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HUMAN-CAPITAL EXTERNALITIES IN CHINA

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ABSTRACT

This paper provides evidences of heterogeneous human-capital externality using CHIP 2002, 2007 and 2013 data from urban China. After instrumenting city-level education using the number of relocated university departments across cities in the 1950s, one year more city-level education increases individual hourly wage by 22.0 percent, more than twice the OLS estimate. Human-capital externality is found to be greater for all groups of urban residents in the instrumental variable estimation.

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I. Introduction

Are human-capital externalities important in swiftly growing economies like China? In Lucas (1988), human-capital externalities generate the increasing returns that enable long-run economic growth. Rauch (1993) and Moretti (2004a) document the strong correlation across American metropolitan areas, between area-level human capital and individual earnings, holding individual years of schooling constant. In this paper, we examine whether these correlations also exist in China, and whether human-capital externalities appear stronger for more- or less-educated workers.

Over the past thirty years, China's average years of schooling have increased from 3.7 to 7.5 (Barro and Lee, 2011).[1] Typical individual based estimates of the impact of schooling on earnings would imply that a four-year increase in education should lead to a 50 percent increase in earnings. In China, private returns to higher education, compared with below-high-school education, have been estimated to be about 30 percent in 2013 (Liang and Lu, forthcoming).

Yet over the past 30 years, China's per capita GDP has gone up by more than 1200 percent. If education has played a significant role in China's rapid growth, then education's aggregate impact must be vastly larger than its individual impact, which suggests a large role for human-capital externalities. Moreover, human-capital externalities can also help to explain why returns to higher education have kept rising, although the number of college graduates has increased to about seven million in 2017 after great expansion in college enrollment since the late 1990s, when the number was one million.

If we follow Rauch (1993) and estimate human-capital spillovers using ordinary least squares (OLS) at the city level for China, we find that for every extra year of schooling at the city level, individual hourly earnings increase by 8.36 percent, holding individual-level and other city-level characteristics constant. For male workers, one year of city-level schooling increases earnings by 9.19 percent. For female workers, one year of city-level schooling increases earnings by 7.06

[1] According to our own estimation based on the population censuses, the average education level increased from 5.2 years in 1982 to 8.2 years in 2010. The number of average education in 1982 is calculated by the authors, while that in 2010 is reported by National Bureau of Statistics.

percent when we consider total salaries for female workers. If anything, the benefits of area-level education appear to be stronger for less educated workers in terms of both magnitude and statistical significance.

As Acemoglu and Angrist (2001) and others have emphasized, there are significant problems with regressing individual earnings on average years of schooling: omitted unobserved human capital and omitted area-level characteristics. Places with unobserved advantages in economic opportunity might also attract workers who are more skilled along unobserved dimensions, which would bias the coefficient upwards. Places with more consumption amenities might also attract more educated workers, and such amenities are typically associated with lower wages in a spatial equilibrium. If the location of skilled workers is fixed, then added migration of less skilled workers to more productive areas could lead toward downward bias in the OLS coefficient, since more productive areas will have a lower average skill level.

There are two typical approaches to addressing these biases: shocks to people and shocks to place. Shocks to people, like the U.S. Moving to Opportunity Experiment, randomly allocated people across space, which addresses unobserved personal attributes. Shocks to places, like the compulsory schooling laws used by Acemoglu and Angrist (2001), or the location of land-grant colleges used by Moretti (2004a), address omitted place-based characteristics, but typically cannot address subsequent sorting on unobservables.

China contains two unique attributes which allow us to address both forms of omitted characteristics simultaneously. During the early years of communism, some areas experienced a radical reduction in their local education institutions, for largely political reasons, and other areas saw their educational institutions grow, again largely because of politics. These changes are robustly correlated with education levels today—each extra department is associated with about 0.032 extra years of average schooling in the area— but not correlated with city characteristics in 1953. Moreover, these department relocations are uncorrelated with investments in infrastructure or capital during the 1950s and 1960s. The economic development strategy during the Great Leap Forward was focused on industrialization, not education.

The second attribute of China is the *Hukou* system, which largely confines urbanites in the cities in which they were born, coupled with the controls of the pre-1990 planning era. Today, rural dwellers are essentially free agents, since they lack *Hukou* rights everywhere, but urban-born citizens sacrifice wildly if they move across areas. Using a nation-wide representative survey for 1 percent of the population in 2005, we estimate that only 4.47 percent of the residents with non-agricultural *Hukou* (household registration identity) and aged 18-65 are migrants across cities.

Moreover, the location of the parents of urban-born workers in 2002 and later, were largely determined during the planned period of China's economy. Their parents, especially if they were well educated, were allocated across locations by the system, not by their free choice, while the *Hukou* identity of their children was largely inherited from their parents. There is little evidence to suggest that more skilled people were sorted by the system into more educated areas, and plenty of evidence to suggest that they often were not. The Cultural Revolution was a particularly extreme case of skilled workers being sent to less skilled areas. Even though the younger college graduates can change their *Hukou* in the city where they work, they can be excluded in our supplementary estimation using the 2005 1 percent population survey, which contains the information of *Hukou* currently and 5 years before.

Consequently, we interpret the impact of department relocations on urban-born workers in 2002 as a relatively clean experiment illustrating the impact of area-level education on individual earnings. The experiment is not perfect. We cannot be sure the department relocations are perfectly orthogonal to all other city characteristics. We cannot be sure that there is no selective historical migration in our estimation using urban sample, although we have excluded current migrants without local *Hukou*. Yet given the difficulties with measuring these human-capital externalities, we believe that this provides a plausible addition to literature.

Our instrumental variables estimate is that on average, an extra year of schooling is associated with 22.0 percent higher hourly wages across cities. The measured effect is more than double the effect estimated by OLS. This larger effect could reflect omitted variables that are correlated with the instrument, but it could also reflect the true impact of area education on productivity. If less skilled people move disproportionately to more productive areas, then the true treatment effect of skills on productivity should be substantially higher than the OLS estimate. We investigate this hypothesis by examining the connection between population flows and academic relocations. We find that population growth seems to have been 1.2 percent higher between 1953-2000 for each extra academic department. The extra supply of labor force in more educated areas might readily explain why the OLS estimate is about one-half of the instrument variables estimate.

We also examine whether these effects are stronger on the most or least skilled. Unlike the OLS results, the instrumental variables results suggest that area-level education has almost the same effect on differently skilled workers. The difference in coefficients is not statistically significant, but since the department shifts seem to have disproportionately attracted the more skilled, the changing pattern of heterogeneous treatment effects between the OLS and instrumental variables results is compatible with the view that extra departments attracted skilled workers who depressed wages for skilled workers.

Even if the area-level impact of area years of schooling is 22.0 percent per year instead of 8.36 percent, the growth of Chinese education is still far from being able to explain the country's massive increase in earnings. Even if a year of schooling increased earnings by 40 percent, four extra years could not explain a 1200 percent rise in per capita GDP. Considering that college graduates, together with other migrants, are moving to large cities with higher educational levels and greater human-capital externalities (Liang and Lu, forthcoming), the role of education for fast growth should have been more important. Another possibility is that human-capital effects at the country level are far higher than effects at the district level, but that is mere speculation.

The next section presents a simple model of human-capital externalities that justifies our estimating equation. Section III describes our data and presents the OLS results. Section IV describes the university relocations and shows correlations between these variables and earlier growth and investment in other area level characteristics. Section V presents our core instrumental variable results and Section VI concludes.

II. Skills and Location

We begin with a model of skills and location designed to fit the Chinese setting. There are two types of labor: skilled labor (H) and unskilled labor (L). We will assume that all skilled workers have *Hukou* status in their city, which induces them to stay in their own location. Consequently, there is an exogenous number of skilled workers H_c in each location, which in our empirical work, will be determined by the relocation of academic departments during the 1950s. Unskilled workers are mobile, and free migration ensures that each unskilled worker receives a utility level of $\underline{U}_L$.

Each firm produces commodities which are sold on a global market at a price of one, using a Cobb-Douglas production function in labor quality (h), traded capital (K), non-traded capital (Z) and labor quantity (N): $A_c h^{\alpha} K^{\beta} Z^{\gamma} N^{\delta}$, where A_c represents the productivity in city c which will also depend on that city's education level.

Labor quality is defined as $\frac{H}{H+L}$. The total population "N" equals H+L. Cities are endowed with a quantity of skilled labor in the city denoted H_c and non-traded capital which is denoted Z_c. Traded capital is elastically supplied at a price of r.

Total welfare for either skill group equals $Earnings * N^{-\phi}$, where N represents total city size and ϕ represents the impact of urban congestion on welfare. We mean the term $N^{-\phi}$ to capture the downsides of density including congestion, pollution and high housing costs. To capture the possibility of local human-capital externalities, we assume that $A_c = A_{0c} H_c^{\vartheta}$.

If we let N_c denote total city population, h_c denote H_c/N_c, W_c^L denote wages for less skilled workers in the city, W_c^H denote wages for more skilled workers in the city and $\Gamma = Log\left(\left(\frac{\delta-\alpha}{\underline{U}_L}\right)^{1-\beta}\left(\frac{\beta}{r}\right)^{\beta}\right)$, then it follows that:

(1) $Log(N_c) = \frac{1}{(1+\phi)(1-\beta)-\delta+\alpha}\left((\alpha+\vartheta)Log(H_c) + Log\left(A_{0c}Z_c^{\gamma}\right) + \Gamma\right)$

(2) $Log(h_c) = \frac{1}{(1+\phi)(1-\beta)-\delta+\alpha}\left(\left((1+\phi)(1-\beta)-\delta-\vartheta\right)Log(H_c) - Log\left(A_{0c}Z_c^{\gamma}\right) - \Gamma\right)$

(3) $Log(W_c^L) = Log\left(\underline{U}_L\right) + \phi\left((\alpha+\vartheta)Log(H_c) + Log\left(A_{0c}Z_c^{\gamma}\right) + \Gamma\right)$

(4) $Log(W_c^H) = Log\left(1 + \frac{\alpha(H_c+L)}{H_c(\delta-\alpha)}\right) + Log\left(\underline{U}_L\right) + \phi\left((\alpha+\vartheta)Log(H_c) + Log\left(A_{0c}Z_c^{\gamma}\right) + \Gamma\right)$

If we assume that $Log(H_c)$ and $Log\left(A_{0c}Z_c^{\gamma}\right)$ are uncorrelated, and the variances of these two terms are σ_H^2 and σ_A^2, and if we regress wages for less skilled workers ($Log(W_c^L)$) on the log of human capital in the city ($Log(h_c)$), we will recover

(5) $\hat{B}_L^{OLS} = \frac{\left((1+\phi)(1-\beta)-\delta+\alpha\right)\left(\left((1+\phi)(1-\beta)-\delta-\vartheta\right)\phi(\alpha+\vartheta)\sigma_H^2 - \phi\sigma_A^2\right)}{\left((1+\phi)(1-\beta)-\delta-\vartheta\right)^2\sigma_H^2+\sigma_A^2}$

If we have an instrument for H_c, then the estimated coefficient would equal

(5') $\hat{B}_L^{IV} = \phi(\alpha+\vartheta)\left(1 + \frac{\alpha-\vartheta}{(1+\phi)(1-\beta)-\delta-\vartheta}\right)$

The instrumental-variables estimate equals the OLS coefficient when $\sigma_A^2 = 0$. When $\sigma_A^2 > 0$, the instrumental-variables estimate is larger than the OLS coefficient. The downward bias in the OLS coefficient occurs because when areas have exogenous production advantages, including non-traded capital, then this will attract more less skilled workers. This will bias the coefficient downwards.

III. Data Description and Ordinary Least Squares Results

We now apply our theoretical framework to Chinese data. We use individual-level data from the 2002, 2007 and 2013 Chinese Household Income Project Surveys (CHIP2002, CHIP2007, CHIP2013) for urban households. These data were collected in collaboration with the National Bureau of Statistics of China using a two-stage stratified systematic random sampling scheme. The surveyed cities and county towns were selected randomly in the first stage. In the second stage, households were selected using a multiphase sampling scheme.

The 2002 survey covers 70 cities and county towns from 10 provinces, namely, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Sichuan, Yunnan and Gansu, as well as two municipalities, Beijing and Chongqing, with a sample size of 6,835 households and 20,632 individuals. The 2007 sample covers 19 cities and county towns from seven provinces, Jiangsu, Zhejiang, Guangdong, Anhui, Henan, Hubei and Sichuan, and two municipalities, Shanghai and Chongqing. The 2007 survey covers 5,000 households and 14,699 individuals. The 2013 urban samples are from 124 cities from 12 provinces and two municipalities, Beijing and Chongqing. It covers 6,674 households, and 19,987 individuals. The data sets contain a wide range of individual demographic and economic information such as information on gender, education and work experience.[2]

The individuals included in this study have local household registration (*Hukou*) identities, which means that rural residents and migrant workers are excluded from the study. Since migrant workers selectively choose where to work, while local urban residents usually do not migrate across cities

[2] For detailed description on sampling methods and data of CHIP 2002 and 2007 surveys, see Gustafsson, Li, and Sicular (2008) and Li, Sato, and Sicular (2013). The 2013 information is estimated from the data set.

because of the high migration costs associated with *Hukou* identity, our results are more likely to reflect the causality from city characteristics to individual-level wage.[3] The data of city-level per capita schooling are from population census data in 2000. Other city level characteristics are from *China City Statistical Yearbook.*

The empirical model is an extension of standard wage equation as follows:

$$(1)\ \ln\left(wage_{ij}\right) = \beta_1 H_c + \beta_2 H_{ij} + \beta_3 X_{ij} + \beta_4 X_c + \varepsilon_{ij}$$

where $\ln\left(wage_{ij}\right)$ is the logarithm of individual-level hourly wage or monthly wage, H_c is the average years of schooling at city level, and the coefficient β_1 captures the human capital externality, H_{ij} is individual's years of schooling, X_{ijj} is a vector of individual characteristics, including experience (age minus years of schooling minus six), gender, marital status, ethnicity, occupation, and industry.

The term X_c captures city-level variables other than education that may influence wages. We include road area per capita in 2000, the ratio of secondary industry's GDP to tertiary industry's and the size of the city. We capture city size both with two indicator variables whether the city is in the top or middle tercile of population size, and with indicator variables denoting whether the city is a provincial capital or municipality.

We report results with both hourly and monthly wages. A small fraction of samples did not report their working hours, so we cannot compute hourly wage for that sample, and we exclude them from both the hourly wage and monthly wage regressions to keep the samples comparable.[4]

In Table 1, our first OLS regression finds that one more year of city-level education is associated with a 13.8 log point increase in hourly wage and an 11.9 log point increase in monthly wage, respectively, when we do not control for other city characteristics. When we control for other city characteristics, the coefficients of city-level education fall to 0.084 and 0.067 for hourly wage and monthly wage respectively.

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[3] Actually, we replicated all the results using samples including migrants, most of whom are rural-to-urban migrants. All the results remain with only slight changes in coeffecients and statistical significance.

[4] Including these samples without hourly wage does not significantly alter the results of wage regression.

We supplement these findings by using the urban sample of the 2005 one percent population survey. The OLS estimation shows that one more year of city-level education is associated with a 6.12 log point increase in hourly wage. In Table 1, the estimated social returns to education are typically larger using the hourly rather than the monthly wage, perhaps because the hourly wage more directly captures productivity. The estimated private return to years of schooling are 0.0612 and 0.0478 for hourly and monthly earnings, respectively, suggesting that in China, the social returns to schooling are far higher than the private returns.

[Table 1 about here.]

The positive relationship between city-level education and individual wages could easily reflect a tendency of people who are richer or have more unobserved human capital, to sort into cities with higher human capital. One test of this hypothesis is whether individuals with more non-labor income sort into more skilled cities, since individuals with higher non-labor income are wealthier but should not have differential returns to participating in more skilled labor markets. Using CHIP 2002 data, we compute the level of non-labor income, measured as the difference between total income and labor income. Non-labor income is not significantly related to city-level education.[5] This result mitigates the view that the positive relationship between labor income and city-level education is driven by the sorting of exogenously wealthier individuals. Unfortunately, for identification, it remains quite plausible that sorting on unobservable characteristics mirrors sorting on observable characteristics.

The regressions show gender differences in the Chinese labor market, which are smaller for hourly wages than monthly wages. The larger monthly wage gap is driven partially by the fact that women work less. Hourly wages show greater and more significant returns to experience than monthly wages. Younger workers work longer hours. Road development is associated with higher income, and so is city size.

[5] To save space, this result is not reported here but is available upon request.

We next explore the complementarity between area-level human capital and individual-level characteristics, including individual education. We run separate regressions for samples with 9 years of education or less, 9 to 12 years of education and more than 12 years of education. Area-level human capital has a positive impact on both hourly and monthly earnings for all three groups. But the effect of area skills is weakest for the most skilled workers, presumably because an abundance of skills satiates the demand for the skilled.

City-level education has the strongest positive effect on the least educated group of workers. Presumably, this effect reflects that while skilled people substitute for one another, an unskilled person may complement a skilled individual, either in the same firm or by providing services for the skilled. We will revisit these patterns when we turn to our instrumental variables estimates.

Table 2 shows that private returns to education and experience are most significant for most educated workers. The gender gap in both hourly and monthly wage is smaller for the most skilled workers, perhaps because less skilled workers specialize in manual labor while more skilled workers are more likely to work with their minds.

[Table 2 about here.]

To investigate cross-industry differences, we divided our samples into three industrial groups: abstract services, manual services, and manufacturing. Abstract services are defined as “finance and insurance,” “real estate,” “health, sports and social welfare,” “education, culture and arts, mass media and entertainment,” “scientific research and professional services,” and “government agents, party organizations and social groups.” They are meant to reflect human capital intensive occupations. Manual services include “transportation, storage, post office and communication,” “wholesale, retail and food services,” and “social services.”

The impact of area-level education is slightly higher in manufacturing jobs, but lower in manual services and even insignificant in abstract services. These differences may be explained by the substitution effects among skilled labors that reduce positive human-capital externalities in more skill intensive service jobs. This will also be revisited in the instrumental variable estimation.

[Table 3 about here.]

The impact of area education is larger for male workers than for female workers. As male workers work more hours, they may have more interactions with others, which could lead them to benefit more from the skills of the workers that surround them.

[Table 4 about here.]

Among China's city dwellers with urban household registration (*Hukou*), some were born in rural area and moved to cities later in their life. Once they get their urban household registration, they often stay for their whole lives, because local public-service access is based primarily on residents' household registration. In the CHIP 2002 data, we know whether an urban resident was born in a rural area.[6] As in the US, Chinese cities with bigger population size and better educated residents gained more in population growth (Chen and Lu, 2012). We can expect that rural-urban migrants would be optimally choosing across cities, while city dwellers need to stay in their home district to enjoy their *Hukou* status.

Consequently, we expect the selection effect to be greater for rural-born residents, while urban dwellers should have experienced a greater treatment effect from living in the city, at least if some part of the urban productivity premium is achieved over time (Glaeser, 1999). When we distinguish urban residents into "urban-born" and "rural-born," we find that the impact of area-level education is stronger on rural-born workers. Rural-born workers' hourly and monthly wages increase by 19.8 percent and 25.7 percent respectively as average education in the city increases by one year. Urban-born workers' hourly and monthly earnings increase by 13.9 percent and 12.7 percent as average education in the city increases by one year. The difference suggests that sorting is a significant issue.

[Table 5 about here.]

[6] In CHIP 2007, we do not have a similar variable to distinguish migrants from local.

To check the robustness of our results, we exclude those workers who report their working time as less than 7 hours per week or if their monthly wage is the lowest 10 percent. The coefficients become slightly lower but still highly significant.

[Table 6 about here.]

IV. University Relocation and Shifting Education Levels

There are two significant omitted variables problems associated with identifying place-based effects, such as human-capital externalities or agglomeration effects: individual omitted characteristics and place-based omitted characteristics. Omitted individual variables are always likely to be important when measuring human-capital externalities, since it is hard to imagine that a place would attract more formal skills without also attracting more informal skills. Omitted place-based variables may be more likely to be important when measuring agglomeration economies, since it is hard to imagine an unobserved place-based productivity shifter that doesn't increase both population and productivity. However, it is possible and even likely, that both problems operate in both estimation exercises.

As our model discussed, omitted place-based variables may bias measured human-capital externalities downward if they impact the location of the unskilled more than the location of the skilled. If the unskilled follow productivity, but the skilled are fixed by the registration system, then measured skill levels will be lower in more productive areas. Unobserved productivity differences only bias human capital externality regressions if more productive places attract a greater share of skilled workers.

There are two reasonable quasi-experimental approaches to addressing both empirical problems: shocks to people and shocks to place. Shocks to people occur when policies, such as the U.S. Moving to Opportunity Experiment or the random assignment of immigrants to Swedish cities, randomly locate some people in some places and other people elsewhere. These shocks address the problem of unobserved individual heterogeneity, but they do not address the problem of unobserved place-based heterogeneity. A policy that randomly assigns some people to Detroit and some people to New York will identify the effect of being in New York vs. Detroit, but not why New York has a different effect.

Shocks to place, by contrast, do not directly address the unobserved personal heterogeneity, but they can identify the channel of a place-based effect if it exists. For example, a randomly placed million-dollar plant in an area (Greenstone, Hornbeck and Moretti, 2010), is a shock to place that may well identify an agglomeration effect. If researchers can hold the characteristics of the people constant, perhaps with panel data before and after the event, then they can also address omitted individual personal characteristics. But without such controls, they can also identify the combined effect of the place-based intervention and subsequent sorting of individuals.

In this paper, we use China's university relocations of 1952 as an external shock to Chinese cities that should operate through the area's human capital stock. Universities have strong effects on human capital accumulation. Although university development usually depends on historic factors and economic growth, modern China experienced a unique, large-scale relocation of university departments in the 1950s, shortly after the foundation of the People's Republic of China.

The influence of the Soviet Union persuaded Chinese leaders to follow their highly specialized university system, which focused on concrete skills rather than liberal arts. The number of comprehensive universities was greatly reduced. They were replaced by single discipline colleges of science or liberal arts, or multi-disciplinary universities of science and technology. Many colleges specialized in iron and steel, geology, mining, water conservancy, and aviation. A large number of normal universities were established during the movement of relocating university departments.

Moreover, to spread communist ideology, the Party wanted to remove the influence of the pre-existing education system. Party leaders didn't trust the intellectuals who grew up under the governance of the National Party and were trained in the U.S. or Europe. Until the first half of 1952, education reform was gentle and modest. As the economy improved, and following the accomplishment of land reform, Chairman Mao changed his attitude about capitalism. In the second half of 1952, the great transformation of capitalism to socialism was launched.

In the field of education, the central task was to serve the socialist transformation. As stated in the Agenda of National Relocation of University Departments that was released in 1952: "the higher education system in old China basically served imperialism and anti-revolutionary governance, and was a product of the past semi-colonial and semi-feudal society," and "Without a thorough adjustment and fundamental reform of the old education system and old higher education framework, the country's construction cannot go ahead smoothly."

To carry out the plan of relocating university departments, the central government established the Ministry of Higher Education in 1952. With the support of local governments, the nation-wide movement of reallocating university departments was almost realized in 1952. Financial input was also supportive for the education reform. From 1950 to 1952, education expenditures accounted for 5.49 percent of national total fiscal expenditures. The basic construction of infrastructure for education accounted for 5.7 percent of the national total investment accomplished for infrastructure.[7] By contrast, in 1949, only 4.1 percent of national spending went for the combined category of culture, education and medical care.[8]

All the private colleges and universities were nationalized. The total number of higher educational institutions was reduced from 211 to 182. Specialized technology schools accounted for 137 of the schools. All political science, sociology, psychology and anthropology departments were cancelled, while finance and law were compressed. The number of comprehensive universities shrank from 55 to 13. The percentage of students majoring in the humanities and social sciences dropped from 33.1 percent to 14.9 percent.[9] In the 1950s, when multi-disciplinary trends became popular in the development of science, China became a country with few comprehensive universities, and few students majoring humanities and social sciences.[10]

The relocation of university departments occurred not only across institutions, but also across regions. Staff and students, as well as facilities and libraries, were moved. Modern Chinese history tells us which departments were moved in or out of a university.[11] Among the 502 departments moved out of a school, 282 moved to different cities. Among the 623 departments moved in, 333 came from a different city. The discrepancy between the number of departments moved in and out reflects the creation, destruction, division and merge of departments.

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[7] Data source: The Central Institute for Educational Studies (eds.), *The* Memorabilia of China's Education Development (1949-1982), Education Science Press, 1983, P. 71.

[8] The numbers are quoted from Li (2004).
[9] The numbers are quoted from Li (2004).
[10] The brief history of the relocation of university departments is based on Li Yang (2004).
[11] All the data we construct for the relocation of university departments are from Ji (1990).

We don't have complete data of the number of university staff and students who migrated during the movement, but the information is available for 314 top scientists who experienced the movement of the relocation of university departments. Among them, 74 percent, or 232 of the 314, were relocated to other universities, colleges or institutions. According to the information provided in the appendix to Shen (2008), 43 out of 158 top scientists who changed their working units within university system were moved to different cities during the relocation of university departments. According the same source, 38 out of 74 top scientists who were moved out of universities to other institutions migrated to other cities. Out of the seventeen who moved from other units to universities, ten left their current cities. An extreme case is Zhejiang University, where 22 out of 24 top scientists who were moved were sent to different provinces.[12]

One understanding of the university department reallocation movement is that the central government wanted to equalize the spatial distribution of universities. Data show that the Gini coefficient of university numbers at the provincial level declined from 0.56 in 1949 to 0.43 in 1957. It is worth stressing that the Gini figures are somewhat difficult to compare because of the shift in the number and nature of universities. Until the end of 1953, the numbers of universities in the North, Northeast, and Northwest increased significantly, while the East and Southwest lost universities (Shen and Liu, 2008).

Lacking the numbers of university departments and staff in the 1950s, we ran a simple correlation between the city-level numbers of departments that had moved in and moved out.[13] The correlation coefficient is 0.44, showing a slightly positive correlation between the two, meaning that the places that gained more also lost more. This correlation suggests a broad pattern of churning, but it does not favor particular spots.

Figures 1a to 1d show the maps of the number of universities, the number of departments moved in, moved out and the net number of departments moved in. Again, from the maps, we can see that the cities where more departments were moved out also gained more departments. The net number of departments moved in does not follow a clear spatial pattern.

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[12] The original information of the top scientists is from the Compiling Team of Scientists Biographies (ed.), *The Biographies of Modern Chinese Scientists*, Vols. 1-6, Science Press, 1991-1994.
[13] The two variables are constructed by the author, based on Ji (1990).

[Figures 1a, 1b, 1c, 1d about here.]

For university department relocations to provide a valid shock to place, these relocations must be orthogonal to initial city characteristics and orthogonal to subsequent national actions that could easily shape the course of urban success. Table 7 examines the correlation between department relocation and city characteristics as the first population census in 1953. We regress the number of relocated departments on the initial number of departments, urban population size, and location dummies for the North, Northeast, Northwest, East and Southwest, with the Middle-south omitted as the reference group.[14]

The results show that cities with more departments initially do send and receive more departments. The correlation of initial number of departments with the net change in departments is statistically insignificant and modest in size. The correlation of net change in departments with city size is also statistically insignificant and modest in magnitude, although the correlation between city size and number of departments moved in is significant. These results cannot prove that the department shifts were random, but they are somewhat reassuring.

The Southwest and Northwest dummies are significant when the dependent variable is the number of departments moved in, but the null hypothesis of united insignificance of the regressors cannot be rejected. Moreover, none of the regional dummies significantly predict the net change in the number of departments at city level. The results are somewhat different from Shen and Liu's (2008) results on changes in numbers of universities at great regional level.

This quasi-experiment is not a true experiment. Moreover, data limitations make it impossible for us to know whether there are other place-level variables that are correlated with changes in the number of departments. Yet the history of the era doesn't suggest any obvious link between

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[14] During 1950-1954, China was governed by six great regions for party, administrative and military affairs. The North included Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia. The Northeast administered Liaoning, Jilin and Heilongjiang. The East covered Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi and Shandong. Henan, Hubei, Hunan, Guangdong, Guangxi and Hainan belonged to the Middle-South. Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang were in the Northwest region. These six great regions are also used to look at the regional distribution of university numbers before and after the relocation movement in Shen and Liu (2008).

economic forces and the decision to relocate departments. Moreover, the modest 1953 data that we have also fails to show any obvious correlations.

[Table 7 about here.]

Even if the department relocations were independent of city characteristics in 1952, they might impact economic development through channels other than education. For example, if a school educates national leaders, they may feel a connection with a locality and favor it. Alternatively, a school might have been favored in 1952 because it had politically powerful graduates who might have also favored the locale in other ways.

Fudan University, a top university in China today but weak before 1952, seems to provide anecdotal evidence for such forces. The president of Fudan in 1952 was Mr. Chen Wangdao, who was also among the first generation of CCP members and had a close relationship with the central government. Other anecdotes, however, point in the opposite direction, in some cases, because connected scientists didn't necessarily want to stay at their university.

During the university relocation, many top scientists of Zhejiang University in Hangzhou, the capital city of Zhejiang Province, were moved to Fudan. Zhejiang University lost significantly during the relocation. It was among the top and comprehensive universities before the movement, but specialized in science and technology thereafter, and its ranking fell.

The presidents of Zhejiang University were Ma Yinchu during 1949 to 1951, and Sha Wenhan during 1952 to 1953. Mr. Ma was a Ph. D. in economics from Columbia University and worked as Deputy Director of the Economic and Financial Committee of State Council, the Vice Chairman of Eastern China Military and Political Committee, and was a member of the First, Second and Fifth Standing Committee of the People's Congress, and the Second, Fourth and Fifth Standing Committee of the National Political Consultative Conference. Mr. Sha was sent to the Soviet Union to study Marxism in 1929, and worked as a leader in Jiangsu Province and Shanghai. When he took over the job of President of Zhejiang University, he was Governor of Zhejiang Province. So, a university could still lose mightily despite having powerful, well-connected leaders.

One test of the hypothesis that connected cities received universities is whether university relocations predict other forms of government investment in the 1950s and 1960s. Any correlation between physical investment and department reallocation would compromise our instrument. To test this possibility, we construct a city-level investment data set.[15] In Tables 8 and 9, we regress per capita fixed capital investment and infrastructure investment averaged over 1953-1969 on changes in the number of academic departments in the city.

The first three regressions in Table 8 show per capita fixed capital investment averaged over 1953-1969 on number of departments moved in, moved out, and the net change in the number of departments. The next three regressions repeat these three, controlling for per capita fixed capital investment averaged over 1945-1952. In none of the regressions are the changes in the number of departments (in, out, or net) significant either statistically or economically. Per capita fixed capital investment during 1945-1952 is always significant. Controlling for earlier investment eliminates some of the noise in the level of later investment.

Table 9 repeats these regressions using per capita infrastructure investment as the dependent variable. Again, changes in the number of departments are not significantly correlated with the investment variable.

[Tables 8 and 9 about here.]

Based on the above analysis of the history, the relocation of university department in the 1950s is plausibly a place-specific shock to city-level human capital. Besides the migration of staff and students during the movement, local middle-school students were given more quotas in the admission of local universities under the higher education system.

Yet as discussed earlier, shocks to place don't necessarily solve the problem of omitted individual characteristics, which can still make inference difficult. In this case, we cannot observe a panel closely before and after the shock. We must instead rely on institutional features of China between

[15] We owe Binkai Chen for his great help in construction of the historical data of investment. Please see the appendix for the details of how the data are constructed.

the 1950s and the early 1990s. During this period, college and university graduates were generally assigned to their jobs through the planned system. That planned system did not particularly favor the sorting of skilled people into skilled places. Indeed, the Cultural Revolution did just the opposite. Only in recent decades has it become possible for skilled workers to readily move across metropolitan areas, and even there, the *Hukou* system limits migration.

In our analysis, we seek to limit the impact of migration and selection based on unobservable attributes. Consequently, we focus on individuals who have the local *Hukou*, especially who report being born in an urban area. Those individual mobility choices would have been largely constrained by *Hukou*. Workers in 2002 would have had their location of birth determined entirely by the planned system. By using the relocation of departments and focusing on urban workers, we are trying to identify a place-based treatment that is orthogonal both to ex ante city characteristics and ex post investment in physical capital. Moreover, the educated workers at least had little ability to select across place.

This does not mean that our experiment is perfectly clean. Few shocks to place resemble laboratory experiments. But the nature of decision-making in 1952, and the constraints on mobility during the planned era, turn this into a relatively clean setting to examine the impact of a shock to area-specific human capital. As such, we do not view our results as definitive estimates of the human-capital externalities, but as contributions to a broad literature on this important topic.

V. Human-capital externalities based on University Relocation

Based on the history of university relocation, we construct our instrumental variable, the net number of departments moved into a new city. For the baseline regression, the weak instrument F test yields a value of about 20.1 as reported in Table 10. In all the remaining IV estimations, the weak instrument F tests always yield a value of 12.31. After using IV, the human capital externality is raised to 22.0 percent, more than twice the OLS estimates for hourly wage. This means the OLS estimation mainly suffers from missing a variable bias that is downward due to labor market competition. If we use the 2005 1 percent population survey data, the human capital externality is raised from 0.0612 in OLS estimation to 0.219 percent in IV estimation, exactly the same as using CHIP data. In Table 10, human capital externality is still positive, but not significant at 10 percent level for monthly wage formation. This means the hourly wage bears more information of productivity, and it's affected more significantly by human capital externality.

[Table 10 about here.]

If labor market competition tends to reduce the estimated impact of human-capital externalities in OLS estimation, this downward bias should be greater for college graduates, because they compete with each other as they agglomerate. When comparing Table 11 with Table 2, we find that our IV estimates show a greater change in the coefficient on city-level education for more skilled labor. The magnitude of the difference between the coefficients of city-level education for different education groups almost disappears in the IV estimation. Again, when using the hourly wage, the human capital externality is both more economically and statistically significant for all three groups.

[Table 11 about here.]

The estimated magnitude of the human-capital externalities still differs substantially between service and manufacturing in the IV estimations. For all three industries, the coefficients of city-level education almost double or triple the corresponding OLS coefficients. For abstract services, though the coefficient increases significantly after using IV, this effect is still lower than the estimated human-capital externalities within manual services and manufacturing jobs. This difference may occur because college graduates in abstract services receive higher amenities, in lieu of payment, or because they expect to earn even higher wages over time.[16]

[Table 12 about here.]

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[16] We also used IV estimation for gender heterogeneity of human capital externality. Men's coefficients for city-level education are still greater than women's, though both almost double after using IV.

VI. Conclusion

Since Alfred Marshall, economists have wondered whether knowledge spillovers make places more productive. Marshall's hypothesis seems to imply that skilled places will be particularly productive, and such spillovers also lie behind many theories of economic growth. China's rapid economic expansion occurred at the same time as a massive increase in the level of China's schooling. That schooling may have played a major role in China's success, but only if education did more than merely increase private returns. In this paper, we estimate the social returns to schooling at the city level in China.

We use university relocation in 1952 as an external shock to city-level education in China. Some cities gained by moving university departments in from other cities, while some cities lost by moving university departments out. Before using instrumental variable, the OLS regressions show that one year more in the city-level education leads to an 8.36 percentage point increase in hourly wage. After using our IV approach, the estimated human capital externality increases to 22.0 percent, more than twice the OLS estimates. The gap between OLS and instrumental variables estimates may result from the disproportionate migration of less skilled workers in the more productive cities. We find that after using IV, the change in the estimate of human capital externality is greater for the most skilled workers.

This paper argues that not only in developed countries, but also in developing countries like China, human-capital externalities are both statistically and economically significant. In the past 40 years, China has had a great achievement of human capital accumulation. Human-capital externalities amplify the returns to education and help explain why China has grown. Yet even with these large human capital externality estimates, education does not explain all or most of China's growth since 1990. If education explains that growth, then national returns to human capital must be even larger than the regional returns to human capital. More plausibly, much of China's growth also reflects other changes, including capital deepening and the opening of trade with the rest of the world.

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Appendix: Data for city-level investment

In *China Compendium of Statistics 1949-2004* (NBS, 2005), the provincial-level historical data of investment variables include investment in fixed assets, investment in capital construction, and investment in innovation. In general, investment in fixed assets is the sum of investment in capital construction, and investment in innovation, except for some missing values of investment in innovation. Investment in capital construction is the closest variable we can find for infrastructure investment.

To construct city-level investment data, we used enterprise census data in 1995, which surveyed the enterprises' year of establishment and their original values of fixed assets. By assuming the enterprises' original values of fixed assets were purchased in their year of establishment, we aggregated enterprise-level original values of fixed assets, and got city-level and provincial-level fixed assets throughout 1949 to 1978. Then we computed each city's share in the provincial investment. This share is used to time provincial-level investment in fixed assets and investment in capital construction to construct the corresponding two variables at the city level.

The second step is to match the city-level investment data with China's city-level population census data in 1953 and 1964. Then we computed city-level investment variables by taking the average of investment variables from 1953-1969 divided by the population in 1964 to get the per capita investment variables from 1953-1969. By the same token, we computed city-level investment variables by taking the average of investment variables from 1949-1952 divided by the population in 1953 to get the per capita investment variables from 1949-1952.

Figure 1a: The Quantity of Universities in the 1950s

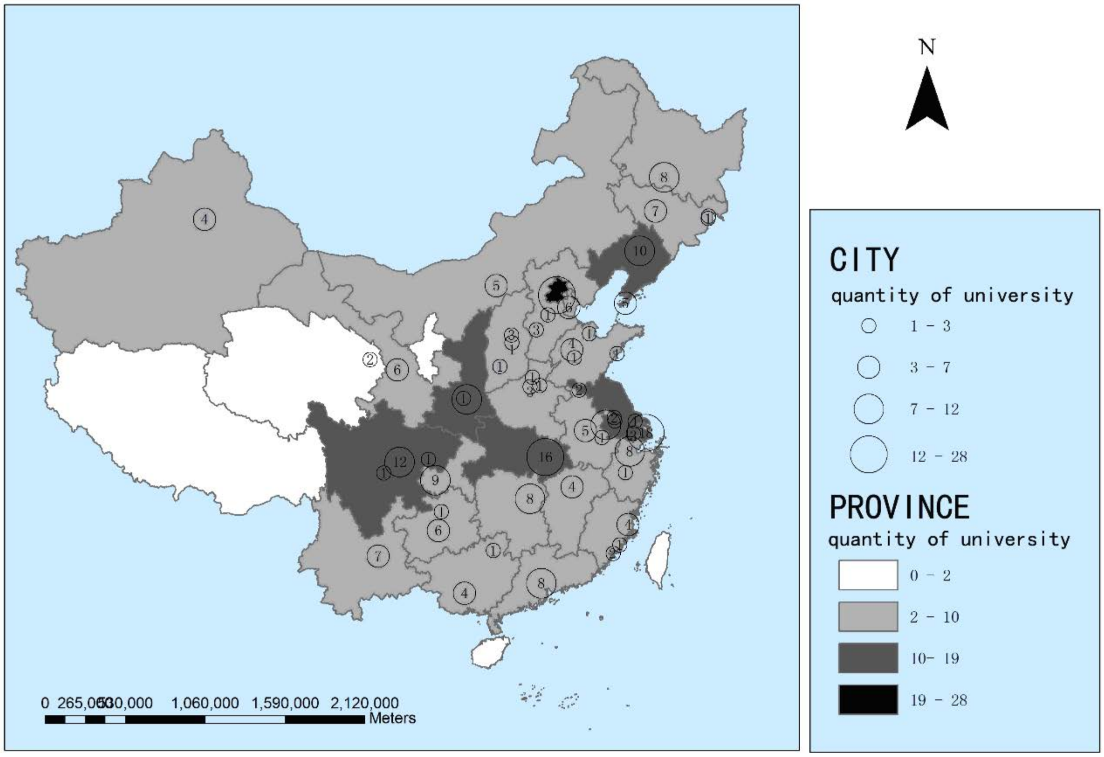
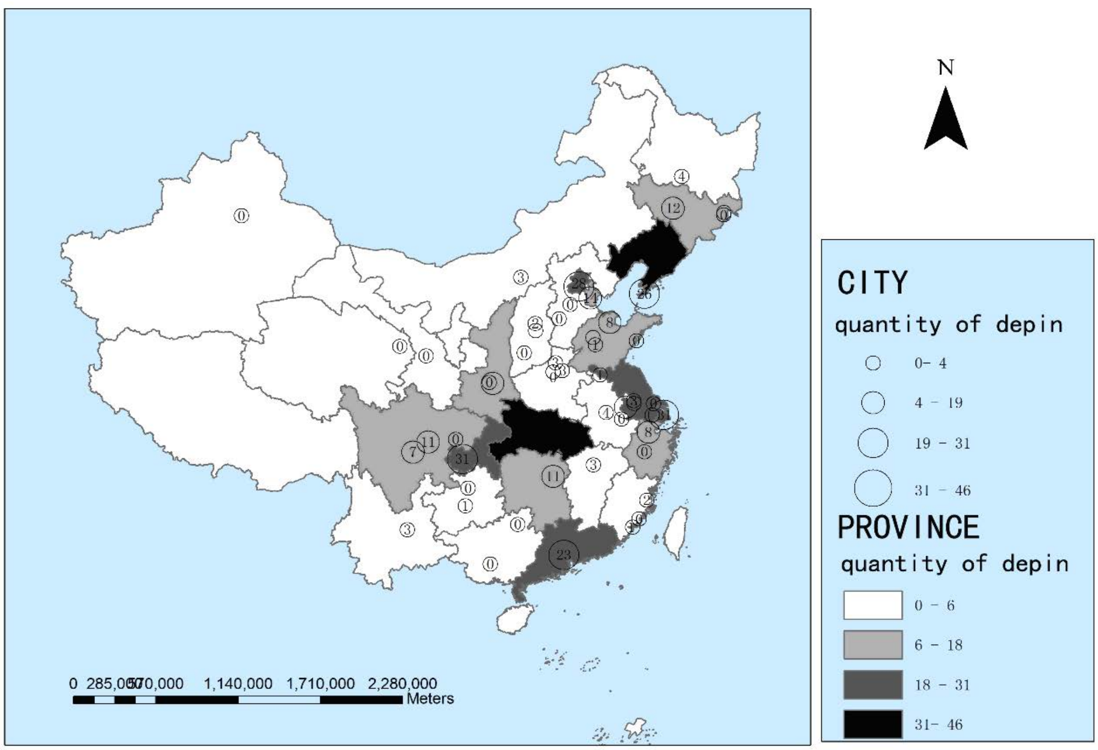
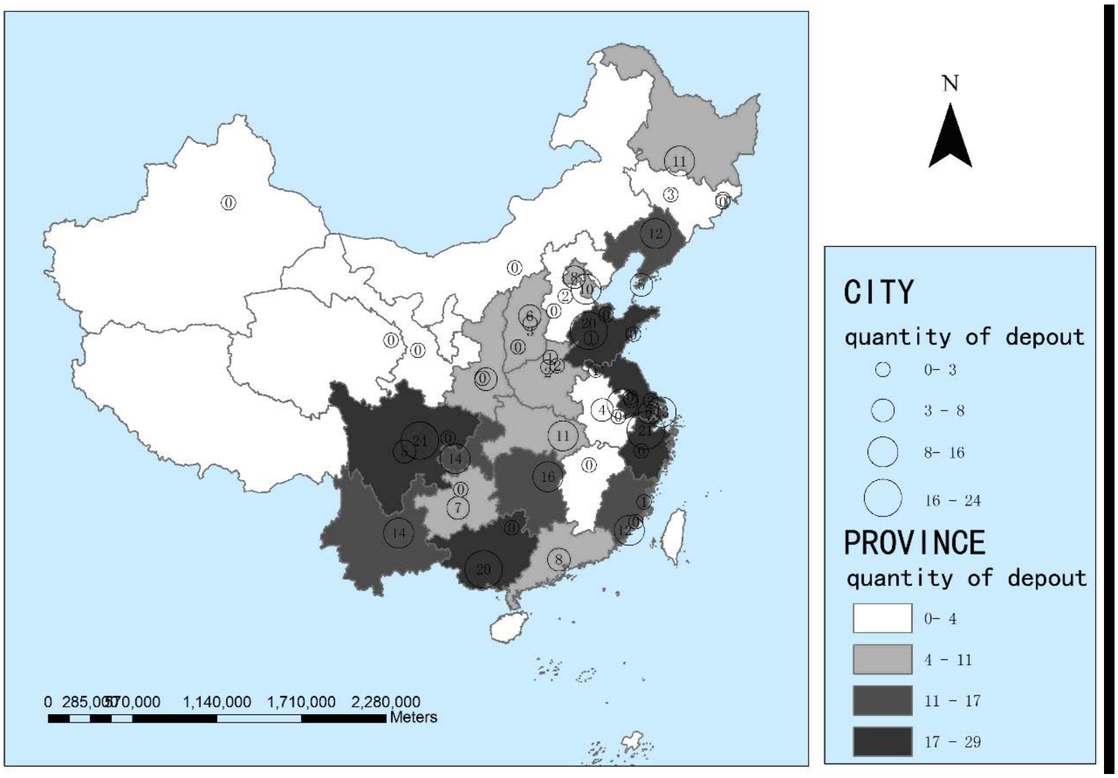


Figure 1b: The Quantity of University Departments Moved to a New Location



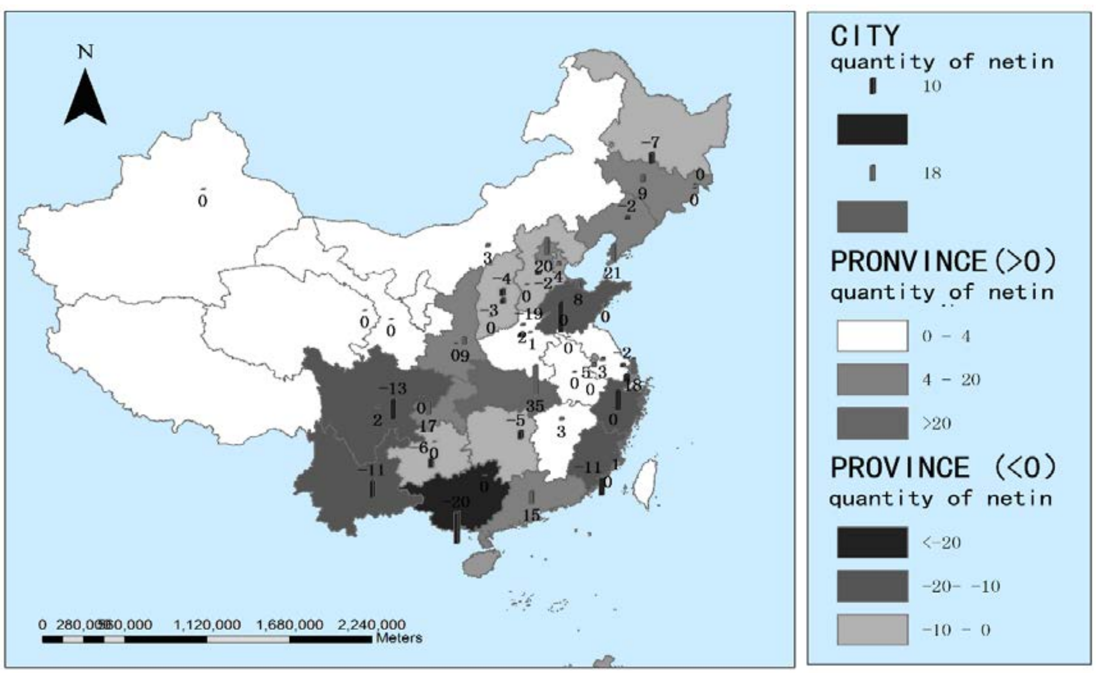
Note: "dep in" = department moved to new location

Figure 1c: The Quantity of University Departments Moved Out of Original Location



Note: "depout" = department moved out of original location

Figure 1d: The Net Number of University Departments Moved to a New Location



Note: Taiwan is blank because of no data.

Table 1: Human Capital Externality

	(1)	(2)	(3)	(4)
	lnwagehour	lnwagemonth	lnwagehour	lnwagemonth
educity	0.138***	0.119***	0.0836***	0.0666**
	(0.0283)	(0.0281)	(0.0306)	(0.0322)
edu	0.0614***	0.0480***	0.0612***	0.0478***
	(0.00420)	(0.00319)	(0.00426)	(0.00337)
exp	0.00900***	0.00216***	0.00922***	0.00236***
	(0.00130)	(0.000804)	(0.00127)	(0.000837)
expsq	-0.00119***	0.00000738	-0.00118***	0.0000154
	(0.0000873)	(0.0000320)	(0.0000841)	(0.0000303)
gender	-0.171***	-0.220***	-0.169***	-0.219***
	(0.0104)	(0.00907)	(0.0105)	(0.00900)
marriage	0.252***	0.178***	0.237***	0.166***
	(0.0299)	(0.0224)	(0.0289)	(0.0221)
ethnicity	-0.491***	0.144***	-0.487***	0.151***
	(0.0842)	(0.0316)	(0.0845)	(0.0319)
bigcity			0.0848	0.0704
			(0.0687)	(0.0680)
medcity			-0.0510	-0.0657
			(0.0631)	(0.0599)
structure			0.0510	0.0554
			(0.0441)	(0.0393)
lnroad			0.246***	0.202***
			(0.0571)	(0.0539)
_cons	0.188	5.119***	0.173	5.162***
	(0.269)	(0.269)	(0.290)	(0.281)
Observations	25428	25428	25428	25428
R-squared	0.664	0.483	0.673	0.496

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of dummies of occupation, sector, ownership types of working units, year 2007, and year 2013 are not reported.

Table 2: Heterogeneity of Human Capital Externality by Education Group

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		Log hourly salary			Log monthly salary	
	edu≤9	9<edu≤12	edu>12	edu≤9	9<edu≤12	edu>12
educity	0.0985***	0.0888***	0.0769*	0.0734**	0.0658*	0.0674+
	(0.0290)	(0.0324)	(0.0396)	(0.0283)	(0.0364)	(0.0410)
edu	0.0250***	0.0163	0.0458***	0.0208***	0.0118	0.0436***
	(0.00554)	(0.0144)	(0.0129)	(0.00459)	(0.0115)	(0.0115)
exp	0.00878***	0.00905***	0.0105***	-0.00249**	0.00261***	0.00854***
	(0.00194)	(0.00119)	(0.00119)	(0.00107)	(0.000916)	(0.00114)
expsq	-0.000926***	-0.00174***	-0.00296***	0.00000167	-0.0000269	-0.000242
	(0.0000693)	(0.000167)	(0.000616)	(0.0000337)	(0.0000862)	(0.000368)
gender	-0.209***	-0.182***	-0.138***	-0.265***	-0.219***	-0.167***
	(0.0180)	(0.0132)	(0.0157)	(0.0170)	(0.0128)	(0.0137)
Observations	8794	8634	8000	8794	8634	8000
R-squared	0.593	0.675	0.709	0.437	0.448	0.494

Notes: $^{+}$, *, ** and *** respectively denote significance at 15 percent, 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 3: Heterogeneity of Human Capital Externality by Industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log hourly salary			Log monthly salary		
	abstract	manual	manufacture	abstract	manual	manufacture
Educity	0.0425	0.0893***	0.109***	0.0391	0.0618*	0.0998***
	(0.0307)	(0.0325)	(0.0353)	(0.0325)	(0.0322)	(0.0352)
Edu	0.0628***	0.0381***	0.0363***	0.0630***	0.0340***	0.0349***
	(0.00425)	(0.00465)	(0.00462)	(0.00372)	(0.00429)	(0.00452)
Exp	0.00987***	0.000484	0.00285***	0.00863***	-0.00101	0.000553
	(0.00102)	(0.00106)	(0.000990)	(0.000936)	(0.000915)	(0.00112)
Expsq	-0.000575***	-0.000249***	-0.000190***	-0.000341***	0.0000197	-0.0000332
	(0.0000994)	(0.0000681)	(0.0000524)	(0.0000712)	(0.0000610)	(0.0000410)
Gender	-0.133***	-0.196***	-0.185***	-0.155***	-0.239***	-0.230***
	(0.0138)	(0.0142)	(0.0169)	(0.0136)	(0.0147)	(0.0155)
Observations	7903	9367	8139	7903	9367	8139
R-squared	0.456	0.396	0.486	0.483	0.473	0.519

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 4: Heterogeneity of Human Capital Externality by Gender

	(1)	(2)	(3)	(4)
Dep. Var.	Log hourly salary		Log monthly salary	
	male	Female	male	female
educity	0.0919***	0.0706**	0.0765**	0.0524+
	(0.0304)	(0.0320)	(0.0314)	(0.0341)
Observations	14259	11169	14259	11169
R-squared	0.672	0.672	0.493	0.477

Notes: +, *, ** and *** respectively denote significance at 15 percent, 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 5: Heterogeneity of Human Capital Externality by Birth Place

	(1)	(2)	(3)	(4)
Dep. Var.	Log hourly salary		Log monthly salary	
	Urban born	Rural born	Urban born	Rural born
educity	0.139***	0.198**	0.127**	0.257***
	(0.0497)	(0.0798)	(0.0497)	(0.0780)
Observations	4,405	974	4,405	974
R-squared	0.355	0.333	0.336	0.326

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 6: Human Capital Externality for Active Workers

	(1)	(2)	(3)	(4)
Dep. Var.	Log hourly salary		Log monthly salary	
	Lowest 10 percent excluded	Working hour≥7	Lowest 10 percent excluded	Working hour≥7
educity	0.0797***	0.0733**	0.0652**	0.0699**
	(0.0265)	(0.0332)	(0.0280)	(0.0327)
Observations	22888	18510	22888	18510
R-squared	0.490	0.496	0.568	0.540

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 7: University Relocation and Regional Characteristics

	Departments in	Departments out	Net departments in
No. of Universities	1.170***	0.748***	0.421
	(0.242)	(0.214)	(0.334)
Population in 1953	0.0267**	-0.00201	0.0287
(in 10,000)	(0.0125)	(0.0111)	(0.0173)
Northeast	-3.097	-2.466	-0.631
	(3.403)	(3.009)	(4.694)
North	-6.480**	-4.381	-2.099
	(3.148)	(2.784)	(4.343)
East	-4.920*	-1.244	-3.676
	(2.700)	(2.387)	(3.724)
Southwest	-3.279	1.621	-4.899
	(3.249)	(2.873)	(4.481)
Northwest	-6.158*	-5.781*	-0.378
	(3.599)	(3.182)	(4.964)
Observations	53	53	53
R-squared	0.676	0.404	0.278
F-value	13.40	4.35	2.48

Notes: *, **, and ***: Coefficient different from zero at 10 percent, 5 percent, and 1 percent significance levels, respectively. Standard errors are in parentheses.

Table 8: The Determinants of Per Capita Fixed Asset Investment in the 1950s and 1960s

	(1)	(2)	(3)	(4)	(5)	(6)
department_net	0.013			0.002		
	[0.017]			[0.013]		
department_out		0.020			0.002	
		[0.020]			[0.016]	
department_in			0.027			0.004
			[0.017]			[0.014]
fix_4952				0.408***	0.408***	0.403***
				[0.077]	[0.077]	[0.080]
Constant	-15.036***	-15.144***	-15.183***	-8.069***	-8.081***	-8.180***
	[0.136]	[0.175]	[0.161]	[1.312]	[1.347]	[1.397]
Observations	48	48	48	48	48	48
R-squared	0.013	0.021	0.055	0.395	0.395	0.395

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Standard errors are in parenthesis.

Table 9: The Determinants of Per Capita Infrastructure Investment in the 1950s and 1960s

	(1)	(2)	(3)	(4)	(5)	(6)
department_net	0.015			0.004		
	[0.017]			[0.013]		
department_out		0.012			-0.007	
		[0.022]			[0.017]	
department_in			0.022			-0.000
			[0.016]			[0.014]
infra_4952				0.387***	0.397***	0.391***
				[0.075]	[0.075]	[0.078]
Constant	-15.075***	-15.134***	-15.192***	-8.444***	-8.226***	-8.372***
	[0.136]	[0.176]	[0.160]	[1.281]	[1.314]	[1.363]
Observations	45	45	45	45	45	45
R-squared	0.019	0.008	0.042	0.403	0.404	0.402

Notes: *, ** and *** respectively denote significance at 10 percent, 5 percent and 1 percent. Standard errors are in parenthesis.

Table 10: IV Estimation for Human Capital Externality

First stage		Second stage		
Dep. Var.	educity		loghrsal	logsal
department_net	**0.0323*** **	educity	0.220*	0.185+
	(0.00922)		(0.119)	(0.118)
		edu	0.0562***	0.0435***
			(0.00504)	(0.00413)
		exp	0.00825***	0.00151+
			(0.00139)	(0.000956)
		expsq	-0.00115***	0.0000391
			(0.0000791)	(0.0000390)
		gender	-0.173***	-0.222***
			(0.00972)	(0.00860)
F test	12.31	Observations	25428	25428
		R-squared	0.665	0.485

Notes: $^{+}$, *, ** and *** respectively denote significance at 15 percent, 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. The coefficients of other control variables are not reported in both the first and second stage regressions to save space.

Table 11: IV Estimation for Heterogeneity of Human Capital Externality by Education Group

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log hourly salary			Log monthly salary		
	edu≤9	9<edu≤12	edu>12	edu≤9	9<edu≤12	edu>12
educity	0.243**	0.202**	0.234+	0.216*	0.159+	0.199
	(0.117)	(0.101)	(0.156)	(0.120)	(0.101)	(0.149)
Observations	8794	8634	8000	8794	8634	8000
R-squared	0.583	0.670	0.699	0.418	0.440	0.479

Notes: $^{+}$, *, ** and *** respectively denote significance at 15 percent, 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.

Table 12: IV Estimation for Heterogeneity of Human Capital Externality by Industry

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Log hourly salary			Log monthly salary		
	abstract	manual	manufacture	Abstract	manual	manufacture
educity	0.172+	0.271*	0.252**	0.139	0.181+	0.220*
	(0.112)	(0.142)	(0.127)	(0.106)	(0.118)	(0.121)
edu	0.0598***	0.0301***	0.0307***	0.0607***	0.0287***	0.0301***
	(0.00498)	(0.00584)	(0.00594)	(0.00453)	(0.00506)	(0.00498)
exp	0.00903***	-0.000835	0.00180	0.00798***	-0.00188*	-0.000326
	(0.00131)	(0.00130)	(0.00127)	(0.00110)	(0.00111)	(0.00122)
expsq	-0.000543***	-0.000203***	-0.000180***	-0.000317***	0.0000500	-0.0000250
	(0.0000999)	(0.0000640)	(0.0000571)	(0.0000702)	(0.0000588)	(0.0000459)
Observations	7903	9367	8139	7903	9367	8139
R-squared	0.441	0.370	0.471	0.474	0.462	0.507

Notes: $^{+}$, *, ** and *** respectively denote significance at 15 percent, 10 percent, 5 percent and 1 percent. Robust standard errors clustered at city level are in parenthesis. To save space, the coefficients of other control variables are not reported.