figure .6: Distribution of college and non-college educated workers for Qinghai and Tianjin
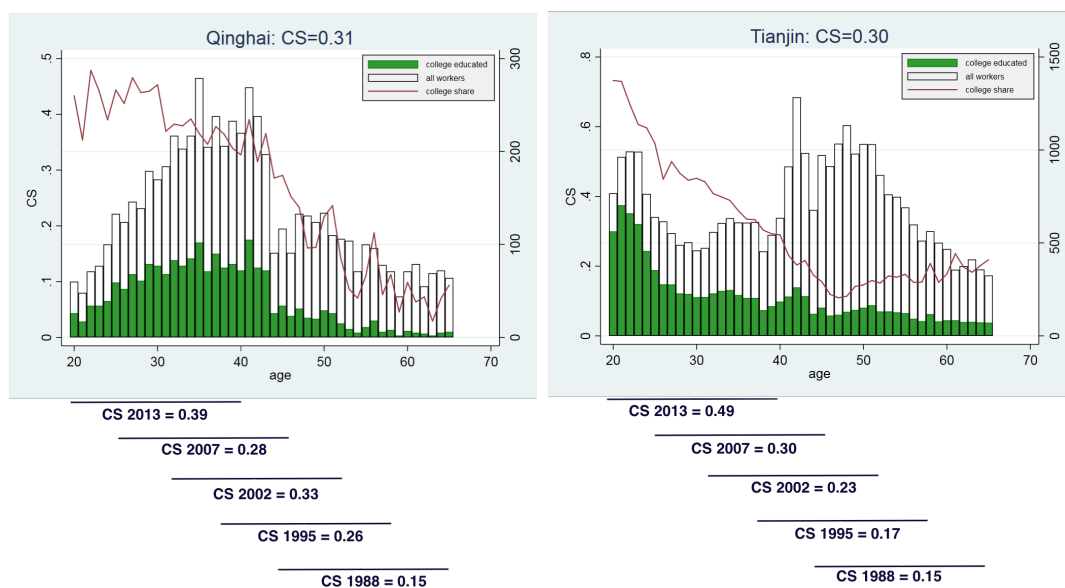
Data source: inter-census 2005 of China. The graphs show the distribution of population in the labor markets of two urban cores–The urban core of Quighai province and the urban core of Tianjin city–and the number of college educated workers for each age. Each line below the graphs, represents a range of ages that translate into the workers between the ages of 28 and 48 for that year. In other words, CS 2013 is the college share of workers between the ages of 20 and 40 who will be between 28 and 48 in 2013. The college share of individuals between 28 to 48 years old for each CHIP year is drawn from the corresponding age groups in 2005.

Figure .7: Distribution of Migration in China 2005
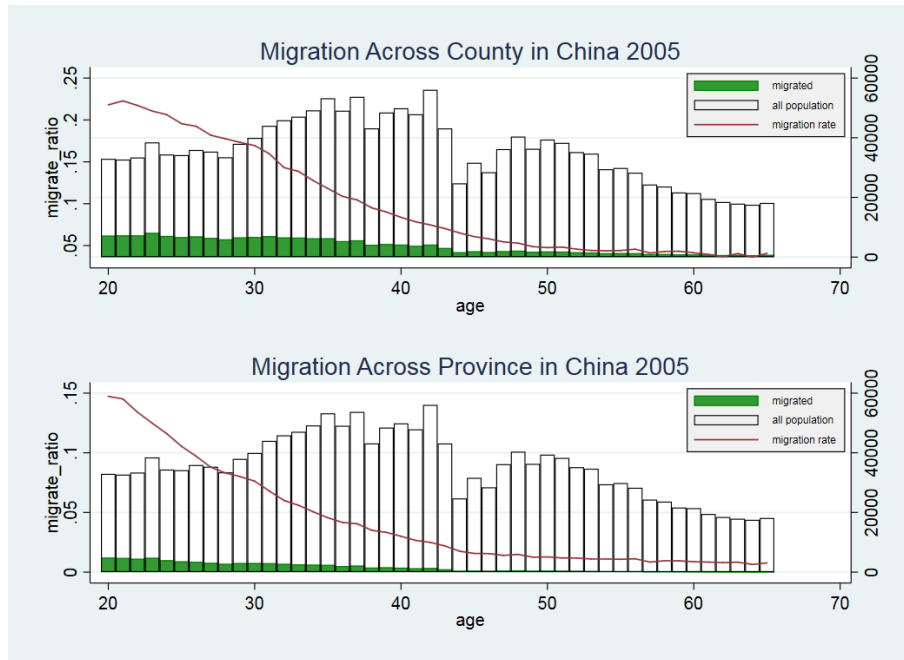
Data source: inter-census 2005 of China.

Figure .8: Distribution of Migration in China 2000
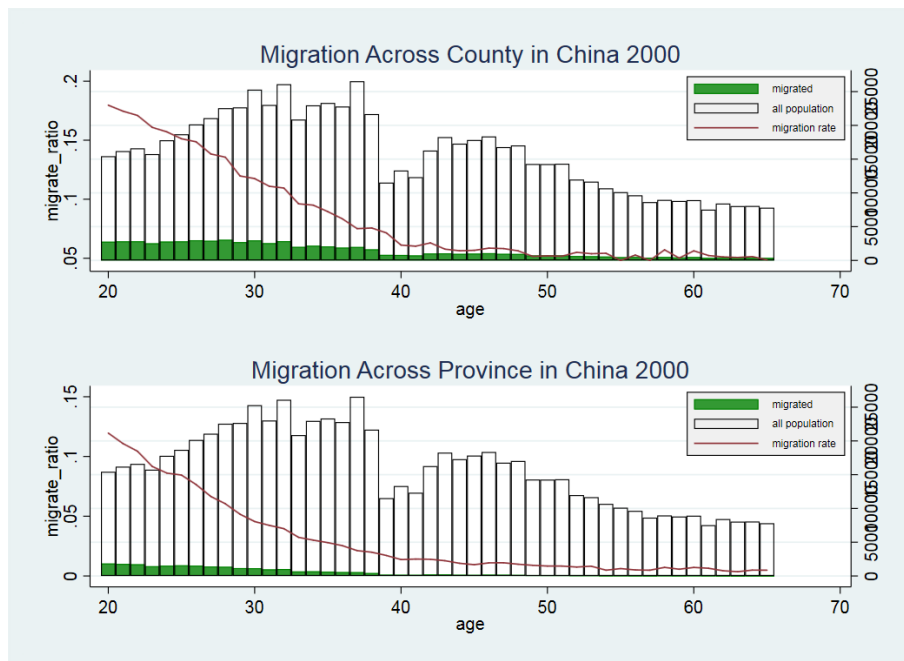
Data source: census 2000 of China.

Table .9: Quality of instruments of age structure in 1990 for college share 2000-2010

	(1) Changes in college share 2000-2010
share of young people between 16 and 25(Young Share)	-0.58***
	(0.15)
Young Share*Young Share	0.49***
	(0.16)
share of old people between 61 and 70(Old Share)	-1.31***
	(0.51)
Old Share*Old Share	7.61***
	(3.28)
Change in log employment	-0.014
	(0.015)
Regional dummies	YES
Constant	0.27***
	(0.038)
R-squared	0.1988

 Notes: Results of regressing the change in college share 2000-2010 at urban cores level on a constant and variables in the left-most column using OLS. Number of observation is 134. The quadratic specification for Young Share and Old Share implies that the marginal effect of Young Share and Old Share on the change in college share would be negative for small values of Young Share and Old Share; for large values the effect is positive.

Table .10: Human capital spillovers from higher education at urban core level: constant-composition approach 2000-2010

	(1)	(2)	(3)	(4)
Change in college share	1.598***	1.705***	3.280***	3.594***
2010-2000 (Δ CS)	(0.429)	(0.461)	(0.968)	(1.093)
Log-change in aggregated		0.0197		0.00327
employment (Δ log L)		(0.0786)		(0.0822)
Constant	0.681***	0.640***	0.547***	0.456***
	(0.0391)	(0.0559)	(0.0796)	(0.112)
Region Dummies	NO	YES	NO	YES
Observations	134	134	134	134

Notes: Constant-composition average wages constructed with married males.
Regressions in columns (1) and (2) are estimated by OLS and regressions in columns (3) and (4) are estimated by 2SLS.
The dependent variable is the change of the log average wage holding skill-composition constant over time.
Observation unit is city-year.
Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table .11: Human capital spillovers by education level

Dep. Var: average wage holding skill composition constant	(1)	(2)	(3)
Log-change in aggregated	0.00327	-0.107	-0.0884
employment (Δ log L)	(0.0822)	(0.0941)	(0.129)
Change in college share	3.594***		
2010-2000 (Δ CS)	(1.093)		
Change in high school share		-1.705***	
2010-2000 (Δ HS)		(0.627)	
Change in primary school share			1.700
2010-2000 (Δ PS)			(1.381)
Constant	0.456***	0.831***	0.995***
	(0.112)	(0.0345)	(0.158)
Region Dummies	YES	YES	YES
Observations	134	134	134

Notes: Constant-composition average wages constructed with married males.

All regressions are estimated by 2SLS.

The dependent variable is the change of the log average wage holding skill-composition constant over time.

Observation unit is city-year.

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table .12: Human capital spillovers: high vs. low population density

Dep. Var: average wage holding skill composition constant	(1) ($\geqq$ 3000people/sq. km)	(2) ($<$ 3000people/sq. km)
Change in college share	6.676***	-0.370
2010-2000 (Δ CS)	(2.348)	(1.558)
Log-change in aggregated	0.157	0.151
employment (Δ log L)	(0.203)	(0.120)
Constant	-0.0623	0.805***
	(0.347)	(0.119)
Region Dummies	YES	YES
Observations	44	90

Notes: Constant-composition average wages constructed with married males.

All regressions are estimated by 2SLS.

The dependent variable is the change of the log average wage holding skill-composition constant over time.

Observation unit is city-year.

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table .13: Summary Statistics

	2000		2010	
	Mean	Standard Deviation	Mean	Standard Deviation
Firm-specific variables				
TFP	0.014	0.365	0.345	0.354
Human capital firms[a]	-0.009	0.584	-0.104	1.040
market share	0.058	0.140	0.038	0.110
Herfindahl-Hirschman Index	0.129	0.161	0.087	0.128
Log average capital of other firms	10.689	0.743	11.603	0.720
Log average capital of other firms per worker	4.602	0.502	5.266	0.565
Log average capital of other firms in 2 digit industry	9.571	1.497	10.528	1.446
Log average capital of other firms per worker in 2 digit industry	4.023	1.091	4.589	1.218
Average FDI weighted by capital share	0.057	0.183	0.056	0.190
Average FDI weighted by employment share	0.050	0.168	0.055	0.182
City-specific variables				
College Share	0.026	0.021	0.066	0.042
Employment share of industrial sector	0.426	0.129	0.445	0.133
Log cargo (10,000 tons)	8.147	0.791	9.055	0.785
Green land per capita (m^2)	23.790	30.920	43.266	55.505
Net number of department moved in	0.240	4.533	0.240	4.533
College enrollment rate	0.456	0.654	1.799	2.300
Population density (person / km^2)	439.236	323.269	470.766	335.304

Notes: There are 19,276 firms observed in both 2001 and 2011. These firms are located in 233 Chinese prefectural cities.
a: Firm human capital measured by log of ratio of firm wage to city-industry average

Table .14: Estimates of Human Capital Spillovers Among Chinese Firms

	(1)	(2)	(3)	(4)	(5)
College share	1.607***	1.527***	0.824***	1.647***	0.847***
	(0.216)	(0.309)	(0.227)	(0.269)	(0.204)
Human capital firm	0.059***	0.054***	0.048***	0.053***	0.048***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
market share	0.080**	0.098**	0.082**	0.122***	0.131***
	(0.033)	(0.042)	(0.035)	(0.043)	(0.037)
HHI	-0.111***	-0.053	-0.025	-0.058	-0.042
	(0.037)	(0.040)	(0.029)	(0.040)	(0.032)
Employment share	-0.152***	-0.162**	-0.131***	0.054	-0.009
of industrial sector	(0.044)	(0.063)	(0.049)	(0.087)	(0.064)
Log cargo	0.004	0.006	-0.006	0.018*	0.004
	(0.009)	(0.013)	(0.009)	(0.011)	(0.007)
Observations	38,552	38,552	38,552	38,552	38,552
R-squared	0.217	0.697	0.796	0.700	0.820
City Effects	YES				
Firm Effects		YES	YES	YES	YES
Industry * Year Effect			YES		
Province * Year Effect				YES	
Industry * Province * Year Effect					YES

There are 19,276 firms observed in both 2001 and 2011. These firms are located in 233 Chinese prefectural cities.

Standard errors in parentheses, and they are clustered at city-year level.

*** p<0.01, ** p<0.05, * p<0.1.

Table .15: Robustness Checks

	(1)
Add population density	1.019***
	(0.237)
Add ln average k outside firm	0.845***
	(0.215)
Add ln average k per worker outside firm	0.900***
	(0.214)
Add ln average k outside 2 digit industry	0.792***
	(0.209)
Add ln average k per worker outside 2 digit industry	0.800***
	(0.206)
Add FDI share	0.851***
weighted by capital-share in 2 digit industry	(0.204)
Add FDI share	0.850***
weighted by employment-share in 2 digit industry	(0.204)

Notes: There are 19,276 firms observed in both 2001 and 2011.
These firms are located in 233 Chinese prefectural cities.
Each entry is from a separate regression.
Standard errors in parentheses, and they are clustered at city-year level.
*** p<0.01, ** p<0.05, * p<0.1.

Table .16: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)
Enrollment rate	0.015***	0.015***	0.009***	0.015***	0.009***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Human capital firm	0.059***	0.053***	0.047***	0.053***	0.048***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Market share	0.081**	0.104**	0.084**	0.125***	0.132***
	(0.033)	(0.042)	(0.035)	(0.043)	(0.038)
HHI	-0.109***	-0.046	-0.023	-0.062	-0.049
	(0.037)	(0.041)	(0.029)	(0.040)	(0.031)
Employment share	-0.198***	-0.205***	-0.153***	0.041	-0.011
of industrial sector	(0.048)	(0.068)	(0.045)	(0.083)	(0.058)
Log cargo	-0.010	-0.007	-0.013	0.019	0.005
	(0.012)	(0.016)	(0.010)	(0.013)	(0.008)
Observations	38,552	38,552	38,552	38,552	38,552
R-squared	0.217	0.696	0.796	0.700	0.820
City Effects	YES				
Firm Effects		YES	YES	YES	YES
Industry X Year Effects			YES		
Province X Year Effects				YES	
Province X Industry X Year Effects					YES

There are 19,276 firms observed in both 2000 and 2011. These firms are located in 233 Chinese prefectural cities.

The city-specific human capital is measured as the number of college enrollments per one hundred people.

Standard errors in parentheses, and they are clustered at city-year level.

*** p<0.01, ** p<0.05, * p<0.1.

Table .17: Instrumental Variable Approach: Effects of Changes in College Share on Firms'
Productivity

	(1)	(2)	(3)
First stage			
Net N of dep. moved in		0.001**	
		(0.0005)	
Green land per capita			0.0002***
			(0.00007)
Second stage			
Δ College share	1.698***	2.270***	2.118**
	(0.317)	(0.873)	(0.933)
Δ HC firm	0.054***	0.054***	0.054***
	(0.005)	(0.005)	(0.005)
Δ Market share	0.098**	0.095**	0.096**
	(0.042)	(0.042)	(0.043)
Δ HHI	-0.063	-0.075	-0.072*
	(0.041)	(0.046)	(0.043)
Δ Employment share of industrial sector	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Δ Log cargo	0.006	0.012	0.011
	(0.013)	(0.015)	(0.017)
Constant	0.263***	0.234***	0.242***
	(0.021)	(0.046)	(0.050)
Observations	19,276	19,276	19,276
R-squared	0.025	0.024	0.024

 Changes in college share are instrumented by number of net departments moved in and green
land per capita (square meters) in column (2) and (3) respectively.
 Standard errors are in parentheses.
 *** p<0.01, ** p<0.05, * p<0.1

Table .18: Validation of instrumental variable using 2000 data

	(1)	(2)	(3)	(4)	(5)	(6)
	log per capita Infrastructure Investment			log per capita GDP		
N of dep. moved in	0.047***			0.041***		
	(0.010)			(0.008)		
N of dep. moved out		0.074***			0.057***	
		(0.012)			(0.010)	
Net N of dep. moved in			-0.002			0.004
			(0.011)			(0.010)
Constant	7.384***	8.121***	8.741***	8.881***	9.561***	9.944***
	(0.687)	(0.616)	(0.705)	(0.579)	(0.528)	(0.594)
Observations	233	233	233	233	233	233
R-squared	0.477	0.513	0.416	0.432	0.452	0.364
Province Effects	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table .19: Validation of instrumental variable using 2010 data

	(1)	(2)	(3)	(4)	(5)	(6)
	log per capita Infrastructure Investment			log per capita GDP		
N of dep. moved in	0.041***			0.041***		
	(0.008)			(0.008)		
N of dep. moved out		0.053***			0.052***	
		(0.010)			(0.010)	
Net N of dep. moved in			0.007			0.008
			(0.010)			(0.010)
Constant	9.532***	10.260***	10.536***	10.469***	11.210***	11.460***
	(0.587)	(0.542)	(0.602)	(0.591)	(0.547)	(0.606)
Observations	233	233	233	233	233	233
R-squared	0.351	0.358	0.275	0.419	0.422	0.351
Province Effects	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table .20: Validation of instrumental variable using changes between 2000 and 2010

	(1)	(2)	(3)	(4)	(5)	(6)
	log per capita Infrastructure Investment			log per capita GDP		
N of dep. moved in	-0.006			0.001		
	(0.006)			(0.004)		
N of dep. out		-0.020***			-0.005	
		(0.007)			(0.004)	
Net N of dep. moved in			0.009			0.005
			(0.007)			(0.004)
Constant	2.149***	2.139***	1.795***	1.589***	1.649***	1.516***
	(0.420)	(0.384)	(0.407)	(0.247)	(0.229)	(0.239)
Observations	233	233	233	233	233	233
R-squared	0.646	0.658	0.648	0.464	0.467	0.468
Province Effects	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table .21: Heterogeneity of human capital spillovers across city size and city density (cities classified by entire population)

	(1) Small cities	(2) Big cities	(3) Less dense cities	(4) Denser cities
Δ College share	0.645	2.650***	0.921	2.675***
	(1.326)	(0.526)	(1.536)	(0.334)
Δ HC firm	0.045***	0.060***	0.052***	0.055***
	(0.004)	(0.004)	(0.004)	(0.004)
Δ market share	0.054	0.199***	0.074*	0.138**
	(0.040)	(0.062)	(0.042)	(0.060)
Δ HHI	-0.007	-0.138***	0.013	-0.164***
	(0.038)	(0.044)	(0.037)	(0.042)
Δ employment share of industrial sector	-0.000	-0.001*	-0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
Δ log cargo	0.017	0.029	-0.001	0.019*
	(0.014)	(0.018)	(0.017)	(0.010)
Constant	0.293***	0.194***	0.312***	0.193***
	(0.033)	(0.038)	(0.062)	(0.021)
Observations	8,113	11,163	8,679	10,597
R-squared	0.017	0.030	0.019	0.035

Notes: There are 19,276 firms observed in both 2001 and 2011. These firms are located in 233 Chinese prefectural cities. In column 1 and 2, cities are grouped as small or big cities according to the cutoff of 5.7 millions which is the median size of prefectural cities. Both rural and urban population are considered when constructing the cutoff point.

In column 3 and 4, cities are grouped as less dense or denser cities according to the cutoff of 650 people per square kilometer which is the median population density of the prefectural cities. Both rural and urban population are considered when constructing the cutoff point.

Standard errors are in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table .22: Heterogeneity of human capital spillovers across city size and city density (cities classified by metropolitan population only)

	(1) Small cities	(2) Big cities	(3) Less dense cities	(4) Denser cities
Δ College share	-2.486	2.946***	1.205	2.778***
	(2.369)	(0.606)	(1.081)	(0.409)
Δ HC firm	0.046***	0.057***	0.049***	0.058***
	(0.005)	(0.004)	(0.004)	(0.004)
Δ market share	0.089**	0.116*	0.088**	0.120**
	(0.040)	(0.059)	(0.043)	(0.056)
Δ HHI	-0.008	-0.133***	-0.079**	-0.056
	(0.037)	(0.042)	(0.039)	(0.042)
Δ employment share industrial sector	0.001	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Δ log cargo	0.008	0.031**	-0.032**	0.056***
	(0.011)	(0.013)	(0.016)	(0.010)
Constant	0.373***	0.173***	0.316***	0.170***
	(0.053)	(0.039)	(0.049)	(0.023)
Observations	6,732	12,544	9,679	9,597
R-squared	0.006	0.029	0.022	0.029

Notes: There are 19,276 firms observed in both 2001 and 2011. These firms are located in 233 Chinese prefectural cities. In column 1 and 2, cities are grouped as small or big cities according to the cutoff of 1.5 millions which is the median size of prefectural cities. Only urban population is considered when constructing the cutoff point.
In column 3 and 4, cities are grouped as less dense or denser cities according to the cutoff of 1200 people per square kilometer which is the median population density of the prefectural cities. Only urban population is considered when constructing the cutoff point.
Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table .23: Heterogeneity of Human Capital Spillovers: state owned firms vs. private owned firms

VARIABLES	(1) State firms	(2) private firms
Δ College share	1.107	3.071***
	(0.779)	(0.440)
Δ HC firm	0.050***	0.054***
	(0.006)	(0.003)
Δ market share	0.039	0.151***
	(0.056)	(0.043)
Δ HHI	0.001	-0.119***
	(0.052)	(0.033)
Δ employment share of industrial sector	-0.001	0.000
	(0.001)	(0.000)
Δ log cargo	-0.028*	0.034***
	(0.016)	(0.009)
Constant	0.355***	0.166***
	(0.041)	(0.023)
Observations	5,475	13,789
R-squared	0.023	0.020

Notes: There are 19,276 firms observed in both 2001 and 2011. These firms are located in 233 Chinese prefectural cities.
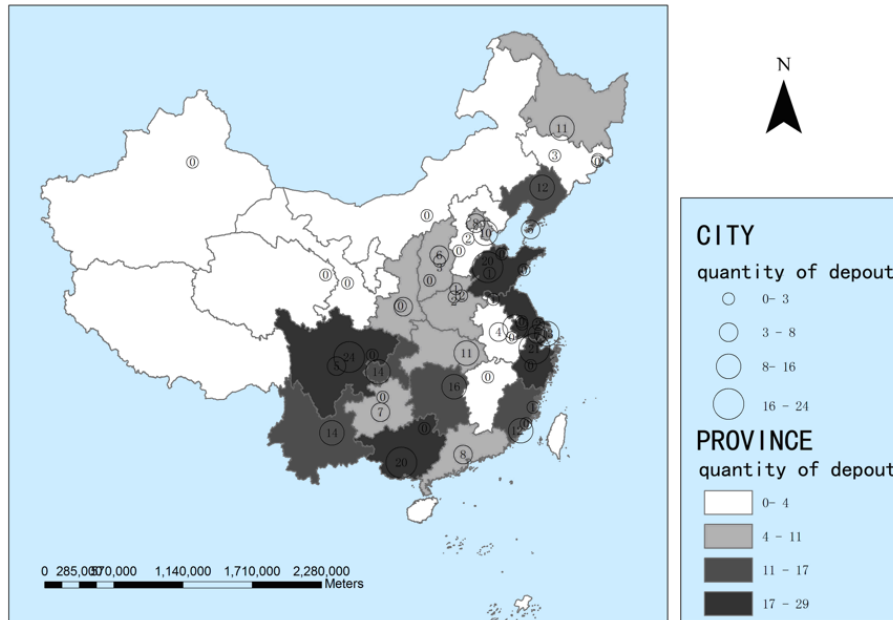Standard errors clustered at city level are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

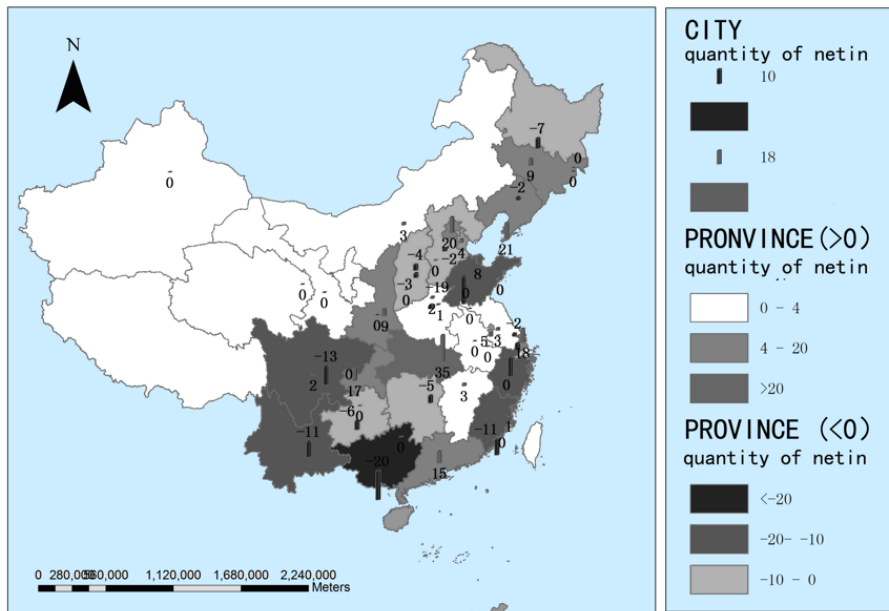Figure .9: The Quantity of University Departments Moved In
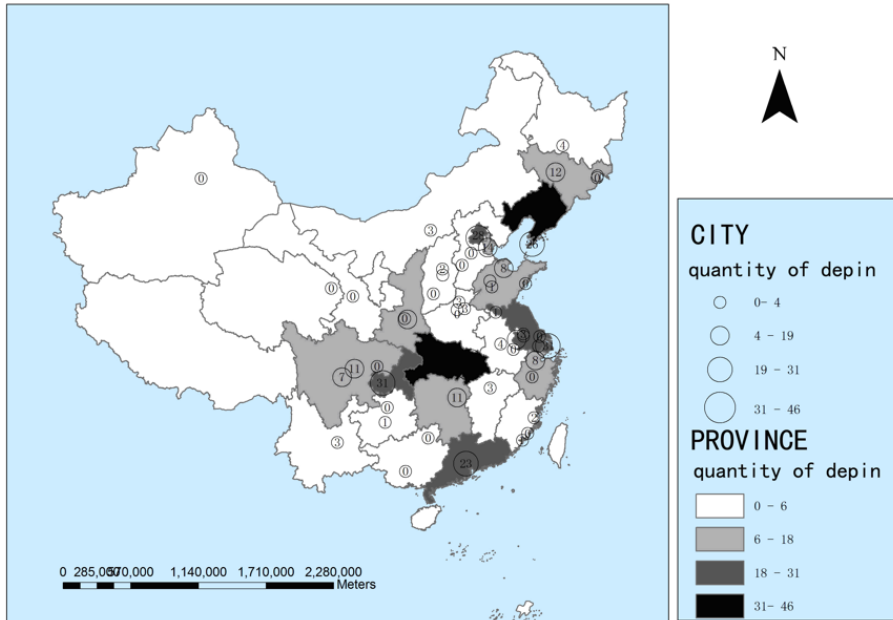
Source: Glaeser and Lu 2018

Figure .10: The Quantity of University Departments Moved Out

Source: Glaeser and Lu 2018

100

Figure .11: The Net Number of University Departments Moved In

Source: Glaeser and Lu 2018

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