Inclusive Urban Employment:

How Does City Scale Affect Job Opportunities for Different People?*

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Abstract: This paper investigates the influence of city scale on employment using data from China. Probit models of employment determination are estimated. The historical population growth during China's planned economy, when migration was directed by the government and voluntary location choice was prohibited, is used as the instrumental variable of current population size. Instrumental variables estimates show that it is more likely for individuals to gain employment in big cities. A one percent increase in city scale increases one's employment probability by between 0.044 and 0.050 percentage points. Moreover, the scale advantage of big cities is heterogeneous among individuals with different levels of human capital, with the least-skilled workers benefiting the most.

Key Words: Agglomeration economy; Population; Employment; Human capital

JEL Classification: J08; J24; R12

* The authors gratefully acknowledge funding by the National Natural Science Funds (71273055 and 71133004) and the National Social Science Funds (13&ZD015). Financial supports for the 2002 and 2007 CHIP surveys by the Ford Foundation, the National Foundation of Social Sciences of China, SIDA, AusAid, the University of Western Ontario, Beijing Normal University, Hitotsubashi University, the Ontario Research Foundation, and the JSPS (Global COE program and Grants-in-Aid for Scientific Research) are also gratefully acknowledged. This research is also supported by the Fudan Lab for China Development Studies, and the JSPS Grants-in-Aid for Scientific Research No. 24330083. We thank Shihe Fu, Cheryl Xiaoning Long, Guanghua Wan, Wing Thye Woo, Lixin Colin Xu, and conference participants at the 2013 Asian Economic Panel, the 2010 International Symposium on Contemporary Labor Economics, the 2010 Shanghai Workshop of the Ronald Coase Institute, the Sixth Biennial Conference of the Hong Kong Economic Association, the 2012 Conference on Urbanization and Urban Economics Studies in China and the 2012 International Workshop on Regional, Urban and Spatial Economics in China for helpful discussions and comments. All remaining errors are our own.

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1. INTRODUCTION

In line with inclusive growth, which means "broad based growth, shared growth, and pro-poor growth", cities are engines of modern economic growth and sources of nonfarm employment. Inclusive growth implies an equitable allocation of resources with benefits incurred to every section of the society (World Bank, 2009). Employment should be the most important channel for different people to share the fruits of urban development. But how to maximize job opportunities for individuals by choosing a both efficient and equitable urban development pattern is still unclear.

There are debates about the optimal pattern of urbanization and urban development all over the world. Countries such as Japan and Korea have implemented policies restricting the population growth of big cities. The Japanese government began to restrict the growth of Tokyo and its surrounding areas since the 1950s. For example, the first National Capital Region Development Plan was approved in 1958, attempting to restrict the expansion of industries and universities within Tokyo's existing built-up area and separate Tokyo from its suburban satellites. Similarly in Korea, industrial controls on big cities were imposed since the early 1980s, such as the Capital Region Rearrangement Plan in 1984, with the purpose of preventing city sprawl and encouraging manufacturing industries to relocate away from Seoul. Many other developing countries face choices about how to promote urbanization. Therefore, the pattern of urbanization during development is an essential issue. In China, some scholars believe that giving priority to small- and medium-sized cities during development promotes urbanization not only by lowering migrant workers' psychological costs of rural–urban migration, but also by lowering cities' construction costs. However, others think that big cities should be given priority during development so that firms and individuals can benefit from economic agglomeration.[4] Because governments lack a clear understanding of agglomeration and its economic benefits, contemporary policies in China tend to restrict the growth of big cities, while the growth of small and medium-sized cities is encouraged for a long time. [5]

The urbanization of a country can be evaluated from many different perspectives. Promoting employment is one important perspective to realize inclusive economic growth. However, there is little evidence concerning the effects of economic agglomeration on employment to guide government policy. This paper seeks to study the influences of city scale on employment, and provides evidence on how urbanization should proceed in order to promote employment. Individual-level data from China are used to estimate probit models of employment determination. Being aware of the potential endogeneity bias of city scale measured by population size, we use the historical population growth during China's planned economy as the instrumental variable (IV) of current population size. IV estimates show that it is more likely for individuals to gain employment in big cities. To be specific, we find that one percent increase in city scale increases one's employment probability by between 0.044 and 0.050 percentage points. Moreover, regression results show that the scale advantage of big cities is heterogeneous among individuals with different levels of human capital. Although everyone benefits from living in big cities, it is the least-skilled workers that benefit the most, further highlighting the inclusiveness of city growth. Therefore, encouraging economic agglomeration and the growth of big cities is consistent with inclusive economic growth.

[4] For a detailed review of related arguments and the literature, see Lu, Xiang and Chen (2011).

[5] This is partly reflected in the household registration system (the *hukou* system) in China, which restricts the inflow of rural residents into cities by treating unfairly—in terms of social security benefits and public services—migrant workers who are not officially registered in the cities where they work. Urban *hukou* status in big cities such as Beijing, Shanghai and Shenzhen is particularly difficult to obtain, especially for low-skilled workers. This is because education or skill requirements are high for migrants who want to change their *hukou* status to local.

The rest of the paper is organized as follows. In Section 2, we review related literature. Section 3 describes the data and model used. In Section 4, we report the basic estimation results. Section 5 reports the heterogeneous effects of city scale across different education groups, and Section 6 concludes.

2. LITERATURE REVIEW

Studies in new economic geography and labor economics confirm that agglomeration raises factor prices. Higher factor prices are sustained by increases in productivity. Marshall (1890) was the first to recognize the sources of urban agglomeration economies; namely, input sharing, labor market pooling and knowledge spillovers. However, it is only since the study of Krugman (1991) that economic agglomeration has been analyzed within a coherent theoretical framework. The key prediction of the monopolistic competition model from new economic geography depends on the assumptions of increasing returns to scale, consumer preferences for variety, and transportation costs. Given these assumptions, firms choose to locate near large markets, where demands for their products are higher. In equilibrium, aggregate outputs and factor prices such as wages and land rents are higher in such locations (Fujita, Krugman and Venables, 2001; Duranton and Puga, 2004; Redding, 2009). Moreover, labor productivity in these locations must also be higher to compensate for higher factor prices. Otherwise, profit-maximizing firms would move to places in which factor prices were lower. Where economic activities agglomerate, productivity increases are generated by input sharing, skill matching and knowledge acquisition, as summarized by Gill and Kharas (2007). Moreover, as cities expand, urban diversity may fertilize new ideas and expand industrial scope (Jacobs, 1969). Sveikauskas (1975) finds that wages are higher in larger cities. Doubling a city's population raises labor productivity by between 4.77% and 6.39%. The positive influence of city scale on labor productivity is confirmed by Glaeser and Resseger (2009). In their study, metropolitan area population is used to measure scale, and variables such as a city's average product per worker, median household real income and hourly wages of workers are used to measure city productivity. Both individual-level and city-level regression results show that city scale enhances city productivity, especially when a city has a higher share of college graduates. Au and Henderson (2006) estimate net urban agglomeration economies using data from China. Their evidence of an inverted U-shaped relationship between real income per capita and total city employment implies that increases in city size raise productivity in the early stages of city development.

The existing literature has focused mainly on the influences of agglomeration on productivity, while its effect on employment is seldom examined despite its policy significance. In equilibrium, employment is simultaneously determined by labor demand and supply. An increase in city scale raises labor supply. However, at the same time, labor demand increases where economic activity agglomerates because of higher productivity. As long as the labor supply curve is upward sloping, increases in labor productivity resulting from economic agglomeration shift the labor demand curve outward. As a result, both equilibrium wages and employment rise. Therefore, if job opportunities are created more rapidly than labor supply increases, especially when the scale economy effect is strong, individual employment prospects are better in big cities.

Studies in new economic geography devote much attention to the tradable sector. However, the nontradable sector also constitutes a major source of employment in the modern economy. Taking into consideration the nontradable sector strengthens the effect of agglomeration on employment. According to Moretti (2010), an exogenous increase in labor demand in the tradable sector increases citywide equilibrium wages and employment, and thereby a city’s aggregate income level. As a result, cities’ demands for local nontradable goods are higher, and more employment opportunities are thus created in the nontradable sector. According to Moretti’s (2010) IV estimates, in the US, each additional job in a city’s manufacturing sector generates 1.59 additional jobs in that city’s nontradable sector. Similar mechanisms may also exist in China. If labor productivity is enhanced and more job opportunities are created in the tradable sector as a result of economic agglomeration, increases in a city’s aggregate income will lead to higher aggregate demand for nontradable service goods, which will create more job opportunities in the nontradable sector. Therefore, the positive influences of economic agglomeration on employment may be strengthened when the nontradable sector is taken into account.

Hence, the existing literature provides a sound basis for analyzing the relationship between city scale and employment. Moreover, we argue that the agglomeration effect of city scale may be heterogeneous for individuals with different skill levels. There are three possible reasons for such heterogeneity. First, because most low-skilled service jobs in the nontradable sector are occupied by low-skilled workers and because economic agglomeration expands the nontradable sector, low-skilled workers may benefit disproportionately from living in big cities. Studies have shown that skill-biased technological change has not been deleterious to the employment prospects of low-skilled workers in the US. Rather, more low-skilled workers find jobs in the manual services sector, because these jobs are not sufficiently routine to be done by machines. Autor, Levy and Murnane (2003) model the influence of computerization on job skill demands. They argue that procedural and codifiable routine jobs such as bookkeeping can more easily be done by computer capital. By contrast, computers can complement the work of manual workers such as truck drivers and professionals such as doctors. Therefore, as the use of computers in production becomes more prevalent, both low-skilled manual jobs and skilled professional jobs are created. This is documented as the "job polarization" phenomenon in the literature. Evidence based on US data shows an increasing trend for labor input in manual and professional jobs. Similarly, Manning (2004) finds evidence of increased demand for low-skilled workers. He finds that over time, low-skilled jobs have become more concentrated in the nontradable sector in both the US and the UK and such employment increases are increasingly dependent on the physical proximity to skilled workers. This is partly a result of consumption spillovers from skilled workers. This is confirmed by Mazzolari and Ragusa (2013), who argue that skilled workers have higher opportunity costs of time, and therefore spend a greater proportion of their incomes on low-skilled services such as baby-sitting, catering and cleaning, which are market-substitutes for home production activities. Regression results based on data at the Metropolitan Statistical Area level show that a one-standard deviation differential increase in a city's wage bill share of its top decile of wage earners, which is used as a measure of city level income inequality in their study, leads to a 0.5 standard deviation percentage increase in the city's number of hours worked in home services; this result is robust across different specifications. Therefore, with the expansion of cities and the concentration of skilled workers, low-skilled workers may benefit disproportionately from increased city scale as more employment is created in the low-skilled services sector.

Second, the existence of knowledge spillovers and the complementarity between low-skilled and high-skilled workers in production may affect how individuals with different skill levels benefit differently. Many studies find evidence of knowledge spillover effects in cities. The concentration of people—particularly skilled workers—in cities enhances learning opportunities. This increases labor productivity in big cities. Rauch (1993) finds that cities with higher levels of human capital have higher wages and higher land rents. Similarly, Moretti (2004a, 2004b) finds that a one percentage point increase in the share of college graduates is associated with 1.2-1.7 percentage points increase in wages and 0.5-0.6 percentage points increase in productivity. If knowledge spillover plays an important role in city agglomeration and if the agglomeration effect is primarily from the concentration of high-skilled workers, the positive effect of city scale for high-skilled workers might be offset by the more intense job market competition among them, thus reducing their benefits from living in big cities. This argument has been empirically tested from the wage perspective. Moretti (2004c) finds that knowledge spillover is the strongest for low-skilled workers. Every one percentage point increase in the city's share of college graduates raises wages of high school drop-outs by 1.9%. However, for high school graduates and college graduates, these effects are only 1.6% and 0.4%, respectively.

Third, heterogeneous effects of knowledge and innovation in different jobs may affect individuals working in different occupations. Compared with relatively low-skilled occupations, skilled occupations rely more on knowledge and innovation. Therefore, as cities grow and knowledge spillover effects become larger, labor demand may increase disproportionately in skilled occupations, thereby raising employment probabilities for skilled workers more than for unskilled workers. However, unskilled labors may also benefit more, if they enjoy larger knowledge spillover benefits when they move from a small city to a big one.

Based on the existing literature, we hypothesize that not only may individuals' employment probabilities be higher in big cities because of those cities' higher labor productivity levels, but also that individuals with different skill levels may benefit differently. This is empirically tested in our study.

3. DATA AND MODEL SPECIFICATION

To estimate the effect of city scale on employment, and to determine whether this effect is heterogeneous across individuals with different skills, we use individual-level data from the 2002 and 2007 Chinese Household Income Project Surveys (CHIP2002, CHIP2007) 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.[6] 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. 5,000 households and 14,699 individuals are covered in the 2007 survey. All individuals we use in regressions have local urban *hukou* identities, which means that rural residents and migrant workers are excluded.[7] The data sets contain a wide range of individual demographic and economic information such as information on gender, education and work experience. This makes it possible to estimate the effect of city scale on employment probabilities more accurately by controlling for relevant individual characteristics.

Our basic identification strategy relies on comparing employment probabilities for otherwise similar individuals who live in cities with different scales. To measure city scale, we use the city's population or, in alternative regressions, the city's number of college graduates. As we argued in the Introduction, economic agglomeration may increase one's employment probability in different ways. Agglomeration may enhance labor productivity and thereby increase firms' labor demand. Agglomeration may increase diversity and thus foster the emergence of new ideas and new industries. Agglomeration may also raise a city's total income. Higher income creates higher demand for local nontradable goods and thereby more employment opportunities in the nontradable goods sector. The employment effects of agglomeration in the nontradable goods sector may be strengthened if city scale expands primarily through a concentration of skilled workers. This is because skilled workers have relatively higher demand for low-skilled services, and thus their increased presence may boost labor demand for low-skilled workers. Therefore, we argue that individuals are more likely to gain employment in cities with larger populations or in those with larger numbers of college graduates. This is the first hypothesis

[6] 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 (forthcoming).

[7] Migrants are not included in our sample, although including them does not significantly change our results concerning city scale and employment probability. Because of the *hukou* system in China, most city-based migrants are employed. Unemployed migrants generally leave the cities to return to rural areas because they do not have the same access to public services and social security, such as education and unemployment insurance, that other city residents have. Regression results with migrants included are available upon request.

we test.

Data on city populations and numbers of college graduates are taken from the Fifth Census of the People's Republic of China, conducted in 2000. We also control for other city-level characteristics that may influence employment. The data on city-level characteristics are calculated from the Annual Survey of Industrial Firms in 2000 and *China City Statistical Yearbooks* (National Bureau of Statistics of China, 1997–2001).

The econometric model to be estimated is an individual-level probit model, which specifies one's employment probability as follows.

$$\text{Prob}(\text{Employed}_{ij} = 1) = \Phi(\mathbf{X}_{ij}^{'}\beta + \pi_1 \text{Scale}_j + \mathbf{City}_j^{'}\alpha)$$

The subscripts *i* and *j* are used to represent individual *i* living in city *j*. Our sample is restricted to the working age population, namely, males between the ages of 16 and 60 and females between the ages of 16 and 55 following China's official definition. Those who are not in the labor force are not included in the sample, including individuals with an urban status of officially off duty (*lixiu*), retirees, those unable to work, full-time homemakers, full-time students, those waiting for job assignment and those entering further education.[8] The dependent variable, Employed, is a dummy variable that takes the value of unity if an individual is employed[9] and is zero otherwise.

On the right-hand side of the equation, $\mathbf{X}_{ij}$ is a vector of individual characteristics that influence employment, including gender, marital status, years of education, potential work experience and its square, Communist Party membership, and ethnic minority status.[10] Including age in the regressions would cause collinearity because potential work experience is calculated as age minus years of education minus six. Therefore, we did not control for age in our regressions. Scale_j represents city

[8] Individuals who are waiting for a job assignment or entering further education account for 0.639% of the working age population in our sample. According to standard terminology from labor economics, these individuals should be regarded as not being in the labor force. However, excluding these individuals from the sample may disguise the true unemployment rate. Therefore, we ran regressions based on including them in the unemployed population. This adjustment did not affect our main results. Regression results with individuals who are waiting for a job assignment or entering further education included are available upon request.

[9] In CHIP questionnaires, there is one question asking the respondent's current status in the city. Those who chose "Working or employed" in the 2002 survey or "Employed, farmer or self-employed" in the 2007 survey are defined as being employed.

[10] Individuals with potential work experience outside the range 0 to 44 are excluded from the sample, as are individuals with more than 22 years of education. These individuals account for only 0.96% of our estimation sample. Our results are robust to including these individuals in the sample.

scale, and is measured as the natural logarithm of the city's population or, in alternative regressions, as the city's number of college graduates.[11] The coefficient of interest is π_1, which is an estimate of the effect of city scale on employment. According to our discussions, if this coefficient is positive (as expected), then individuals are more likely to gain employment in big cities.

Other city-level characteristics that may influence one's employment probability are included in the vector $\mathbf{City}_j$. These are the city's Gini coefficient of employments for four-digit manufacturing industries, average FDI as a proportion of average GDP for 1996–2000, average investment in fixed assets as a proportion of average GDP for 1996–2000, the average ratio of tertiary sector output to secondary sector output for 1996–2000, average intrabudgetary government expenditure as a proportion of average GDP for 1996–2000, road network area per capita in 2000, the city's number of buses for every 10,000 persons in 2000, the share of workers employed in state-owned or collectively-owned enterprises in total manufacturing employments in 2000, and a dummy variable indicating whether a city is a provincial capital. We control for these effects to reduce potential omitted variables bias arising from demand and supply shocks in the urban labor market.

A city's agglomeration effect has long been argued to be results of urbanization (the size of a city) or localization (the concentration of an industry) (Rosenthal and Strange, 2004). Theoretically, apart from city scale, localization may also influence city employment because specialization increases productivity (Marshall, 1890). Meanwhile, city scale and its level of localization might be correlated though the sign of correlation is not pre-determined. Therefore, including both city scale and a localization index in regressions may alleviate missing variable bias. Though localization is generally measured at industry level to reflect the concentration of employment within industries all over the country, in our study, we need estimates of within city localization to show its influences on city employment. When industries are localized, it is likely that they are located in some cities, making these cities more specialized. The Gini coefficient of employments in manufacturing industries partly reflects the within city concentration of employments in different industries. Higher Gini coefficients

[11] A city's population is made up of its urban and rural populations, as recorded in the Fifth Census. We use the city's urban population to measure city scale. According to the Census data, individuals who do not have urban *hukou* status but who are permanent residents of the city are included in the urban population. Including permanent residents in the urban population yields a more accurate measure of city scale in the context of China. This is because permanent residents generally work in the city for more than six months of the year, and thus contribute to city development. However, *hukou* restrictions in China mean that they are not regarded as urban residents, and cannot benefit equally from the urban public services system.

imply higher concentration of employments and higher degrees of specialization. Therefore, the Gini coefficient of employments in manufacturing industries is used to partly capture the consequence of industry localization.

A city's investment is correlated with both its scale and the employment probabilities of its residents. Because economic agglomeration boosts productivity, large cities attract more investment and, thus, city scale and investment are correlated. In addition, as a driving force for economic growth, investment may influence one's employment probability. Therefore, excluding variables related to city investment may bias estimation of the effect of city scale on employment. To deal with the potential for omitted variables bias resulting from labor demand shocks, we include in the regressions city-level FDI and investment in fixed assets.

We control for a city's industrial structure for two reasons. First, a city's industrial structure is correlated with its scale. With the expansion of cities, industries may upgrade and local governments may implement different policies to support the development of different industries. Second, the secondary and tertiary sectors may have different job creation capabilities, and individuals with different skill levels may have different comparative advantages in different occupations. Therefore, a city's industrial structure may influence employment.

Government expenditures are included in the regressions mainly to control for the effect of government interventions that influence employment. The degree of government intervention in economic activity may differ across cities with different scales. Variables related to a city's infrastructure, such as its road network area and bus services, are also included in the regressions. On the one hand, improvements in city infrastructure increase residents' communication efficiency and enhance the quality of matching in the labor market. Therefore, labor productivity is higher and individuals' employment prospects are better in cities with better infrastructure. On the other hand, improvements in city infrastructure may attract workers from other cities, and thus may influence city scale.

We further control the city's share of workers employed in state-owned or collectively-owned enterprises in total manufacturing employments as China experienced significant labor market changes in the mid-1990s. Ownership structures differ across cities with different scales. Meanwhile, the large number of workers laid off during the period may influence future city employment. Besides, a dummy variable indicating whether a city is a provincial capital is included to control for unobservable city characteristics related to a city's administrative infrastructure, which is expected to affect city scale and employment simultaneously.

TABLE 1 presents definitions of the variables included in our regressions. Summary statistics are reported in TABLE 2.

<TABLE 1 and TABLE 2 here>

4. CITY SCALE AND EMPLOYMENT: REGRESSION RESULTS

In this section, we present the estimated effects of agglomeration on employment based on individual-level data from CHIP2002 and CHIP2007. Probit results are presented in TABLE 3. To save space, we divide the table into two parts: the coefficients of city scale and individual characteristics are displayed in column (1) and column (2); the coefficients of other city characteristics are reported in column (3) and column (4). In Regression 1, the natural logarithm of the city's urban population is used as a measure of city scale. Having controlled for individual characteristics and city characteristics, we find that city scale has a significantly positive effect on one's employment probability. A one percent increase in a city's urban population increases one's employment probability by 0.016 percentage points. Alternatively, we use a city's number of college graduates to measure city scale in Regression 2, and still find the effect of city scale on employment to be significantly positive. A one percent increase in a city's number of college graduates raises one's employment probability by 0.019 percentage points on average.

<TABLE 3 here>

However, as we argued in Section 2, probit estimates of the effects of city scale on employment may be biased for two reasons. First, employment may affect city scale because individuals may locate where they are more likely to find a job. Such two-way causality between city scale and employment may bias our estimates upward. Second, unobservable demand and supply shocks from the urban labor market may bias our estimates by affecting city scale and employment simultaneously. Therefore, in all subsequent regressions, we use IV. Our instrument for city scale in 2000 is the natural logarithm of the city's population growth between 1953 and 1982. The 1953 population data are taken from the People's Republic of China's first census, conducted in 1953, and the 1982 population is from the third census of China, conducted in 1982.

With the foundation of People's Republic of China in 1949, planned economy was instituted in China. In accordance with the planned economy, migration was strictly administered by the central government (Ge and An, 2010). There were primarily three kinds of migration from 1953 to 1982. The first kind was the migration of military soldiers. From 1953 to 1959, many production and construction corps' (PCC, *Shengchan Jianshe Bingtuan*) were set up in the frontier regions such as Heilongjiang, Inner Mongolia, and Xinjiang. These PCCs were generally semi-military governmental organizations, serving to promote economic development and ensure social stability in these areas. For example, the Xinjiang Production and Construction Corps (XPCC, *Xinjiang Shengchan Jianshe Bingtuan*), one of the largest and most famous PCCs during that time, was founded in 1954 on the basis of soldiers from both the Chinese People's Liberation Army and Xinjiang's local army.

The second kind of migrants was workers from the more advanced coastal regions who moved to inland provinces of China in order to help those places develop. The migration of these workers was also administered by the government. One typical example is the Third Front Construction program (*Sanxian Jianshe*). In 1964, the Central Committee of the Communist Party of China led by Mao Zedong envisaged three lines of defense (coastal, central and western), and thus proposed the Third Front plan in order to strengthen the development of western China. Western China was regarded as the third line of defense and thus would be least damaged if by any chance war breaks out. As a result of the low skill level of those places during that time, workers from the coastal area, especially those with high skill levels, were dispatched to these provinces. As an example, from 1965 to 1971, the net inflow of population in Sichuan province was 530 thousands, among which 400 thousands were workers and technicians (Liu, 1988).

The third kind of massive migration during that time was resulted from the Down to the Countryside Movement (*Shangshan Xiaxiang Yundong*) in the late 1960s and early 1970s. Economic growth and production was severely damaged by the Cultural Revolution, leading to great reductions in employments in cities. In order to alleviate employment pressure, Mao Zedong encouraged educated young people (mostly high-school graduates) to move to the countryside and learn from farmers there.

As a result, a great many young people were sent to the countryside and employed in the farming sector. However, according to Ge and An (2010), the migration scale due to the Down to the Countryside Movement was quite limited, and all cities, no matter big cities or small cities, became sources of migrants. Therefore, there is no apparent direction in the third kind of migration.

Apart from migration administered by the central and local governments, voluntary migration was negligible during that period because of the strict *Hukou* system (Zhao, 2004). Under the *Hukou* system, place-to-place migration was controlled by public security bureaus (Cai and Wang, 2008). Moving to another city without being approved by the government was nearly impossible because food, clothes and other necessities had to be purchased using coupons distributed by the local government. Migrants without permission were sent back home if identified.

As we can see from the previous paragraphs, migration was administratively controlled during 1953-1982, and the direction of large scale migration was generally results of geographic considerations (such as frontier areas in PCCs and inland areas in the Third-Front construction plan). Therefore, migration in this period, though may affect future city scale, is uncorrelated with the disturbance terms. Furthermore, the natural growth rate of cities during this period was not correlated with the economic conditions of the city either. Lacking earlier data, in FIGURE 1, we plotted a city's GDP per capita in 1990 (the earliest available city level GDP data) against the city's natural growth rate in 1982, calculated as its birth rate minus death rate.[12] No apparent correlation between these two variables is revealed. The coefficient of correlation is only -0.023. To sum up, both administrative migration and natural growth of the population during the period are uncorrelated with disturbance terms, and voluntary migration was negligible. Therefore, city population growth from 1953 to 1982 is used as a credible instrument in our study. As a further test, in FIGURE 2 and FIGURE 3, we plotted a city's GDP per capita in 1990 against the natural logarithm of the city's population growth and the city's population growth rate during 1953 to 1982, respectively. No apparent correlation was revealed either. The coefficients of correlation are -0.017 and -0.099, respectively.

<FIGURE 1, FIGURE 2 and FIGURE 3 here>

[12] Cities included are those surveyed in either CHIP2002 or CHIP2007. However, Shenzhen constitutes an outlier in FIGURE 1 through FIGURE 3, and is thus excluded. As the first Special Economic Zone in China, Shenzhen's GDP per capita in 1990 was over seven times as large as the average GDP per capita of all other cities in our sample.

Instrumental variables estimates are presented in TABLE 4. In Regressions 3 and 4, respectively, a city's urban population and a city's number of college graduates are used as scale measures. The first-stage regression results show that increases in a city's population in history (1953 to 1982) has significantly positive effects on current (2000) city scale. According to the results in column (1), with other city-level characteristics controlled for, every one percent increase in a city population growth from 1953 to 1982 increases a city's urban population in 2000 by 0.61 percent. The F value of the coefficient is 39.52. Therefore, weak instruments are not a concern. Similar results are obtained when a city's number of college graduates is used as a scale measure. In this case, the F value for city scale in 1953 in the first stage is 51.02.

<TABLE 4 here>

We calculate the marginal effects of city scale on employment using Newey's two-step estimator. When city scale in 2000 is measured as the natural logarithm of the city's urban population, we find that a one percent increase in city scale leads to a 0.050 percentage points increase in one's employment probability. Similarly, as shown in column (2) for Regression 4, a one percent increase in a city's number of college graduates increases one's employment probability by 0.044 percentage points.

The effects of the individual characteristics on employment are as expected and are consistent with existing results. Specifically, men and married people are more likely to be employed. Education improves one's employment situation. An extra year of education increases one's employment probability by approximately 1.16-1.17 percentage points. The estimated return to potential work experience exhibits an inverted U-shaped relationship. Based on using city population and the number of college graduates as scale measures, the turning points are approximately 17.99 years and 17.89 years, respectively. As one becomes more experienced, he/she becomes more skilled. Therefore, more experienced ones are more likely to get employed. However, once one has about 17 years of work experience, the beneficial effect of experience declines mainly as a result of lower physical strength and learning capability as compared with younger workers. Because being a Communist Party member in China is a signal of high ability, we control for party membership. Communist Party members also have better social networks. Both higher ability and better social networks enhance job prospects. Knight and Yue (2008) and Li, Lu and Sato (2009) find that being a Communist Party member significantly increases one's income. Our results show that an individual who is a member of the

Communist Party is more likely to have a job. By contrast, being a member of an ethnic minority significantly decreases one's employment probability, which may result from linguistic disadvantages, cultural differences, or discrimination from the labor market.

We include in our regressions other city-level characteristics expected to affect both employment and city scale. Localization is regarded as a source of city agglomeration effect in literature. Theoretically, localization may influence city employment through the productivity enhancing effect of specialization. Here, the Gini coefficient of employments in Four-Digit manufacturing industries in 2000 is used to partly capture the consequence of localization of industries. This is because that when industries are localized, it is likely that they are located in some cities, making these cities more specialized. A city's industrial level employment data in 2000 are used to alleviate the two-way causality problem. However, as is shown in TABLE 4, coefficients of localization are not significant. However, this is not denying localization's role in agglomeration economy. Increases in city scale may increase city diversity on the one hand, but may on the other hand increase localization because more firms in one industry may relocate to that city due to specialization. Therefore, the role of localization is partly reflected in our city scale measure.

Meanwhile, other labor demand factors such as city investment are controlled in regressions because investment encourages the inflow of workers, especially skilled workers. The inflow of low-skilled workers is inhibited by the *hukou* system in China because it is biased toward skilled workers. Therefore, city investment and city scale are generally positively correlated. On the other hand, investment, as a reflection of the importance of the various driving forces behind a city's economic growth, such as consumption demand and net exports, affects employment. In TABLE 4, we control for two variables related to city investment. The first is a city's FDI, measured as the ratio of the city's average FDI from 1996 to 2000 to its average GDP for the same period. The second variable is a city's domestic investment in fixed assets, measured as the ratio of the city's average investment in fixed assets from 1996 to 2000 to its average GDP for the same period. Average investment levels are used mainly to smooth out the substantial fluctuations in annual investment. Similar with the localization measure, investment data before 2000 are used to circumvent the two-way causality problem between investment and employment. Because data before 1996 have too many missing values, they are excluded when performing IV estimation. Our regression results show that FDI does not significantly affect the employment probability, whereas domestic investment in fixed assets has a significantly negative effect on employment. This suggests that cities that rely more heavily on domestic investment are less efficient at creating jobs than cities that rely more heavily on factors such as consumption demand and net exports. As Lu and Ou (2011) found, local governments in China generally encourage the development of capital-intensive industries because higher tax revenues can be collected from these industries. However, capital-intensive industries do little to create jobs. Therefore, domestic investment does not improve—and may even worsen—an individual's employment situation in China.

To control for the effect of a city's industrial structure on employment, we include in the regressions the average ratio of a city's tertiary sector output to its secondary sector output from 1996 to 2000 (and its square). We find evidence of a U-shaped relationship between the employment probability and industrial structure. The share of tertiary sector output rises gradually during economic development. In the early stages of economic development, the growth of the tertiary sector does not create as many job opportunities as does the secondary sector. Employment relies heavily on labor-intensive manufacturing industries in the secondary sector. As the economy develops further, the tertiary sector begins to create more job opportunities. On the one hand, with the growth of skilled service industries such as finance, international trade and real estate, more skilled workers gain employment in the tertiary sector, in which they earn higher incomes. On the other hand, as incomes in the city grow—particularly those of skilled workers, who have higher demand for local nontradable goods such as catering and baby-sitting—manual jobs for low-skilled workers are created. At the same time, manufacturing firms begin to upgrade or relocate because of rising labor and environmental costs. Therefore, the job creation capabilities of the tertiary sector begin to improve in the later stages of economic development. This explains why our industrial structure indicator has a U-shaped effect on employment. Based on using a city's population and its number of college graduates as scale measures, the turning points for the industrial structure variable are 1.21 and 1.24, respectively. These estimates imply that the tertiary sector must account for at least 54.8% to 55.4% of total nonfarm output to have a positive effect on employment. Approximately 18.82% to 23.86% of laborers in our sample are beyond the turning point. Therefore, in most cities in China, the secondary sector remains the major contributor to employment. However, given continued growth in China's tertiary sector, it is expected to become the driving force of job creation in the future.

Apart from the labor demand factors already mentioned, we also include in our regressions variables related to government expenditure and city infrastructure to control for the effects of labor demand and supply shocks. Theoretically, government expenditure has an ambiguous effect on employment prospects *a priori*. On the one hand, government expenditure can increase labor demand through its multiplier effect, which may increase one's employment probability. On the other hand, however, government investment may squeeze out more efficient private investment, and thus harm employment. Furthermore, government expenditure may encourage the inflow of workers by improving city infrastructure. Therefore, government expenditure is correlated with city scale and can be regarded as a factor that influences labor supply. Similarly, better city infrastructure, such as more roads and buses per capita, enhances communication efficiency among individuals and improves matching quality in the labor market, and can thus boost labor productivity and firms' demand for labor. Moreover, workers prefer to settle in cities with better infrastructure, and therefore city infrastructure is also correlated with city scale. However, the regression results in TABLE 4 show that none of these effects is significant.

Ownership structure, *i.e.* the city's share of workers employed in state-owned or collectively-owned enterprises, is included in regressions as a control of local labor market conditions. The large number of workers laid off during the labor market reforms in the mid-1990s may negatively influence current city employment. However, as regression results show, the coefficients on ownership structure is not significant. One possible explanation is that the drastic employment restructuring and system reform ended around 2001. During the period of 2002-2007, when our data are from, the laid-off problem was not a result of ownership restructuring any more.[13] Neither do individuals living in provincial capitals have significantly different employment probabilities, relative to those from prefecture-level cities or county towns.

5. HETEROGENEOUS EFFECTS OF CITY SCALE ACROSS DIFFERENT EDUCATIONAL GROUPS

Because we pooled all educational groups together in the regressions discussed in the previous section,

[13] For a detailed review of labor market reforms in China, please refer to Meng (2012).

our IV probit results represent average effects of agglomeration on employment. However, agglomeration effects in cities may be heterogeneous across individuals with different skills. In this section, we divide our sample into three subgroups: individuals with no more than nine years of education; those with between nine and 12 years of education; and those with more than 12 years of education. A separate regression is run for each educational group. All individual and city characteristics are controlled for in the regressions. To save space, we only report coefficients of city scale in this section. Panel 1 of TABLE 5 reports the probit results. Irrespective of whether city scale is measured using population or the number of college graduates, city scale has a significantly positive effect on employment for the lowest-education group, that is, for individuals with no more than nine years of education. City scale does not significantly increase the employment probabilities of individuals with higher skill levels. However, unobservable labor market shocks and two-way causality between city scale and employment may have biased our probit results. Therefore, in Panel 2 of TABLE 5, we report IV probit estimates.

<TABLE 5 here>

As in Section 3, we use the natural logarithm of the city's population growth between 1953 and 1982 as the instrument for city scale in 2000. Regression results show that individuals with lower skill levels benefit more from city scale. On average, a one percent increase in the city's population increases the employment probabilities of the least-skilled individuals by 0.078 percentage points. However, marginal effects for the medium-skilled and highest-skilled individuals decrease to 0.049 and 0.038 percentage points, respectively. Similar heterogeneity is revealed when the city's number of college graduates is used to measure city scale. The corresponding marginal effects are 0.068, 0.044 and 0.034 percentage points for the least-skilled, medium-skilled and highest-skilled, respectively. As we have argued in Section 2, the existence of knowledge spillovers and the complementarity between low-skilled and high-skilled workers in production may affect how individuals with different skill levels benefit from city scale. Knowledge spillover has been shown to play an important role in city agglomeration effects (Rauch, 1993; Moretti 2004a and 2004b). When city agglomeration is primarily from the concentration of high-skilled workers, the positive effect of city scale for high-skilled workers might be offset by the more intense job market competition among them, thus reducing their benefits from living in big cities. However, the complementarity between high-skilled workers and low-skilled workers in production may increase the benefits of individuals with lower skill levels. The share of college graduates is generally higher in larger cities. In our regression sample, a city's population and its share of college graduates are positively correlated, with the coefficient of correlation being 0.44. Therefore, with increases in city population or number of college graduates, competition effects among high-skilled workers may reduce their benefits from being in big cities. This is one explanation of our results implying that individuals with lower skill levels benefit more.

Furthermore, different occupational and industrial structures in cities with different scales might also be sources of heterogeneity. Individuals with no more than nine years of education benefit from city scale mainly because more manual jobs are created in larger cities. As we argued in Section 2, low-skilled manual work, such as that done in restaurants catering and baby-sitting, is mainly done by less educated individuals. In TABLE 6, we present the average years of education for individuals working in different occupations. The table shows that manual workers have the least education on average, around 10.82 years compared with 11.00 years for manufacturing workers. Professional workers have the highest average education level at 13.06 years. Therefore, manual workers have the lowest skill level. As cities grow larger and as more skilled workers begin to concentrate in cities, the demand for low-skilled services grows and job opportunities are created in cities for less educated workers. This is partly reflected in Panel 1 of TABLE 7, in which we report the shares of manual jobs for cities with different scales. In TABLE 7, the cities covered by CHIP are divided into three groups according to their population or number of college graduates. The table shows that as a city grows, its proportion of manual workers in all laborers rises. For small cities, manual workers account for 22.2%–22.5% of all laborers. This share rises to 31.5%–31.9% for big cities. Similar trends are apparent in FIGURE 4 and FIGURE 5. In each figure, the citywide share of manual workers in all laborers is measured on the y-axis. The x-axis in FIGURE 4 records city population and that in FIGURE 5 records the number of college graduates (both in natural logarithms). The fitted lines indicate a strong positive relationship between manual work and city scale. Hence, large cities create more manual job opportunities, further increasing the employment probabilities of individuals with the lowest education level in larger cities because there are more manual job opportunities in these cities.

<TABLE 6 and TABLE 7 here>

<FIGURE 4 and FIGURE 5 here>

TABLE 6 shows that medium-skilled workers are concentrated in the manufacturing sector. However, there may be an inverted U-shaped relationship between city scale and the share of manufacturing jobs in a city. In the early stages of city development, manufacturing firms choose to locate in big cities so that they can benefit from economic agglomeration and enhance their productivity. As cities grow, production costs in big cities may increase because of higher wages, land prices, environmental protection requirements, etc. This may allow the services sector, especially skilled service industries such as finance, real estate and international trade, to develop in big cities. Therefore, the share of manufacturing jobs may exhibit an inverted U-shaped relationship with city scale. Panel 2 in TABLE 7 shows the shares of manufacturing workers in cities with different scales. Medium-sized cities have the highest shares of manufacturing jobs irrespective of whether cities are divided into different scale groups according to their populations or numbers of college graduates. Similar trends are evident from FIGURE 6 and FIGURE 7, which indicate inverted U-shaped relationships between city scale and the proportion of manufacturing jobs in all laborers. Therefore, after initially boosting the employment of medium-skilled workers, an increase in city scale lowers the proportion of manufacturing jobs, thus negatively affecting their employment. On average, the positive and negative effects may cancel each other out. However, medium-skilled workers may still benefit from living in big cities because their complementarity in production with high-skilled workers. As is displayed in our regression results, medium-skilled workers gain employment in larger cities more easily, though their benefits are not as high as low-skilled workers.

<FIGURE 6 and FIGURE 7 here>

Highly educated individuals benefit from living in big cities for two reasons. First, knowledge spillover effects are stronger in big cities, where workers—especially skilled workers—agglomerate, because more learning opportunities are created in big cities. Skilled service jobs, such as those in finance, are generally knowledge intensive, and the productivity levels of workers doing those jobs depend crucially on innovation. Therefore, knowledge spillovers have stronger positive effects on skilled service jobs than on other jobs, and this leads to the creation of more skilled service job opportunities and thus improved employment prospects for highly skilled individuals. Second, as cities expand, the manufacturing industry upgrades and the quality of low-skilled service jobs rises; these two factors then boost the demand for skilled workers in these occupations. The share of workers with more than

12 years of education in all manufacturing workers increases as cities expand. Panel 3 of TABLE 7 shows that the share of skilled workers in all manufacturing workers is 19.8% in small cities, 21.5% in medium-sized cities, and 25.7% in big cities. Results are similar if cities are grouped according to their numbers of college graduates. The fitted lines in FIGURE 8 and FIGURE 9 show that large cities have higher proportions of skilled workers in manufacturing. The trend for skilled workers to fill jobs initially done by low-skilled workers is also apparent in manual jobs. Panel 4 of TABLE 7, FIGURE 10 and FIGURE 11 show that as cities expand, more manual jobs are taken by highly skilled workers. Therefore, the most highly educated individuals benefit from living in big cities not only because more professional jobs are created in big cities, but also because more jobs initially done by low-skilled workers are now being filled by skilled workers because of industrial development and higher service quality requirements. However, as we have pointed out, the concentration of high-skilled workers in big cities also intensifies labor market competition, thus reducing their benefits. As is displayed in our regression results, individuals with the highest skill level benefit positively from living in big cities, however their benefits are the lowest across all skill levels.

<FIGURE 8 and FIGURE 9 here>

<FIGURE 10 and FIGURE 11 here>

6. CONCLUSIONS AND POLICY IMPLICATIONS

Urban development and equal job opportunities are essential aspects of inclusive growth. However, many people don't recognize the relationship between city scale and job creation, so policies to diffuse population and industries are adopted sometimes to restrict urban size. While urbanization in China progresses rapidly, debates about the optimal pattern of urbanization and urban development continue. Studies in new economic geography link productivity to city scale and focus on factor prices. However, economists have so far been unclear about the connection between city scale and employment.

Using individual-level data from the Chinese Household Income Project Surveys for 2002 and 2007, we have contributed to the literature by confirming a causal effect of city scale on employment. We found that otherwise similar individuals are more likely to gain employment in large cities. A one percent growth in city scale increases one's employment probability by between 0.044 and 0.050

percentage points. We also found that the city-scale effect is heterogeneous among individuals with different levels of education. Although everyone benefits from living in big cities, it is the least skilled that benefit the most.

This study focuses on the employment promoting effect of city scale. Using the same dataset as this paper, Gao (2014) found that city scale significantly raises individual incomes, both in nominal and real terms. However, employment is an important perspective because unemployed ones cannot directly enjoy the productivity-enhancing effects of economic agglomeration. Our finding contributes to the literature by providing the readers a more complete picture about the labor market effects of economic agglomeration. Results from this paper suggest that policies restricting the growth of big cities are inefficient from the employment perspective. Such policies discriminating unskilled labor are also inequitable because individuals with the lowest skill levels benefit the most from city expansion. With regard to contemporary policy debates in China about whether big cities or small cities should be given priority during development, our results suggest that the benefits of economic agglomeration are important. Moreover, our evidence for China may guide other developing countries in the early stages of urbanization. Economic agglomeration not only raises labor productivity and individual incomes, but also creates job opportunities and increases employment. Therefore, to achieve inclusive economic growth, which emphasizes the creation of job opportunities during development, especially for the poor, economic agglomeration and the development of big cities should not be restricted.

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TABLES

TABLE 1: Definitions of Variables

Variable	Definitions
Individual Characteristics	
Employment	1 for employed and 0 otherwise
Gender	1 for male and 0 otherwise
Married	1 for married and 0 otherwise
Eduyr	Years of education
Exp	Potential experience = Age - Years of education - 6
Expsq	Experience squared
CP	1 for Communist Party members and 0 otherwise[+]
Minority	1 for minority and 0 otherwise
City Characteristics	
Population	Ln (Urban population (million))
College	Ln (Number of college graduates (million))
Popgrw8253[#]	Ln(Population in 1982-Population in 1953)
Localization	The Gini Coefficient of Employments for Four-Digit Manufacturing Industries
FDI	Average FDI in 1996-2000 (10,000 RMB) / Average GDP in 1996-2000 (10,000 RMB)
Investment	Average fixed asset investment in 1996-2000 (10,000 RMB) / Average GDP in 1996-2000 (10,000 RMB)
Industry	The average ratio of tertiary sector outputs over secondary sector outputs in 1996-2000
Industrysq	Industrial structure variable squared
Government	Average intra-budgetary government expenditure (10,000 RMB) / Average GDP in 1996-2000 (10,000 RMB)
Road	Road area per capita in 2000 (m^2)
Transportation	Number of buses for every 10,000 persons in 2000
Ownership	The Share of Workers Employed in State-Owned or Collectively-Owned Enterprises in Total Manufacturing Employments
Capital	1 for province capitals and 0 otherwise
Year07	1 for year 2007 sample and 0 otherwise

Note: [+]Because CHIP 2007 does not have information on individuals' Communist Party membership status, we constructed the party membership variable for the 2007 sample using CHIP 2002 data. An individual's Communist Party membership status is proxied by the city's share of Communist Party members in the 2002 sample. For cities in the 2007 sample that are excluded from the 2002 sample, we proxied the Communist Party membership status of individuals by the national share of Communist Party members in 2002.
[#] A detailed explanation of why we use a city's population growth between 1953 and 1982 as an instrumental variable for city scale in 2000 is given in Section 3.

TABLE 2: Summary Statistics

Variables	Mean	Standard Deviation	Min	Max
Individual Characteristics				
Employment	0.89	0.32	0	1
Gender	0.55	0.50	0	1
Married	0.86	0.35	0	1
Eduyr	11.61	2.94	0	22
Exp	22.13	10.51	0	44
CP	0.24	0.33	0	1
Minority	0.02	0.14	0	1
City Characteristics				
Population	0.79	0.73	-0.94	2.67
College	-1.58	0.95	-3.37	0.83
Popgrw8253	0.39	0.59	-1.82	1.87
Localization	0.69	0.05	0.58	0.77
FDI	0.06	0.06	0.00	0.25
Investment	0.33	0.20	0.18	1.60
Industry	0.88	0.33	0.33	1.74
Government	0.08	0.03	0.05	0.20
Road	5.79	3.03	1.10	17.50
Transportation	9.06	13.79	0.60	95.70
Ownership	0.53	0.18	0.10	0.84
Capital	0.27	0.45	0	1
Year07	0.43	0.49	0	1

TABLE 3: City Scale and Employment (Probit Results)

	（1）	（2）		（3）	（4）
Variables	Regression 1	Regression 2	Variables	Regression 1	Regression 2
Population	0.0163*		Localization	-0.0654	-0.0551
	(0.00955)			(0.0995)	(0.0980)
College		0.0192*	FDI	0.213**	0.178
		(0.0105)		(0.107)	(0.126)
Gender	0.0560***	0.0560***	Investment	-0.0546**	-0.0559**
	(0.00619)	(0.00619)		(0.0273)	(0.0271)
Married	0.0558***	0.0562***	Industry	-0.282***	-0.314***
	(0.0123)	(0.0123)		(0.106)	(0.111)
Eduyr	0.0120***	0.0119***	Industrysq	0.121**	0.132***
	(0.00136)	(0.00137)		(0.0486)	(0.0499)
Exp	0.00542***	0.00541***	Government	0.0976	0.0869
	(0.00118)	(0.00118)		(0.166)	(0.163)
Expsq	-0.000149***	-0.000150***	Road	-0.00212	-0.00208
	(2.51e-05)	(2.51e-05)		(0.00272)	(0.00277)
CP	0.0843***	0.0846***	Transportation	0.000324	0.000188
	(0.00932)	(0.00937)		(0.000507)	(0.000536)
Minority	-0.0334	-0.0343*	Ownership	0.0115	-0.0118
	(0.0205)	(0.0207)		(0.0375)	(0.0410)
			Capital	0.0105	0.00128
				(0.0136)	(0.0175)
			Year07	0.0349***	0.0346***
				(0.00940)	(0.00935)
			Pseudo R^2	0.078	0.078
			Observations	14,960	14,960

Note: The dependent variable is the dummy variable Employment indicating one's employment status. Marginal effects of variables are reported. *, ** and *** respectively denote significance at 10%, 5% and 1%. Robust standard errors clustered at district level are in parenthesis.

TABLE 4: City Scale and Employment (IV Probit Results)

Variables	(1) Regression 3	(2) Regression 4	Variables	(3) Regression 3	(4) Regression 4
First Stage#					
Popgrw8253	0.608***	0.688***			
	(0.0966)	(0.0963)			
Second Stage					
Population	0.291***		Localization	-0.544	-0.357
	(0.106)			(0.594)	(0.594)
College		0.257***	FDI	0.338	0.254
		(0.0970)		(0.832)	(0.810)
Marginal Effect	0.0496***	0.0439***			
Gender	0.321***	0.322***	Investment	-0.437*	-0.415**
	(0.0330)	(0.0332)		(0.229)	(0.206)
Married	0.298***	0.298***	Industry	-2.228***	-2.459***
	(0.0579)	(0.0571)		(0.671)	(0.749)
Eduyr	0.0686***	0.0680***	Industrysq	0.924***	0.995***
	(0.00817)	(0.00816)		(0.305)	(0.325)
Exp	0.0327***	0.0324***	Government	0.0753	0.101
	(0.00681)	(0.00684)		(1.037)	(0.961)
Expsq	-0.000908***	-0.000905***	Road	-0.00606	-0.00873
	(0.000141)	(0.000142)		(0.0178)	(0.0174)
CP	0.502***	0.503***	Transportation	-0.000453	-0.00125
	(0.0549)	(0.0551)		(0.00339)	(0.00350)
Minority	-0.168*	-0.180*	Ownership	0.0751	-0.246
	(0.100)	(0.100)		(0.228)	(0.250)
			Capital	-0.0971	-0.160
				(0.107)	(0.132)
			Year07	0.197***	0.198***
				(0.0589)	(0.0565)
			Observations	14,960	14,960

Note: # is the coefficient of city's population growth from 1953 to 1982 when city's population or city's number of college graduates is regressed on its population growth in history and other variables in the first stage. The dependent variable is the dummy variable Employment indicating one's employment status. Coefficients from maximum likelihood estimation are reported. The marginal effect of city scale is calculated using Newey's two-step method when ivprobit model is estimated in STATA. *, ** and *** respectively denote significance at 10%, 5% and 1%. Robust standard errors clustered at district level are in parenthesis.

TABLE 5: Heterogeneous Effects of City Scale

Years of Education	≤9	9-12	>12
Panel 1: Probit Estimation			
Population	0.0381**	0.0113	0.00858
	(0.0172)	(0.0135)	(0.00850)
College	0.0349*	0.0182	0.0131
	(0.0186)	(0.0148)	(0.00825)
Observations	4,339	5,850	4,771
Panel 2: IV-Probit Estimation			
Population	0.0776**	0.0493**	0.0382***
College	0.0684**	0.0441**	0.0337***
Observations	4,339	5,850	4,771

Note: Each entry is a separate regression with individual- and city-level characteristics controlled. The dependent variable is the dummy variable Employment indicating one's employment status. Entries are the marginal effects of city scale on employment. *, ** and *** respectively denote significance at 10%, 5% and 1%. Robust standard errors clustered at district level are in parenthesis for Probit estimations. Newey's two-step method is employed to estimate the marginal effects for the ivprobit models. However, since clustered standard errors are not allowed using two-step estimation under the code ivprobit in STATA, the significance levels reported in the table are obtained from the maximum likelihood estimation of the coefficients, using robust standard errors clustered at district level.

TABLE 6: Occupation and Education

	Manual	Manufacturing	Professional
Years of Education	10.82	11.00	13.06

Note: Average years of education are calculated for each occupation using data from individuals who are in the labor force in CHIP 2002 and 2007. Manual jobs include: Transportation, storage, post office and communication; Wholesale, retail and food services; Social services. Professional jobs include: Information technology and software; Finance and insurance; Real estate; Health, sports and social welfare; Education, culture and arts, mass media and entertainment; Scientific research and professional services; Government agents, party organizations and social groups. Individuals working in the farming, mineral, construction, electricity, gas and water supply facilities sectors are excluded in the calculation here.

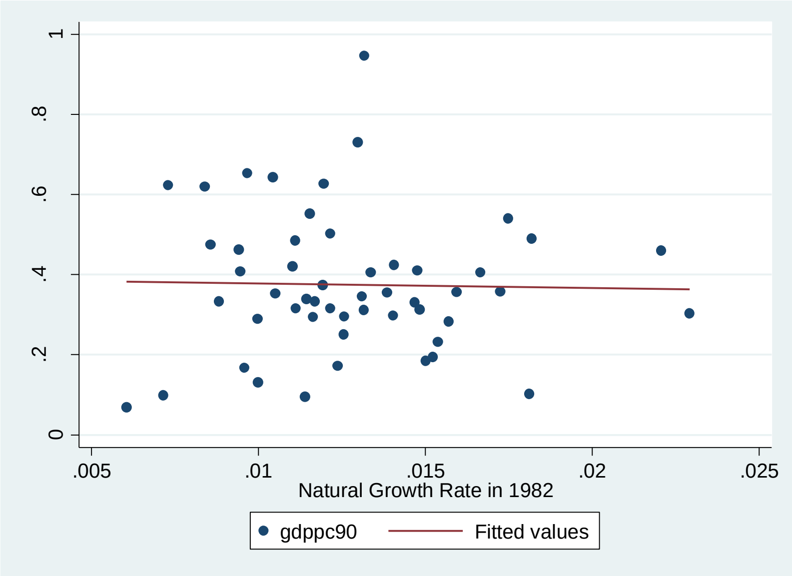
TABLE 7: Distribution of Workers and City Scale

	City Scale		
	Small	Medium	Big
Panel 1: Shares of Manual Job Workers			
Population	0.225	0.245	0.319
College	0.222	0.254	0.315
Panel 2: Shares of Manufacturing Job Workers			
Population	0.183	0.208	0.195
College	0.179	0.207	0.196
Panel 3: Shares of Highest-Educated Workers in Manufacturing Jobs			
Population	0.198	0.215	0.257
College	0.167	0.221	0.260
Panel 4: Shares of Highest-Educated Workers in Manual Jobs			
Population	0.127	0.147	0.231
College	0.122	0.150	0.230

Note: Cities are divided into three groups, namely small, medium and big cities according to their scales. In each panel, the first row is the division of cities according to their populations. The second row is the division of cities according to their scales of college graduates. Cities with scales smaller than the 33.3% percentile of all city scales are grouped as small cities. Cities with scales larger than the 66.7% percentile of all city scales are grouped as big cities. The remaining are medium-sized cities. Each entry is the group's share in all labors.

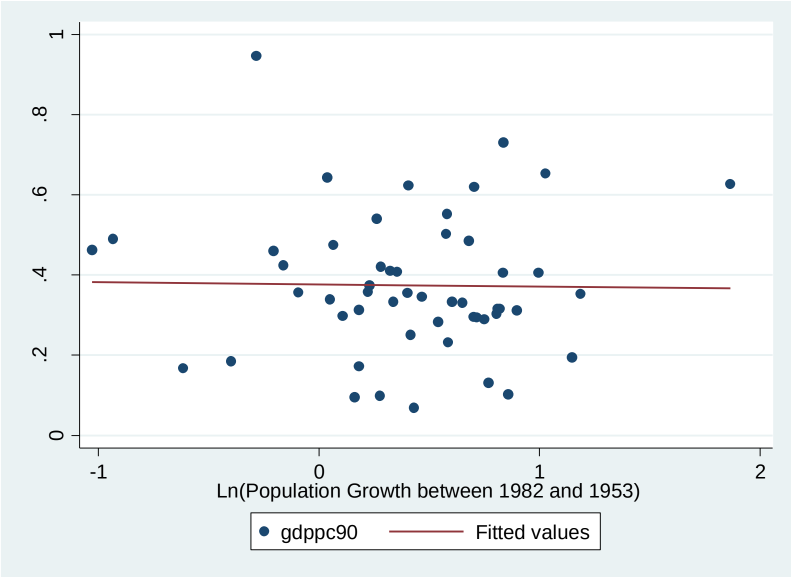
FIGURES

FIGURE 1: GDP Per Capita in 1990 and the Natural Growth Rate of Population in 1982



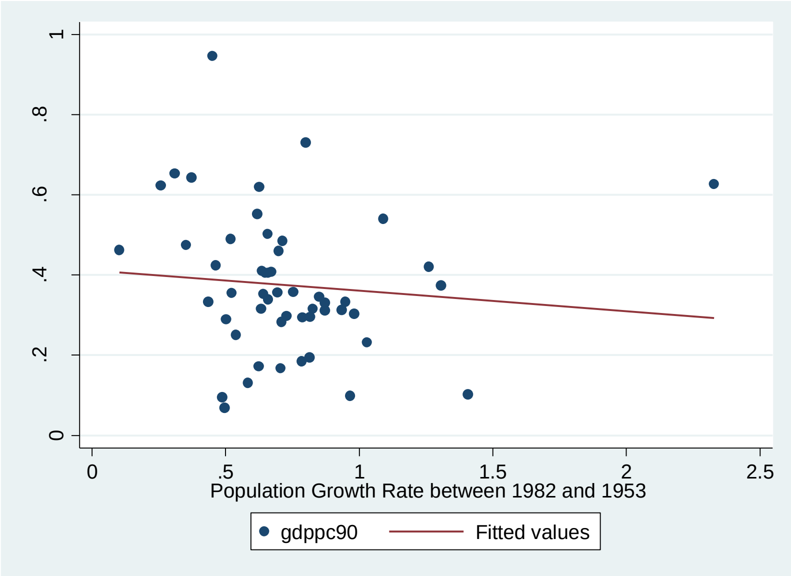
Note: A city's GDP per capita in 1990 is plotted against its natural growth rate of population in 1982 to show there is no apparent correlation between these two variables. Y-axis is city's GDP per capita. X-axis is city's natural growth rate in 1982.

FIGURE 2: GDP Per Capita in 1990 and Population Growth between 1982 and 1953



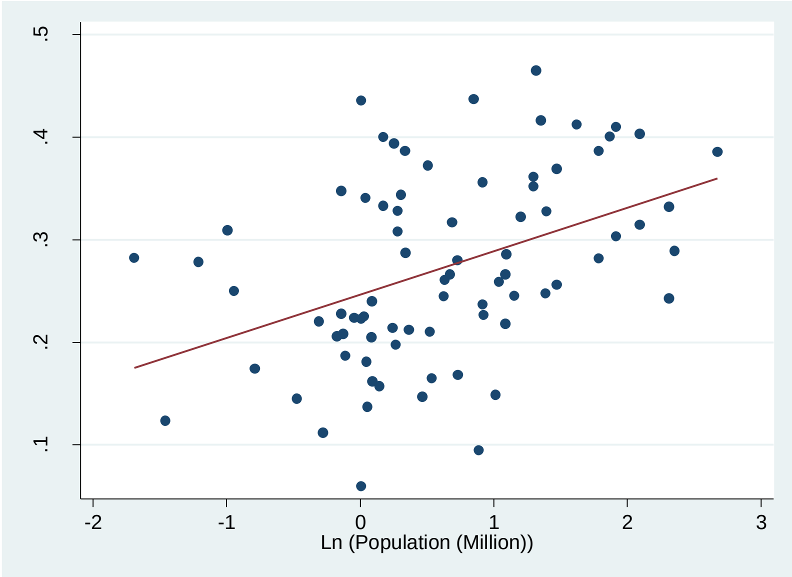
Note: A city's GDP per capita in 1990 is plotted against its population growth between 1953 and 1982 to show there is no apparent correlation between these two variables. Y-axis is city's GDP per capita. X-axis is the natural logarithm of city's population growth from 1953 to 1982.

FIGURE 3: GDP Per Capita in 1990 and Population Growth Rate between 1982 and 1953



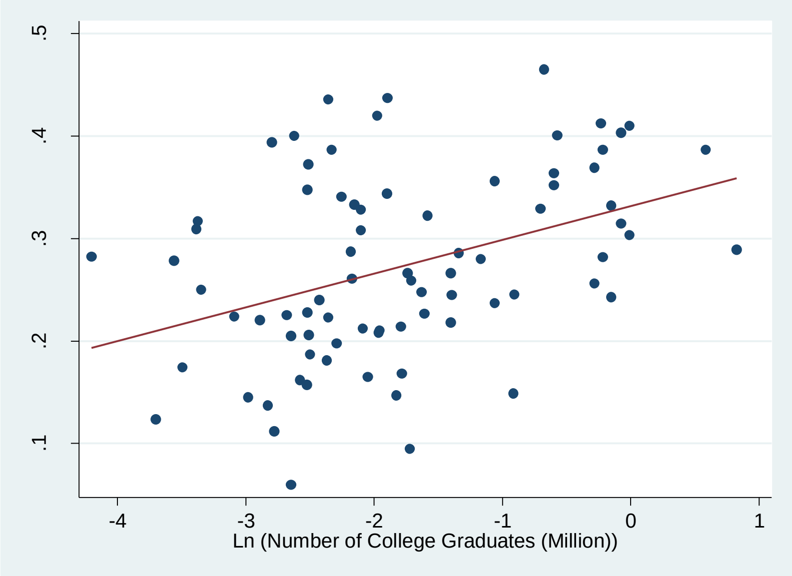
Note: A city's GDP per capita in 1990 is plotted against its population growth rate between 1953 and 1982 to show there is no apparent correlation between these two variables. Y-axis is city's GDP per capita. X-axis is city's population growth rate from 1953 to 1982.

FIGURE 4: Share of Manual Job Workers and City Population



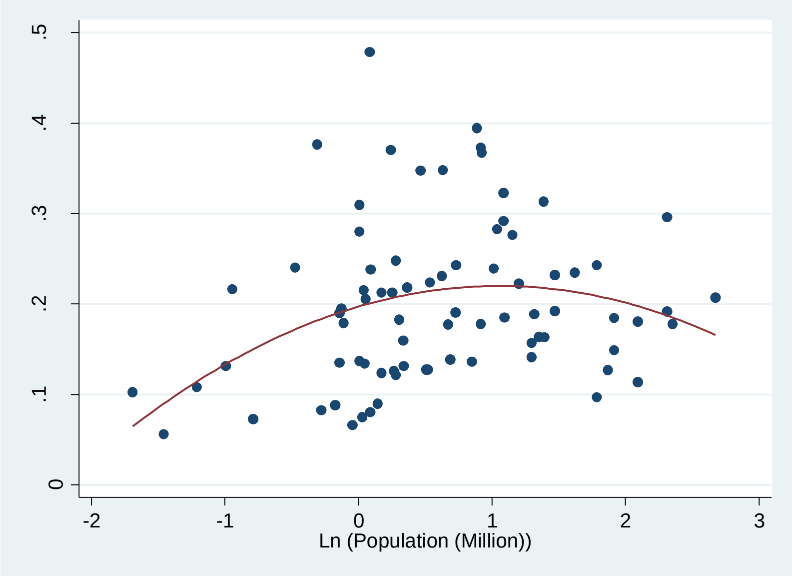
Note: A city's share of manual job workers in all laborers is plotted against the natural logarithm of its population to show there is a positive relationship between these two variables. Y-axis is city's share of manual job workers in all laborers. X-axis is the natural logarithm of city's population.

FIGURE 5: Share of Manual Job Workers and City's Number of College Graduates



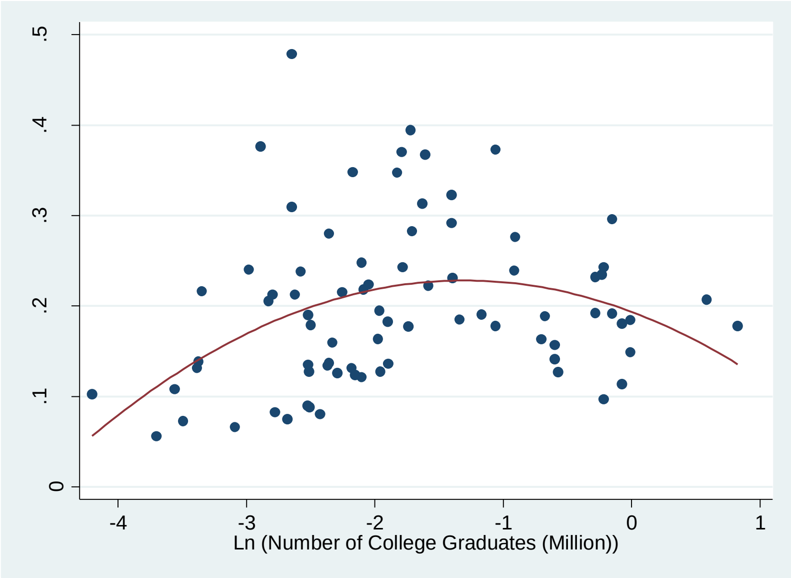
Note: A city's share of manual job workers in all laborers is plotted against the natural logarithm of its number of college graduates to show there is a positive relationship between these two variables. Y-axis is city's share of manual job workers in all laborers. X-axis is the natural logarithm of city's number of college graduates.

FIGURE 6: Share of Manufacturing Job Workers and City Population



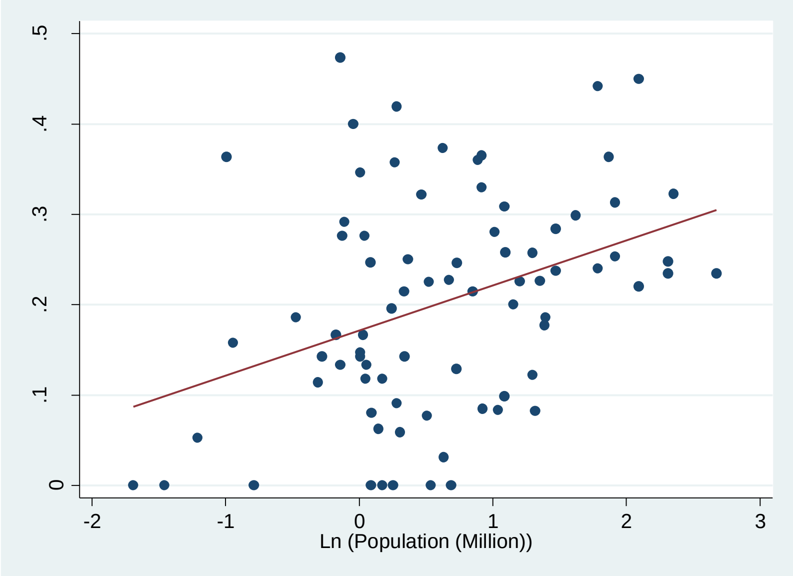
Note: A city's share of manufacturing job workers in all laborers is plotted against the natural logarithm of its population to show there is an inverted U-shaped relationship between these two variables. Y-axis is city's share of manufacturing job workers in all laborers. X-axis is the natural logarithm of city's population.

FIGURE 7: Share of Manufacturing Job Workers and City's Number of College Graduates



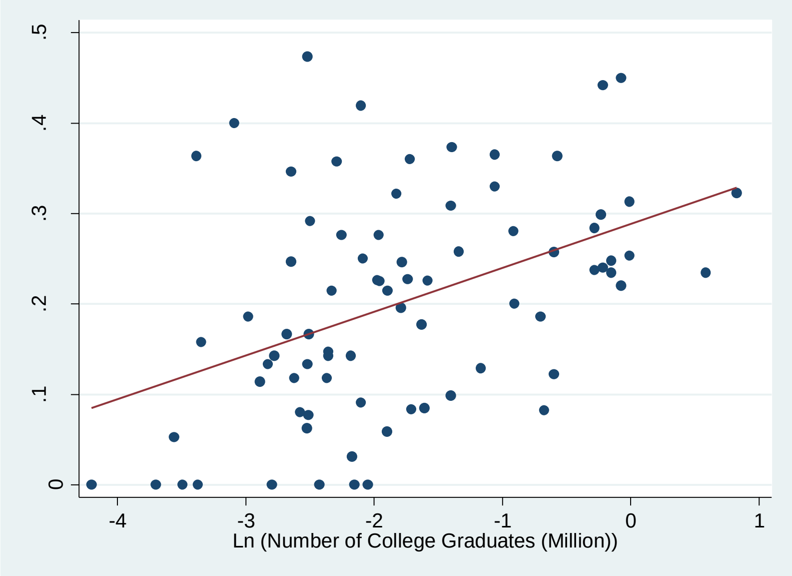
Note: A city's share of manufacturing job workers in all laborers is plotted against the natural logarithm of its number of college graduates to show there is an inverted U-shaped relationship between these two variables. Y-axis is city's share of manufacturing job workers in all laborers. X-axis is the natural logarithm of city's number of college graduates.

FIGURE 8: Manufacturing Upgrading and City Population



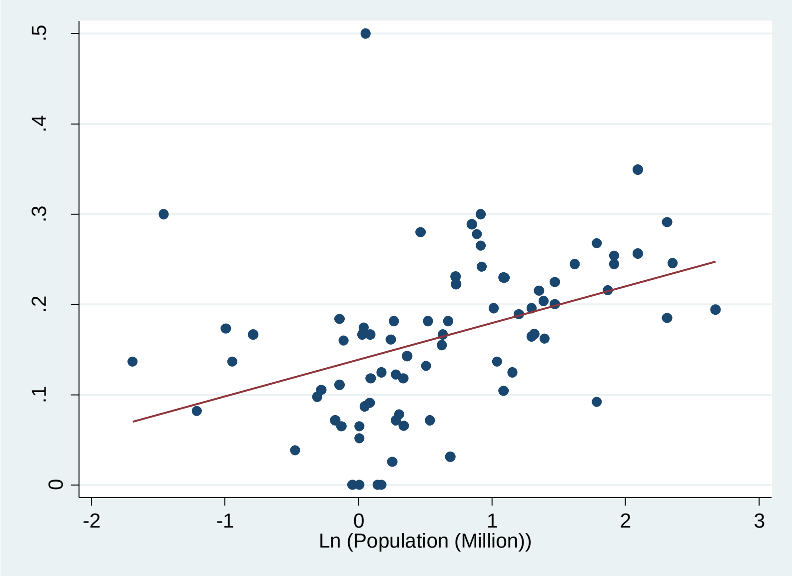
Note: A city's share of workers with years of education greater than 12 years in manufacturing job workers is plotted against the natural logarithm of its population to show there is a positive relationship between these two variables. Y-axis is city's share of workers with years of education greater than 12 years in manufacturing job workers. X-axis is the natural logarithm of city's population.

FIGURE 9: Manufacturing Upgrading and City's Number of College Graduates



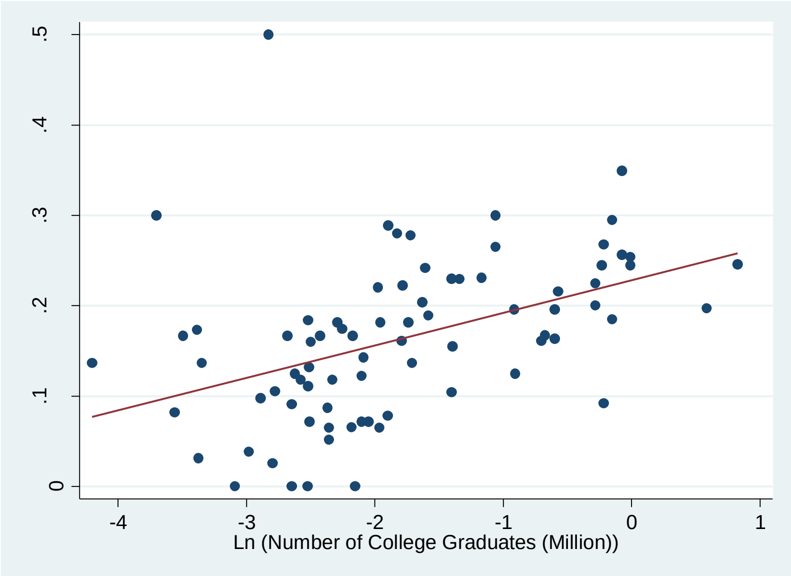
Note: A city's share of workers with years of education greater than 12 years in manufacturing job workers is plotted against the natural logarithm of its number of college graduates to show there is a positive relationship between these two variables. Y-axis is city's share of workers with years of education greater than 12 years in manufacturing job workers. X-axis is the natural logarithm of city's number of college graduates.

FIGURE 10: Manual Jobs Quality and City Population



Note: A city's share of workers with years of education greater than 12 years in manual job workers is plotted against the natural logarithm of its population to show there is a positive relationship between these two variables. Y-axis is city's share of workers with years of education greater than 12 years in manual job workers. X-axis is the natural logarithm of city's population.

FIGURE 11: Manual Jobs Quality and City's Number of College Graduates



Note: A city's share of workers with years of education greater than 12 years in manual job workers is plotted against the natural logarithm of its number of college graduates to show there is a positive relationship between these two variables. Y-axis is city's share of workers with years of education greater than 12 years in manual job workers. X-axis is the natural logarithm of city's number of college graduates.