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Regional distribution and dynamics of human capital in China 1985–2014

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ABSTRACT

This study investigates the regional distribution and dynamics of human capital in China. We develop a new comprehensive human capital measure based on the Jorgenson-Fraumeni (J-F) lifetime income framework, in addition to using the traditional education-based human capital measures. We find that the new J-F human capital measure reflects more closely the regional economic disparity than the education-based measures. We also conduct a Divisia decomposition analysis to investigate the contributions of different factors to the quantity and quality growth of human capital and to regional disparity. Our results show that the regional human capital gaps in China are enlarging in general. Education and urbanization contribute most to human capital growth, while population aging shows a strong negative effect. Our estimates create a new provincial level human capital panel dataset from 1985 to 2014, which is useful for empirical work and policy analysis.

1. Introduction

Human capital has been recognized as an important factor underlying economic growth in China (for example, Li et al., 2017; Su and Liu, 2016).[1] Studies show that human capital investments promote economic convergence (Mankiw et al., 1992) and contribute

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[1] There have been numerous cross-country studies about the effect of human capital on income disparity, for example: Lucas (1988), Barro and Sala-i-Martin (1992), Mankiw, Romer and Weil (1992), Hall and Jones (1999), Bils and Klenow (2000), Hendricks (2002), Gennaioli et al. (2013), Manuelli and Seshadri (2014) and Jones (2014).

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to a reduction in regional inequality in China (Fleisher et al., 2010). Therefore, regional human capital is a vital input to policy design for regional development. In this study, we investigate regional human capital distribution and dynamics in China. Our results have direct policy relevance and can aid empirical research.

China has experienced impressive economic growth over the past 40 years. However, the growth is accompanied by rising regional inequality (Wan, 2007; Fleisher et al., 2010; Lin et al., 2013). The ratio of per capita GDP of the richest province to that of the poorest one was 4.28 in 2016, peaked at 6.57 in 2002. To put this in perspective, in the US, the ratio between the richest state and the poorest state was 2.03 in 2016.[2] Additionally, the Coefficient of Variation (CV) for inter-provincial per capita GDP was 45% in China for 2016, while it was 18% in the U.S. for the same year.[3]

We investigate regional human capital distribution among four regions in China: The East, Northeast, Interior and West.[4] These regions represent different levels of economic development. The East region is along the coastline and is the most developed. The West region is the least developed, while the Interior region is in between in terms of both location and stage of development. The Northeast region was the most developed region in past years but gradually fell behind. Therefore, the human capital distribution among these regions can provide useful information for studying regional inequality.

In China the GDP per worker shows a clear regional pattern as shown in Fig. 1. It is the highest in the East and lowest in the West. More specifically, in 2014, GDP per worker in the West was 52% of that of the East, and the ratio was as low as 39% in 2005. In the Northeast, its GDP per worker was the highest of all regions in 1985 but then dropped continually to about 63% of the East's in 2005. It appears that the regional pattern of GDP per worker relative to the East follows a U-shape, i.e., the regional gaps were relatively small during the early years of economic reform, then increased significantly, and then narrowed after 2005.

When studying human capital, a central issue is the method of measurement. The most commonly used human capital measures are education-based, such as average years of schooling, proportion of labor force with a certain level of education, and various enrollment rates (Barro and Lee, 2013). Education can only partially measure the human capital of an individual because it omits many other aspects, such as on-the-job learning, health, etc. Additionally, education-based measures generally fail to reflect the quality of schooling (Hendricks, 2002; Schoellman, 2012; Manuelli and Seshadri, 2014). Hanushek and Woessmann (2012) shows that quantitative measures of schooling do not adequately capture the effect of human capital on economic growth due to the vast differences in school quality across countries. Additionally, some recent studies, such as Hanushek and Woessmann (2012), use cognitive skills to measure human capital. This measure has substantially raised the explanatory power on economic growth. However, cognitive/non-cognitive measures do not capture all aspects of an individual's human capital, and the data are generally less available, especially in China.

In this study, we develop a new comprehensive human capital measure. Our new measure of human capital stock follows the Jorgenson-Fraumeni (J-F) lifetime income approach (Jorgenson and Fraumeni, 1989, 1992a, 1992b), which is widely used in estimating human capital stock in other countries (Lange et al., 2018). The J-F approach includes various aspects of human capital accumulation, such as education, on-the-job training, and less easily observed components of human capital such as health, abilities, and unobserved school quality.

Additionally, for comparison, we also construct various education-based human capital measures. Therefore, we create a new panel dataset on various human capital measures that covers all provinces in China from 1985 to 2014. The data will be useful for empirical work and policy analysis. For example, the human capital measures in the dataset can be used in estimating production functions, in economic growth models or convergence models, as well as in growth accounting and development accounting analyses. Moreover, in order to explore policy implications on human capital development, we apply Divisia decomposition techniques to investigate how regional factors contribute to the human capital growth.

To the best of our knowledge, there is no study that has yet investigated regional human capital dynamics in China using various measures. Therefore, this study can shed new light on the development of regional human capital and on the internal dynamics of human capital across regions. We find that the human capital stock measure based on the J-F framework relates more closely to regional disparities, while education-based measures, especially average years of education, generally underestimate regional disparities. Our results show that regional human capital gaps are enlarging, especially between the economically advanced East and the other regions. Moreover, we find that education and urbanization contribute the most to human capital quality growth, while population aging appears to have a strong negative effect on human capital in China.

The rest of the paper is organized as follows: Section II summarizes the related literature on human capital measurements and introduces the Jorgenson-Fraumeni approach. Section III presents the data. Section IV discusses human capital estimation methodology in China with the J-F approach. In section V, we discuss regional distributions of human capital in China. In section VI, we introduce the Divisia decomposition methodology and estimate the contribution of various factors to regional human capital growth. Section VII concludes.

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[2] US Data- Bureau of Economic Analysis, real per capita GDP by state, chained 2009 Dollars, https://bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=2#reqid=70&step=1&isuri=1

[3] CV is a standardized measure of dispersion of a probability distribution and is defined as the ratio of the standard deviation to the mean.

[4] Based on the *China Statistical Yearbook 2015* (http://www.stats.gov.cn/tjsj/ndsj/2015/indexeh.htm), the four regions are divided as follows: the East region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the Northeast region includes Heilongjiang, Jilin, and Liaoning; the Interior region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the West region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. We exclude Tibet because of data limitations.

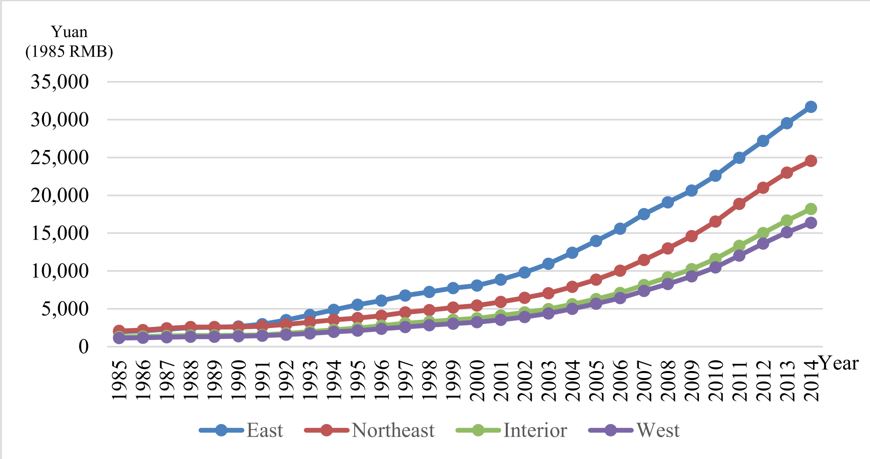

Fig. 1. GDP per worker by region.

2. Literature on human capital measurements

There are different ways to estimate aggregate human capital stock as shown in the review by Le et al. (2003). Kendrick (1976) pioneers the cost-based approach, in which the value of human capital is based on total investment (costs). However, the data requirements are enormous and make it very difficult to apply. The World Bank (2006, 2011) uses a residual-based approach to estimate intangible capital, where the stock of intangible capital is measured as the difference between the total discounted value of each country's future consumption flows and the sum of the tangible components (Ruta and Hamilton, 2007). This approach cannot separate human capital from other intangible capital.

Another method is to translate workers in an economy into unskilled worker equivalents and then sum them up together (Hall and Jones, 1999).[5] Additionally, Jones (2014) proposes a generalized human capital aggregator to estimate human capital stock that relaxes an assumption of perfect substitution among workers with different skills. These approaches also assume that wages are equal to the marginal product of labor. However, they do not produce a monetary value of human capital stock.

The J-F method (Jorgenson and Fraumeni, 1989, 1992a, 1992b) is an income-based approach that estimates an individual's lifetime earnings as his or her value of human capital and sums individuals' nominal lifetime income together to get the aggregate human capital stock. The J-F method has a sound theoretical foundation, i.e., the value of an asset is determined by the market. In addition to capturing more aspects of human capital besides education, the J-F measure has some other advantages. In particular, the J-F framework incorporates age information in calculating an individual's human capital, and thus can captures the effect of age structure (such as population aging) on human capital.

Moreover, the J-F approach can estimate human capital not only for workers but also for young people who are not yet in the labor market, while other measures that use information on earnings can only estimate labor force human capital. Therefore, the J-F method can estimate human capital stock in production use (labor force) as well as human capital reserve (young people). Additionally, the J-F approach estimates human capital as a monetary value and can be easily interpreted. For example, it can be compared with the monetary value of physical capital stock. Moreover, the estimates are directly useful for policy analysis.

As a result, the J-F method is a widely used approach in estimating human capital stock. The OECD Human Capital Consortium used the J-F methodology to estimate human capital for 19 countries (Liu, 2011).[6] The World Bank (Lange et al., 2018) recently adopts the J-F methodology to estimate human capital for 141 countries. Li et al. (2013) applies the J-F method to estimate human capital stock for China at the national level; and Li et al. (2014) estimates J-F based human capital stock for some provinces in China.

Compared to Li et al. (2014), which estimates human capital for some provinces in China, we calculate human capital for all provinces and construct a complete provincial level human capital panel database. We also make a few technical improvements. First, new and updated datasets such as population, school enrollment, etc. are used, and additional household survey data are added in the estimation of the Mincer models.[7] Because of the new data, all provinces are re-calculated for all years, so the results are more accurate compared to

[5] In the neoclassical approach based on unskilled worker equivalents (for example, Hall and Jones, 1999; Jones, 2014), the human capital stock is calculated using the current relative wage as weights when summing up all labor. In this case, for example, if a 23-year-old college graduate has the same wage as a 58-year-old high school graduate, they are considered to have the same amount of "unskilled worker equivalent" units. However, in the J-F framework, they have very different human capital stock due to different age and education. Therefore, the J-F framework can better capture the joint effect of age and education on the amount of an individual's human capital.

[6] The United Nations Economic Conference for Europe, *Guide on Measuring Human Capital* (2016), recommended J-F methodology as one of two approaches to estimating human capital.

[7] Two waves of a new household survey have been added in the calculation since Li et al. (2014), China Family Panel Studies (CFPS), 2010 and 2012.

Li et al. (2014). Second, education is further disaggregated into six categories, i.e., we separate three-year college and four-year university in the tertiary education group, because their market values are different.[8] These more disaggregated education measures require re-formulating and re-tooling all parts of the calculation and reflect more closely the human capital distribution in China.[9]

There are a few limitations of the J-F approach. The J-F framework maintains the neoclassical assumption that wages represent marginal products of labor (Hall and Jones, 1999; Jones, 2014). In this case, wage is affected by physical capital and technology. As a result, the value of human capital will be affected by regional physical capital and total factor productivity (TFP). Additionally, there may be a relatively larger discrepancy between wages and marginal productivity of labor in China because the county is still transitioning to a market economy and the labor market may not be competitive. The J-F method also maintains the assumption of perfect substitution among various types of labor.

3. Data

The first group of data required is population size for subgroups, i.e., population by gender, age, education and location (rural/urban) for each year (referred to as “4-dimension population” hereafter). Such data are available for the census years of 1982, 1990, 2000, and 2010 and for the years with a 1% national population sample survey, 1987, 1995, and 2005. For the missing years, we adopt a perpetual inventory method to estimate the population, as commonly used in the literature for population imputation.[10] However, due to migration across provinces, the imputed population generally differs from actual population sizes because no migration data are available. The discrepancy between the imputed and the actual data on various categories of population is mainly caused by rural-urban and cross-province migration. Therefore, the discrepancy is then used to adjust the imputed population for each year.[11] This process helps capture the impact of migration flow on human capital stock.[12]

The second group of data is a 4-dimension population separately categorized as in-school (students) and out-of-school (non-students). We get in-school population based on the enrollment at different education levels as reported by the Ministry of Education. We estimate enrollment rates for each education category based on the probability of advancing to the next higher education level and the minimum number of years to accomplish a degree.[13]

The third group of data are earnings data at the individual level. This is a major problem for applying the standard J-F framework to China because the earnings data for individuals who differ in gender, age, education and location are not generally available. Therefore, we use the Mincer model (1974) to estimate individual earnings with survey data. However, at the provincial level, this approach requires survey data to be available for each province for all years; moreover, the survey dataset for each province should have enough observations for the urban, rural, male, and female groups. Such survey data are not available for many provinces. As one solution, we augment the traditional Mincer model by incorporating province-specific aggregate variables to capture the province-specific labor market structure that affects individual earnings so that we can use larger national survey samples.

More specifically, the provincial-level Mincer model can be specified as

$$\ln inc_{ij} = \beta_0 + \beta_1 \ln avwage_j + \beta_2 sch_{ij} + \beta_3 sch_{ij}\cdot PGDP_j + \beta_4 sch_{ij}\cdot Pr_j + X_{ij}\delta + u_{ij}, \tag{1}$$

where $\ln inc_{ij}$ is the logarithm of annual earnings of the employed, sch_{ij} is years of schooling, X_{ij} includes other control variables, and u_{ij} is the error term for individual i in province j. For provincial level variables, *avwage* is the average wage of a province; it captures the earnings differentials across provinces due to living costs, total factor productivity and other factors. We use two other aggregate variables to control for province-specific return to education, i.e., *PGDP* is provincial GDP per capita, and *Pr* is the proportion of the labor force employed in the primary industry.[14] Those two variables can help capture the impact of economic development stage and industry structure that will affect the returns to schooling (see for example, Li, 2003; Zhang et al., 2005; and Yang, 2005).[15]

In order to estimate the augmented Mincer model for each province, we use multi-waves of the five well-known household

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[8] In fact, those with a three-year college degree account for a significant proportion of the tertiary education. For example, in 2014, they account for 54.81% of those with tertiary degree (three-year college plus four-year college).

[9] The estimation in this study is based on updated data and China Hunan Capital Report-2017 (http://humancapital.cufe.edu.cn/rlzbzsxm/zgrlzbzsxm2016.htm). The China Human Capital Report series are the most detailed and extensive estimates of human capital for an individual country (Jorgenson, 2018), and it is updated annually.

[10] Refer to “China Human Capital Report-2017.” http://humancapital.cufe.edu.cn/rlzbzsxm/zgrlzbzsxm2017.htm.

[11] For example, based on 2005 population survey data we can impute the size of each sub-group of population for 2006, 2007, and up to 2010. The actual census data are available in 2010, and then we can calculate the discrepancy for each sub-group between the imputed and actual numbers. It is likely that the discrepancy is caused by migration each year between 2005 to 2010. Then we adjust the differences back to each year from 2006 to 2009 (assuming equal amount of migration every year for simplicity). Therefore, we can control for the effect of net migration.

[12] In our estimation, the life-time income of an individual is calculated based on the earnings at the current location. When one moves to a different location, his/her earnings at the new location will be used, and this individual's human capital will be counted as part of aggregate human capital in the new location.

[13] One complication is that an individual may enter school at different ages. We allow for this possibility in the calculation, e.g., the age range for enrolling in elementary school is 5-10, middle school is 11-16, high school 14-19, and college and university 17-22.

[14] We estimate Eq. (5) separately using samples for each of the rural/urban and male/female combinations for each province using survey data. All Mincer parameters are available upon request.

[15] We assume that returns to experience are the same across provinces. We believe that the province-specific variables we included capture the major effect, although there may be other province-specific variables that will affect the earnings structure of an individual.

surveys in China: Urban Household Survey (UHS) 1986–1997; Chinese Household Income Project (CHIP) 1988, 1995, 2002, and 2007; China Health and Nutrition Survey (CHNS) 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011; China Household Finance Survey (CHFS) 2010; and the Chinese Family Panel Studies (CFPS) 2010 and 2012.[16] For missing years, the Mincer parameters are imputed linearly or exponentially. Based on the estimated Mincer models, we can estimate earnings for each location (urban/rural), gender, age, and education category for every year.[17] Note that in rural areas, an individual's earnings come from family farming. We estimate an individual family member's earnings based on the share of hours worked among family members.

4. The J-F framework for China

In order to apply the J-F framework in China, we modified the J-F method. First, due to the lack of earnings data, we incorporated the Mincer model into the China J-F framework. Secondly, we created a cross-province living-cost index to adjust the estimated lifetime income so that the human capital estimates are comparable across provinces. Finally, because of the drastic structural difference between urban and rural areas in China, we calculate human capital separately for the urban and rural populations. This approach generates more accurate estimates of total human capital and allows us to investigate urban-rural disparities in human capital and the effect of urbanization on human capital.

The J-F approach estimates each individual's expected lifetime income and then aggregates all individuals together to get total human capital stock K_t for an economy, as in the following equation,

$$K_t = \sum_s \sum_a \sum_e \sum_r mi_{s,a,e,r,t} \cdot l_{s,a,e,r,t}, \tag{2}$$

where the subscript *t, s, a, e* and *r* denotes, respectively, year, gender, age, educational attainment, and location, and $mi_{s,\ a,\ e,\ r,\ t}$ stands for the lifetime labor income and $l_{s,\ a,\ e,\ r,\ t}$ is the population for the specific category. The data on the 4-dimentional population, i.e., by rural/urban, male/female, education and age are obtained as discussed above. We define s = (male, female), a = (age from birth to retirement), e = (below elementary, elementary, middle school, high school, 3-year college, 4-year university or above), and r = (urban, rural).[18]

In the J-F approach, the life cycle is divided into five stages. At the fifth stage, retirement, future market earnings are assumed to be zero. The preceding four stages include: pre-school, school-only, work-school, and work-only. The estimation is conducted in a backward recursive fashion beginning with the retirement age. More specifically, the lifetime income of an individual at age a is the present value of the expected lifetime income of an individual at age $a + 1$ plus his/her income in the current year, after accounting for the probabilities of being in the labor market or completing another year of school.

The second stage is school-only. In China, due to the nine-year compulsory education system, this stage only applies to elementary and middle school.[19] For the third stage (work-school), an individual might work or go to school. This stage applies to high school or above. In China students rarely work, so we assume that no students work. If someone completed middle school and started to work at age 16, the earnings will increase with years of job experience. However, for those individuals enrolled in high school, they can either finish high school and work or continue to college/university.

We illustrate the method by taking an 18-year-old individual who has completed high school as an example. If this person chooses to work, his/her expected lifetime income would be as follows (we remove the location subscript here for simplicity),

$$mi_{t,s,18,highschcompleted-working} = ymi_{t,s,18,highschcompleted-working} + sr_{t,s,18to19} \cdot mi_{t,s,19,highschcompleted-working} \cdot \frac{1+G}{1+R}, \tag{3}$$

where *mi* stands for lifetime earnings, *ymi* denotes an individual's annual market income adjusted by the probability of being employed, and *sr* is the survival rate. In the J-F framework, future income is projected with an exogenous labor income growth rate G, and R is the discount rate. The real income growth rate is exogenously given, reflecting overall future productivity improvements (Jorgenson and Fraumeni, 1989, 1992a, 1992b). Because the expected lifetime income for the individual at age $a + 1$ would be achieved in year $t + 1$, it is then adjusted by the real income growth $(1 + G)$ and discounted by $(1 + R)$.[20]

[16] UHS: http://www.usc.cuhk.edu.hk/DCS/DCS31-1-86-92.aspx
CHIP: http://www.icpsr.umich.edu/icpsrweb/ICPSR/series/00243
CHNS: http://www.cpc.unc.edu/projects/china/data
CHFS: http://www.chfsdata.org/
CFPS: http://www.isss.edu.cn/cfps/

[17] It is known that if we simply exponentiate the predicted value forln *inc*, the prediction will systematically underestimate the predicted earnings, because of the error term in logarithm. We estimated an adjustment factor, which is related to the variance of error term, to adjust the predicted earnings.

[18] In China, the legal retirement age is 60 years old for males and 55 years old for females.

[19] The compulsory education law in China was implemented in 1986. Based on the law, when a child reaches 6 years old, he/she is required to enroll in elementary school, but the enrollment age can be postponed to 7 years old in less developed areas. In China, the elementary school education is six years in China, and for the middle school and high school education each is three years.

[20] Note that both G and R are constant and are exogenous in the calculation, and they are the same across years. Although the estimated level of human capital is sensitive to the choice of the real income growth rate G and discount rate R, the growth rate of human capital is not G and R are constant across time and their effects are differenced out.

Additionally, if the individual at 18 years old chooses to go to school, he/she can go to three-year college or four-year university in the Chinese higher education system. High school graduate students with higher scores in the national entrance examinations can enroll in university, and those with lower scores can enroll in three-year colleges.[21] The expected income of going to a four-year university is,

$$mi_{t,s,18,university} = sr_{t,s,18to19} \cdot sr_{t+1,s,19to20} \cdot sr_{t+2,s,20to21} \cdot sr_{t+3,s,21to22} \cdot mi_{t,s,22,universitycompleted-working} \cdot \left(\frac{1+G}{1+R}\right)^4, \tag{4}$$

$$mi_{t,s,22,universitycompleted-working} = ymi_{t,s,22,universityompleted-working} + sr_{t,s,22to23} \cdot mi_{t,s,23,universitycompleted-working} \cdot \frac{1+G}{1+R}, \tag{5}$$

As can be seen above, education is one factor affecting the J-F estimate, but other factors like urbanization, age, and gender affect the amount of human capital as well. For example, a labor force with old workers has very different amount of human capital compared to a labor force of the same size but with young workers, even if their level of educational attainment is the same.

We adopt the value for real wage growth rate G in the range of $4\% - 10\%$ for the urban and for the rural areas of each province. The values are based on the average annual growth rate of earnings for 1985–2014 for urban and rural areas separately.[22] We adopt a 4.58% discount rate used by Jorgenson and Fraumeni (1992a) and the OECD consortium (OECD, 2010). It is between the average interest rate on 10-year government bonds (net of inflation, 2.29%) and the average benchmark 5-year lending rate to commercial banks in China for the period from 1996 to 2012 (net of inflation, 5.33%).[23]

Additionally, because earnings may include living cost differences, they may not be directly comparable across provinces. Therefore, we construct a provincial living cost index to adjust earnings.[24] The living cost index construction follows the methodology in Brandt and Holz (2006), based on the prices for a specific basket of goods and using Beijing as the base area and 1985 as the base year adjusted for inflation for each province.[25]

5. Regional distribution and trend of human capital

Based on the above framework, we estimate the human capital stock for 30 provinces from 1985 to 2014 for China and construct a panel dataset. In our estimates, the total human capital (HC) covers all individuals from the newborn to retirement age.[26] It includes young individuals who have not yet entered the labor market (full-time students and those aged 15 or below), which represents the human capital reserve, and the human capital of the labor force (LFHC), which represents human capital in use. We also calculate traditional education-based human capital measures and report three commonly used education measures: average years of education of the labor force (AEDU), the proportion of labor force with high school education or above (PLHS), and the proportion of labor force with college education or above (PLC).

We first compare the disparity of human capital across provinces with the economic inequality measures from 2014. The AEDU of the labor force has the lowest variation, with a CV of 8%, followed by a CV of 27% for the PLHS, and a CV of about 44% for the PLC.[27] For regional GDP per worker, the CV is 44%. Therefore, the PLC reflects the dispersion of GDP per worker most closely, but it covers only a small portion of the labor force (less than 16%). The CV for per capita labor force human capital (PCLF) estimated based on the J-F framework, on the other hand, is 55%, much closer to the dispersion of GDP per worker than the first two education-based measures.

Additionally, as shown in Table 1, for regional inequality, in 2014, the ratio of GDP per worker between the East and West is 1.94; is 1.09 for AEDU, is 1.33 for PLHS, and is 1.33 for PLC.[28] The J-F PCLF shows a much higher regional inequality with a ratio of 1.88, much higher than the ratios of education-based measures above, and is closest to that of GDP per worker.

Moreover, Fig. 2 shows the regional pattern and trend of human capital based on different measures. The measure based on

[21] Based on the data from the *China Educational Yearbook*, the average ratio of new enrollments in four-year universities to those in three-year colleges from 1985-2014 is 1.07. Since 2010, the ratio has been above 1.10.

[22] It is possible to adopt the same value for G for all provinces as we did for the discount rate. However, we take different values to better reflect the long-term exogenous wage growth.

[23] See *Almanac of China's Finance and Banking*, 1997-2013, and *China Statistical Yearbook*, 2013.

[24] Cross-location comparison of human capital based on the J-F approach is still a challenge. It is a main obstacle in the work of the OECD Human Capital Consortium in establishing a comparable cross-country human capital measure using the J-F approach. Our approach of using the living cost index to make the adjustment is only a partial solution.

[25] Note that in Eq. (5), we control for provincial level earnings using the average wage, so that the estimated earnings can reflect local wage standard and local living cost. However, it does not make the estimated earnings comparable across provinces.

[26] In all tables and figures, human capital estimates are measured in real terms, with a 1985 base.

[27] In comparison with Barro and Lee (2013), at the national level, their estimate of average years of education for China is 8.47 for 2010 and 8.24 for 2005; ours is 9.50 and 8.62, respectively. There are a few explanations for the discrepancies. First, our estimates are based on the official age of labor force in China, 16–59 for males and 16–54 for females; but theirs estimates include those aged 15. Second, our education categories reflect more closely the education system in China, especially by separating three-year college and four-year university degrees. Third, we use much more disaggregated data at the provincial level and separate rural and urban areas.

[28] As in Barro and Lee (2013), the cross-country inequality based on average years of education is also much lower than their income difference. For example, the ratio of per capita GDP between US and Jamaica is 10.33, but ratio of average education is 1.34. Data source: https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.

Table 1
Regional comparison of labor force human capital measures (in thousand Chinese RMB).

	Year	East	Northeast	Interior	West
GDP per worker (in real value)	1985	1.96	2.07	1.29	1.13
	1995	5.54	3.77	2.47	2.13
	2005	13.98	8.86	6.27	5.68
	2014	31.71	24.56	18.20	16.38
Average years of education of the labor force	1985	6.40	7.38	5.89	5.49
	1995	7.97	8.48	7.56	6.95
	2005	9.00	9.21	8.72	7.98
	2014	10.16	10.04	9.80	9.30
Proportion of high school or above in the labor force	1985	0.13	0.17	0.10	0.09
	1995	0.18	0.20	0.14	0.13
	2005	0.25	0.25	0.20	0.18
	2014	0.36	0.33	0.30	0.27
Proportion of college or above in the labor force	1985	0.01	0.02	0.01	0.01
	1995	0.04	0.05	0.02	0.02
	2005	0.08	0.08	0.06	0.06
	2014	0.16	0.15	0.12	0.12
Per capita labor force human capital	1985	46.03	38.52	32.48	30.60
	1995	47.97	40.98	34.15	31.85
	2005	110.39	83.78	74.15	63.37
	2014	207.28	144.67	140.98	110.33

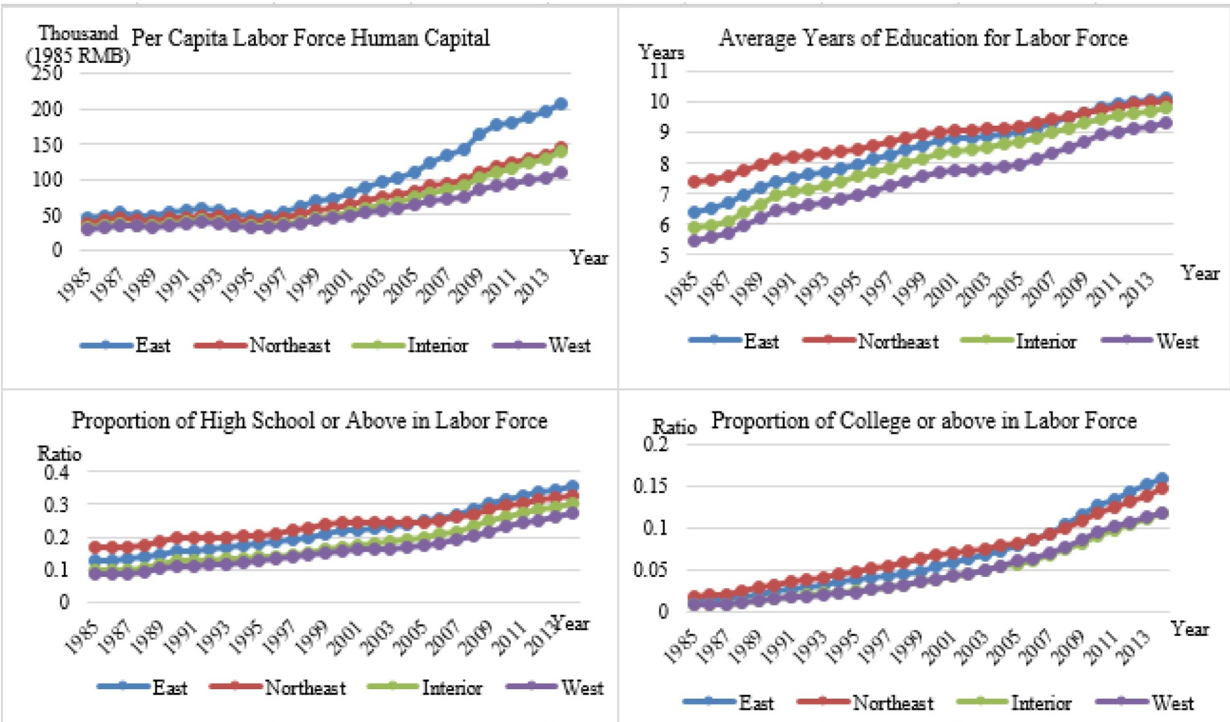

Fig. 2. Per capita labor force human capital (PCLF) and traditional education-based measures.

average years of schooling shows a convergence, opposite to that of the regional GDP per worker in Fig. 1. The PLHS measure appears to be mostly parallel across regions, although the East passed the Northeast around 2005. The PLC measure shows a slightly divergent trend. On the other hand, the PCLF displays a pattern that is closest to that of the regional income, and it also shows that the Northeast falls behind the East much more in human capital than in GDP per worker. Therefore, the education-based measures generally underestimate regional human capital disparity compared to the GDP per worker inequality, while the J-F estimates reflect it more closely.

In terms of dynamics and trend, during the period of 1995–2014, the LFHC for all regions grew at an annual rate of 6–9%. The East grew the fastest: the AEDU and PLHS measures grew at an annual rate of 1–2% and 2–4%, respectively. The annual growth of the PLC is comparable to that of LFHC.

Comparing education-based measures with the J-F measure, we note that, although the proportion of labor force with a college degree is only 14% at the national level in 2014, this portion of labor force represents 30% of total labor force human capital (LFHC) based on the J-F measure. Similarly, the PLHS is 32% of the labor force, but it counts for more than one half of the labor force human capital (51%). Therefore, education is still a major component of the human capital.

Among regions, the J-F total human capital estimates show slow growth before 1995 and much faster growth after that. This is consistent with the economic structural change that occurred in China around 1994–95 period (Fleisher et al., 2010).[29] As shown in Table 2, the East took a lead with an annual growth rate of 9.20% for 1995–2014 while the West and Northeast grew the slowest with an annual average growth rate of 7.01% and 7.17%, respectively. The Interior was in the middle, growing at a rate of 8.14% (see Table 2).[30] As can also be seen in Table 2, the human capital growth is much slower than GDP growth. Overall, the human capital gap between the East and other regions is growing.

We note that the ratio of LFHC/HC, i.e., the share of human capital in use, is below 50% for all regions, with the Northeast having the highest ratio and the Interior having the lowest ratio since 2009. The Northeast has the lowest share of human capital reserve, which is likely caused by its population age structure.[31] In 2014, for the non-retired population, the average age for the Northeast is 32 years old, while it is only 28 years for the Interior and West.

Per capita human capital (PCHC) represents the intensity of human capital. As shown in Table 3, the East has the highest human capital intensity, while the West has the lowest. All the top provinces in PCHC are in the East. In 2014, the three provinces with the highest human capital per capita are Tianjin, Beijing, and Shanghai, while the bottom three are Qinghai, Yunnan, and Gansu, which are all located in the West. Moreover, the gap between the East and other regions, especially the West, is growing. For example, in 1995, the PCHC of the West was around 62% of the East but declined to approximately 50% of the East in 2014.

Human capital can also serve as a beyond GDP measure of economic and social development. In particular, the human capital (expected lifetime income) of a newborn can be a good indicator of the relative stage of economic development. For all regions, the human capital for a newborn has risen rapidly, especially in the East, which has an eight-fold increase from 1985 to 2014. The regional gaps are substantial. Another interesting human capital age is 16, when an individual enters the labor force. The human capital of an average labor market new entrant shows a similar regional pattern as the newborn; the West is approximately 46% of the East in 2014.

6. Factor contributions to human capital growth

In this section, we conduct a Divisia decomposition analysis to investigate the impact of major factors on the growth of human capital based on the J-F measures (for a general discussion of the Divisia index, see Hulten, 1973). A Divisia decomposition can yield valuable information about the growth of human capital and the relationship between the J-F-based human capital and the education-based human capital measures (see, for example, Jorgenson et al., 1987).

6.1. The Divisia decomposition techniques

The J-F based human capital stock at the period t can be written as:

$$K_t = MI_t \cdot L_t = \sum_{i=1}^{n} mi_{it} \cdot l_{it},\ t = 0,\ 1,\ \ldots T, \tag{6}$$

where MI_t is the average lifetime income of an individual and L_t is size of population; mi_{it} is the average lifetime income of a particular group at year t and l_{it} denotes the size of population in the corresponding groups; n is the total number of groups classified by the characteristics of the population.

A human capital index $K_{t/0}$ can be defined as:

$$K_{t/0} = \frac{K_t}{K_0} = e^{\ln MI_t \cdot L_t - \ln MI_0 \cdot L_0} = e^{\int_0^T \frac{\sum_i l_{it} \cdot dmi_{it}}{\sum_i mi_{it} \cdot l_{it}}} \cdot e^{\int_0^T \frac{\sum_i mi_{it} \cdot dl_{it}}{\sum_i mi_{it} \cdot l_{it}}}. \tag{7}$$

In Eq. (7), we define $P_{t/0} = e^{\int_0^T \frac{\sum_i l_{it} \cdot dmi_{it}}{\sum_i mi_{it} \cdot l_{it}}}$ as the Divisia price index and define $Q_{t/0} = e^{\int_0^T \frac{\sum_i mi_{it} \cdot dl_{it}}{\sum_i mi_{it} \cdot l_{it}}}$ as the Divisia quantity index. In order to investigate how the changes in population structure affect human capital growth, we focus on the Divisia quantity index. The Divisia quantity index measures the accumulated weighted growth rate of the population from the last period to the current period, with the corresponding shares of lifetime income as weights.

Therefore, the Divisia quantity index of per capita human capital is (holding prices constant),

[29] Another possible reason is that, after 1995, the depression of wages became smaller due to the development of labor markets.

[30] All growth rates and per capita measures at the regional level are weighted by population or labor force unless otherwise specified. The regional total human capital measures are calculated as a direct summation of human capital of the provinces located in the region.

[31] In this study, 1) non-retired population includes all individuals below the retirement age (including children); 2) labor force includes all individuals aged 16 to retirement age (excluding students); 3) human capital reserve includes children (aged below 16) and full-time students.

Table 2
Average annual growth rates (%).

	Period	East	Northeast	Interior	West
Total human capital	1985–94	3.35	2.27	3.17	3.27
	95–2014	9.20	7.17	8.14	7.01
Labor force human capital	1985–94	3.14	3.66	4.03	4.58
	95–2014	8.86	6.70	7.24	6.23
Total GDP (in real value)	1985–94	12.99	8.36	8.99	9.29
	95–2014	11.61	10.61	11.25	11.28

Table 3
Regional comparison of human capital (in thousand Chinese RMB).

	Year	East	Northeast	Interior	West
Per capita human capital	1985	67.56	55.77	47.59	42.91
	1995	76.43	60.14	52.32	46.95
	2005	205.02	142.86	135.76	115.75
	2014	386.05	258.13	262.36	194.45
Per capita human capital for new born	1985	132.92	105.48	82.49	70.97
	1995	171.49	123.27	98.82	84.63
	2005	657.12	383.79	316.31	255.22
	2014	1218.31	714.84	544.28	369.28
Per capita human capital for age 16	1985	85.17	68.01	56.16	52.50
	1995	111.27	85.78	71.79	67.02
	2005	367.62	266.54	219.73	197.26
	2014	709.87	528.82	428.85	324.46

Note: The PCHC for newborns is higher than that for labor market new entrants due to survival rate and the exogenous growth of earnings G as shown in Eq. (2).

$$AQ_{t/0} = e^{\int_0^T \frac{\sum_i mi_{it} \cdot dl_{it}}{\sum_i mi_{it} \cdot l_{it}}} \cdot e^{-\int_0^T \frac{dL_t}{L_t}}. \tag{8}$$

By taking the logarithm of Eq. (8) and converting to a Törnqvist index discrete approximation (Törnqvist, 1936), we get

$$\begin{aligned} \ln AQ_{t/0} &= \int_0^T \textstyle\sum_i v_{it} \cdot d\ln l_{it} - \int_0^T (d\ln \sum_i l_{it}), \\ &= \textstyle\sum_{t=0}^T \left[\sum_i \bar{v}_{it} \cdot (\ln l_{it} - \ln l_{it-1})\right] - \sum_{t=0}^T (\ln \sum_i l_{it} - \ln \sum_i l_{it-1}) \end{aligned} \tag{9}$$

where $v_{it} = \frac{mi_{it} \cdot l_{it}}{\sum_i^n mi_{it} \cdot l_{it}}$, and $\bar{v}_{it}$ is the average of v_{it} between period t and $t-1$. The Divisia quantity index of per capita human capital equals the Divisia quantity index of total human capital minus the population growth, and it is typically referred to as a quality index in the literature (Jorgenson et al., 1987, 2005). The quality index captures the effect of changes in population (labor force) composition. For example, increasing education attainment will increase the human capital share of the group with a particular level of education, and thus will raise the quality index.

Moreover, following Chinloy (1980), Jorgenson et al. (1987), and Jorgenson et al. (2005), we can use partial Divisia quantity indices to identify the contribution of each human capital characteristic after excluding population growth. More specifically, in the J-F framework, we can establish first order partial human capital indices based on the four human capital characteristics: education (e), age (a), gender (s) and location (r). In particular, the annual contribution of education (e) to per capita human capital can be written as

$$\ln AQ_{t/t-1}^{e} = \sum_e \bar{v}_e \cdot \left(\ln \sum_s \sum_a \sum_r l_{s,a,e,r,t} - \ln \sum_s \sum_a \sum_r l_{s,a,e,r,t-1}\right) - \left(\ln \sum_s \sum_a \sum_e \sum_r l_{s,a,e,r,t} - \ln \sum_s \sum_a \sum_e \sum_r l_{s,a,e,r,t-1}\right), \tag{10}$$

where $\bar{v}_e = \frac{1}{2}(v_{e,t} + v_{e,t-1})$, and $v_{e,t} = \frac{\sum_s \sum_a \sum_r mi_{s,a,e,r,t} \cdot l_{s,a,e,r,t}}{\sum_s \sum_a \sum_e \sum_r mi_{s,a,e,r,t} \cdot l_{s,a,e,r,t}}$, and e refers to the six education levels in our calculation. The contribution of education comes from the growth of the population with a specific level of education and the share of human capital of this education group. As in the case of China, when education expands at the higher level, both the growth and the share of the highly educated group will increase and thus promote the quality growth of the J-F human capital. The contribution of other factors can be defined similarly.

The partial Divisia quality indices can also be computed by multiple characteristics to calculate the joint contribution of factors to human capital growth. For example, the partial Divisia growth rate for human capital per capita, due to the joint effects of age and education, is defined below,

$$d\ln AQ_t^{e,a} = d\ln Q_t^{e,a} - d\ln L_t - d\ln AQ_t^{e} - d\ln AQ_t^{a}. \tag{11}$$

The third order and the fourth order partial Divisia growth rates can be defined accordingly.

Table 4
Factor contributions to human capital quality growth (%).

		Per capita human capital		Per capita labor force human capital	
Region	Factor contributions	1985–1994	1995–2014	1985–1994	1995–2014
East	Urbanization	0.772	1.338	0.527	0.867
	Education	−0.183	0.230	1.648	1.777
	Age	−0.686	−0.948	−0.768	−0.946
	Gender	−0.014	0.018	−0.026	0.038
Northeast	Urbanization	0.321	0.450	0.169	0.225
	Education	−0.234	0.131	1.021	1.220
	Age	−1.116	−1.346	−0.692	−1.365
	Gender	0.006	0.023	0.032	0.050
Interior	Urbanization	0.657	1.649	0.435	0.965
	Education	0.102	0.242	1.800	1.795
	Age	−0.754	−0.619	−0.471	−0.849
	Gender	−0.005	−0.003	−0.023	−0.004
West	Urbanization	1.065	1.713	0.697	1.045
	Education	0.366	0.477	1.648	1.814
	Age	−0.705	−0.544	−0.175	−0.878
	Gender	0.002	0.010	−0.010	0.016

Note: Each number represents the average annual contribution to the growth based on Eq. (10).

6.2. The effect of education and urbanization on human capital growth

Table 4 provides the Divisia decomposition results.[32] Table 5 reports the results of the second order Divisia decomposition. In each table, the results are calculated as an average for two periods, 1985–1994 and 1995–2014. Figs. 3–6 provides a clearer picture of the factor contributions.

A distinguishing feature is that, education and urbanization each shows the largest contribution to human capital growth. More specifically, education contributes the most to the labor force human capital (PCLF), while urbanization has the largest impact on the total human capital (PCHC). As shown in Table 4, in the East, education contributes to the growth of PCHC with an annual rate of −0.18% to 0.23% for the two periods but contributes to the growth of PCLF at the rate of 1.65% to 1.78%, a much larger effect.[33] Because the expansion of education in China has mostly been at the high school and college level, it mainly affects the labor force human capital. For example, from 1985 to 2014, the average annual growth of the proportion of college graduates in the labor force is 10.4%.[34] Among regions, in both periods, education's contribution to PCLF growth in the Northeast is the smallest (around 1.0–1.2%). For all other regions, it is in the range of 1.7–1.8%.

On the other hand, the effect of urbanization is larger for the growth in the quality of the population than for that in the quality of labor force. For example, as shown in Table 4, in the East, urbanization contributes to an annual growth of PCHC 0.78% and 1.34% for the two periods, respectively. Urbanization brings a large number of relatively young but less educated people into the urban areas, and thus greatly increases total human capital due to young age but has only a moderate effect on labor force human capital due to their relatively low education.

The contribution of urbanization to human capital quality also comes from the higher productivity in urban areas. People move from rural to urban areas as a way of human capital investment to increase the value of their human capital (higher expected lifetime income) because of the higher productivity in the urban areas. The rapid urbanization process has been one of the main features of the Chinese economy. In 2009, for the first time, the size of the urban population surpassed that of the rural population. At the national level, the percentage of the urban population increased from about 23% in 1985 to 56% in 2014. Tombe and Zhu (2015) shows that the decline of migration costs in China between 2000 and 2005 contributes to two-fifths of aggregate labor productivity growth. Among regions, urbanization contributes most to the West and least to the Northeast. In the 1995–2014 period, urbanization annually contributes 1.71% to human capital quality growth in the West but merely 0.45% in the Northeast. The West seems to have benefited the most from urbanization.

In contrast to the positive effect of education and urbanization, the contribution of age structure to total human capital is negative for every region in both periods, in the range of −0.5% to −1.3%.[35] The negative effect becomes even more evident in the second period (1995–2014), as shown in Figs. 3–6. This result reflects the impact of population aging and the vanishing of a "population dividend" in China.

[32] Factor contributions are calculated separately first for each province and then are aggregated into regions, with provincial population ratio or labor force ratio as weights for PCHC and PCLF, respectively.

[33] The effect of education for the 1985–1994 period for both east and northeast regions is negative. It is likely that the in-migration and out-migration in those regions changed the educational composition of the population and thus reduced the growth of human capital.

[34] Based on Li and Liu (2014), from 1999 to 2004, the average annual growth in new enrollments of undergraduate students was 29.0%, and for graduate students was 27.8%.

[35] Based on Zhang et al. (2015), age structure is significantly correlated with provincial economic growth rates in China and can explain one-eighth of the persistent inter-provincial income inequality.

Table 5
Factor joint contributions to human capital quality growth (%).

		Per capita human capital		Per capita labor force human capital	
Region	Factor joint contributions	1985–1994	1995–2014	1985–1994	1995–2014
East	Urbanization & education	−0.145	−0.272	−0.297	−0.542
	Education & age	0.720	0.548	−0.801	−0.515
	Urbanization & age	2.154	−0.915	2.066	0.225
Northeast	Urbanization & education	−0.164	−0.287	−0.126	−0.259
	Education & age	0.527	0.634	−0.515	−0.100
	Urbanization & age	−0.339	−2.364	1.280	−1.496
Interior	Urbanization & education	−0.304	−0.383	−0.291	−0.649
	Education & age	0.527	0.650	−0.967	−0.425
	Urbanization & age	1.541	−0.424	2.286	0.183
West	Urbanization & education	−0.464	−0.583	−0.449	−0.797
	Education & age	0.322	0.521	−0.893	−0.312
	Urbanization & age	1.894	−0.820	3.476	−0.347

Note: Each number represents the average annual contribution to the growth based on Eq. (11).

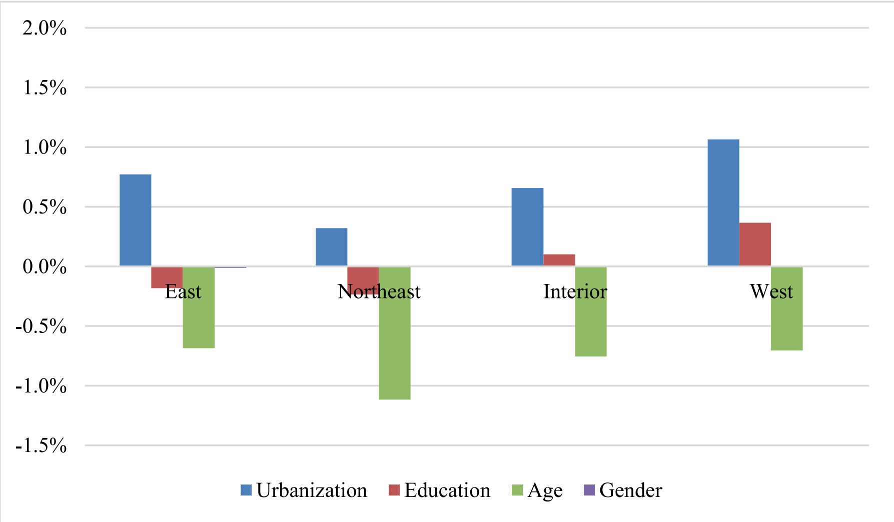

Fig. 3. Factor contributions to human capital quality (PCHC) growth 1985–1994.

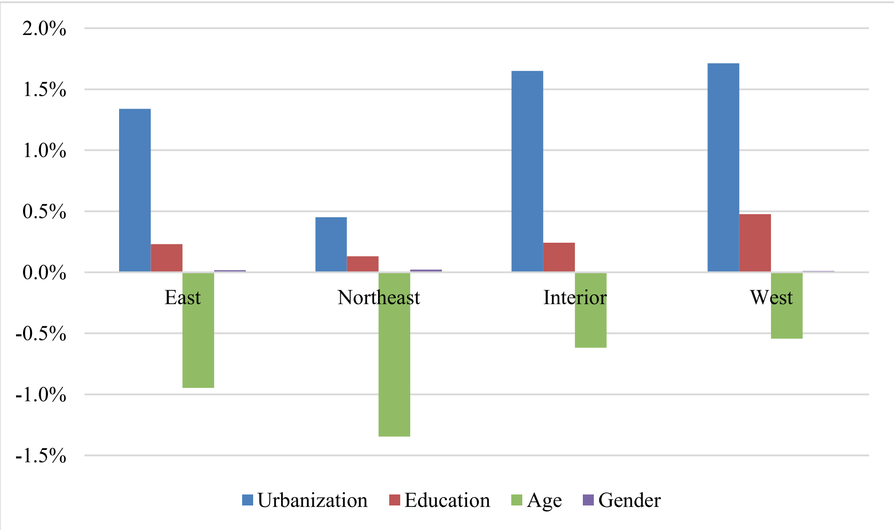

Fig. 4. Factor contributions to human capital quality (PCHC) growth 1995–2014.

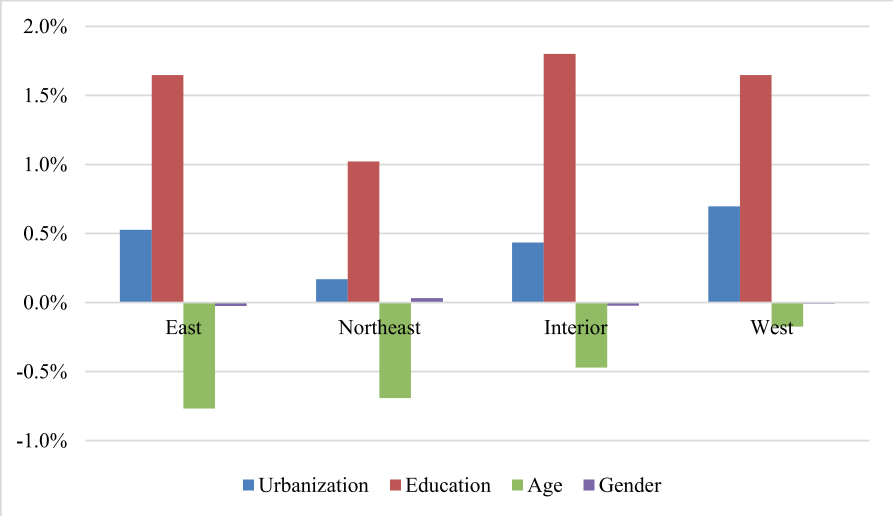

Fig. 5. Factor contributions to labor force human capital quality (PCLF) growth 1985–1994.

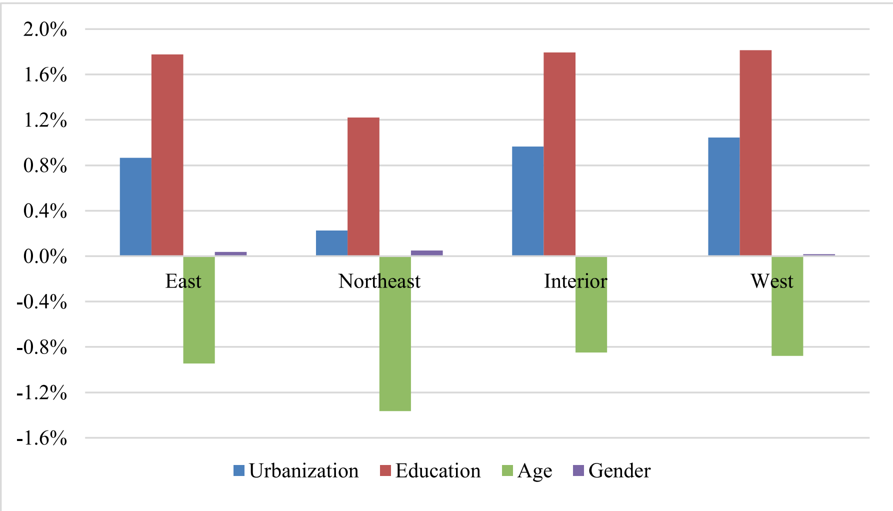

Fig. 6. Factor contributions to labor force human capital quality (PCLF) growth 1995–2014.

In the Northeast, in 1995–2014 period, population aging reduced the growth of PCHC at an annual rate of −1.35% and the growth of labor force quality (PCLF) at a rate of −1.37%. Moreover, for the Northeast, the positive effect of education plus urbanization was almost fully offset by population aging. For all regions, the effect of gender composition is negligible, and there is no significant regional disparity.

The joint effect is calculated based on the second order Divisia decomposition, and it reflects the co-function of the factors after netting out their own partial effect. As shown in Table 5, the most distinguished feature is the joint effect of urbanization and age. It is much larger than other joint effects during 1985–1994, except for the Northeast. For example, for the East, the joint effect of urbanization and age contributes an annual growth of 2.15% to per capita human capital and 2.07% to per capita labor force human capital during this period.

However, the joint effect of urbanization and age changed dramatically from 1985–1994 to 1995–2014. For example, in the East the joint effect on PCHC is 2.15% in 1985–94, dropping to −0.92% in 1995–2014; in the West, it declines from 1.90% to −0.82%. Similarly, for PCLF, this joint effect declines from 3.48% to −0.35%. It is likely that in the earlier years, rural to urban migrants were much younger and significantly improved the age structure in the urban areas, and thus promoted human capital growth. However, in the second period, such an effect is diminishing due to overall population aging.

The Northeast negative joint effect of urbanization and age is much higher than for all other regions, especially for the second period, i.e., it contributed −2.36% to total human capital growth and −1.50% to the growth of labor force human capital. One explanation is that the younger population moved out of the Northeast, then older people within the region moved from the rural to the urban areas, causing the negative joint effects of urbanization and age. From 1995 to 2014, in the Northeast, the total non-retired population declined at an annual rate of 0.2%, but labor force grew at an annual rate of 0.4%. As a result, the share of children in the non-retired population decreased rapidly, affecting the total human capital growth more than that of the labor force human capital.

7. Conclusion

We investigate the regional distribution and dynamics of human capital in China. In addition to the traditional education-based human capital measures, we develop a new comprehensive human capital measure based on the J-F lifetime framework. We modify the J-F methods to adjust for data in China and estimate provincial human capital from 1985 to 2014. We divide China into four regions with different levels of economic development: East, Northeast, Interior and West, and we discuss the regional pattern and trend of human capital. Moreover, we conduct a Divisia decomposition analysis to investigate the contribution of different factors to the quantity and quality growth of human capital.

The results show that the commonly used education-based measures, especially average years of education, generally underestimate regional disparities as represented by GDP per worker; the J-F measures reflect these regional inequalities more closely. However, education accounts for a significant proportion of the J-F measure. Highly educated people count for a much larger share of the J-F based human capital stock compared to their proportion in the labor force.

Based on the J-F measure, human capital in all regions grew slowly from 1985 to 1994, then much faster after 1995. Human capital in the East increased the fastest; the gap between the East and other regions is enlarging. In per capita terms, regional disparity in human capital is substantial, especially between the East and West.

Among factors affecting J-F human capital, education has contributed the largest to the quality growth of labor force human capital. Urbanization, on the other hand, makes the largest contribution to the quality growth of human capital of the total population. However, the change in age structure from population aging has a negative effect on human capital quality, and its negative effect became stronger after 1995.

Among regions, education and urbanization make relatively larger contributions to human capital growth in the less developed West and Interior; in addition, the negative aging effect is relatively smaller in those regions. As a result, those effects show a sign that the less developed regions may be in the process of catching up. However, the Northeast appears to be falling behind in human capital growth, and the contributions from urbanization, education and population aging are all less favorable compared to those in other regions.

Our results show that population aging is increasingly hindering human capital growth in China. The new “Two-child” policy may be able to help offset such a trend.[36] Additionally, given that more than half of the country has already been urbanized, it is likely that education, not urbanization, will eventually play a leading role in regional human capital growth. On the other hand, the Northeast appears to be at a difficult stage in terms of human capital growth; some creative policies are needed to promote human capital investments in this region.

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