Journal of Asian Economics 79 (2022) 101441

Contents lists available at ScienceDirect

Journal of Asian Economics

journal homepage: www.elsevier.com/locate/asieco

Full length article

Human capital dynamics in China: Evidence from a club convergence approach

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ARTICLE INFO

JEL classification:
C33
I25
O15
O53
R11

Keywords:
Human capital
Club convergence
Dynamic factor model
Asia
China

ABSTRACT

This paper investigates the evolution of human capital in China for 31 provinces over the period of 1985–2016 from a club convergence perspective. Per capita human capital stocks, estimated using the Jorgenson–Fraumeni lifetime income approach, are for the first time examined within a non-linear latent factor framework that allows to model a wide range of transition dynamics for each province along the path to convergence. The study finds no overall convergence between provinces in China, however, the results strongly support the existence of multiple convergence clubs. While a small group of provinces are converging toward the highest levels of human capital, most of the other provinces are failing to catch up and form separate clusters that converge to lower equilibria. These regional patterns provide new evidence on the increasing human capital gap between Chinese provinces, posing a significant challenge to a more inclusive and harmonious human and economic development.

1. Introduction

Over the last 40 years, the People's Republic of China (PRC) has undergone a dramatic economic transformation. Its transition from a state-managed economy toward a market-oriented one has been characterized by rapid economic growth, considerable trade performance, and significant poverty reduction (Montalvo & Ravallion, 2010). With the growth of its middle class, the world's largest economy, in terms of purchasing power parity, is changing from a production-led economy into one based on consumption on its journey to achieve high-income status. Moreover, the PRC's equalizing educational policies have targeted the popularization of educational attainment across all of its provinces, as human capital has been recognized, not only as a main driver of economic growth and poverty alleviation, but as a development objective itself (Benos & Zotou, 2014; Sen, 1999). Despite the significant improvements over the last four decades, however, the level of human capital in the PRC remains low in relation to other countries in the Group of Twenty (Lange, Wodon, & Carey, 2018). This is not a minor issue because economies limited by insufficient supply of human capital may fall into the "middle-income trap" (Glauben, Herzfeld, Rozelle, & Wang, 2012; Khor, Pang, Liu, Chang, Mo, Loyalka, & Rozelle, 2016; Mayer-Foulkes, 2008; Zhang, Li, Wang, & Fleisher, 2019). In addition, given the uneven economic development and income disparities across regions (Cheong & Wu, 2013; Pedroni & Yao, 2006; Tian, Zhang, Zhou, & Yu, 2016; Westerlund, 2013), human capital may not have improved equally among Chinese provinces (see, e.g., Fraumeni, He, Li, & Liu, 2019; Li, Liu, Li, Fraumeni, & Zhang, 2014; Valerio Mendoza, 2018). Thus, it is important to establish whether the observed differences between provinces in terms of human capital have reduced over time. Specifically, given the scale of China's territory and population,

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https://doi.org/10.1016/j.asieco.2022.101441
Received 15 January 2021; Received in revised form 6 December 2021; Accepted 1 January 2022
Available online 19 January 2022

it is essential to identify if the less performing provinces are catching up with the rest, or whether some are falling behind, even at risk of entering development traps. To this end, analyzing the dynamics of human capital accumulation across provinces yields important insights on China's harmonizing policies and development path.

Given the empirical context, this paper provides new evidence about the formation of human capital in China by examining human capital across and within provinces from a club convergence perspective between 1985 and 2016. Moreover, while Fraumeni et al. (2019) studies human capital patterns and trends in China, no formal econometric analysis of provincial level human capital convergence has been previously performed. In addition, it makes the following original contributions to the existing literature. First, it investigates the evolution of human capital among provinces by using an income-based human capital stock estimated based on the Jorgenson–Fraumeni (henceforth J-F) lifetime income approach, whereas the vast majority of previous studies have examined human capital in China using conventional statistics such as literacy rates, years of schooling, educational attainment levels, enrollment rates, test scores, teacher–student ratios, flow of graduates, and expenditures (see, among others, Fleisher & Chen, 1997; Fleisher, Li, & Zhao, 2010; Gao, Zhai, & Garfinkel, 2010; Gao, Zhai, Yang, & Li, 2014; Golley & Kong, 2018; Khor et al., 2016; Ratigan, 2017; Wang, 2013).[1] These traditional measures have several limitations as they only consider human capital formed through formal education and do not consider human capital accumulated through on-the-job training and changing health conditions (Li et al., 2013). In contrast, the J-F approach offered here estimates human capital using the present value of the expected future lifetime income of all individuals, which captures returns to long-term investments, including education, work experience, and health, providing a better proxy of human capital than other conventional measures.[2] Accordingly, a recently published article by Zhang and Wang (2021) shows using nonparametric and threshold estimation techniques that the human capital indicator based on the J-F framework does a better job in explaining economic growth and convergence patterns than two commonly used education-based measures included in their analysis. Even more, the paper distinguishes between the total human capital stock and labor force human capital within this framework in order to study human development according to the future and present productive capacity of Chinese provinces separately. Throughout the analysis, human capital estimates are deflated using both a provincial consumer price index and a living cost index. While the former adjusts for inflation over time, it does not address the potential distortions caused by the differences in the cost of living. The latter is thus particularly relevant in a cross-region convergence study for China since it makes the estimates more comparable across provinces by adjusting for their purchasing power based on the varying living costs among them.

Secondly, human capital convergence is for the first time analyzed for the J-F, as well as three other, traditional education-based measures, using the econometric method developed by Phillips and Sul (2007), based on the cross-sectional variance ratio of human capital over time.[3] A handful of works have previously assessed human capital convergence using the concepts of β-convergence and σ-convergence (see, e.g., Coulombe, 2003; Coulombe & Tremblay, 2001).[4] However, these studies apply more traditional convergence tests that depend on limiting assumptions concerning trend stationarity or stochastic non-stationarity of the variable of interest. In contrast, the regression-based approach by Phillips and Sul (2007) does not rely on particular assumptions about stationarity, and therefore enables for transitional divergence and heterogeneity in convergence speeds across regions and over time. This in turn allows to explore a wide spectrum of individual transition paths of human capital development among Chinese provinces. In addition, by employing a stepwise clustering algorithm proposed by Phillips and Sul (2007), the model can endogenously identify subgroups that converge to different steady-state equilibria, i.e., convergence clubs, when overall convergence is rejected within the panel.[5] The results from the convergence club analysis are further complemented in two ways: first, the polarization of human capital is analyzed via the Esteban, Gradín, and Ray (2007) index, which also creates clusters using an endogenous grouping algorithm. Second, human capital is decomposed into its contributing factors following the Kaya-Zenga index proposed by Wang, Guo, Shao, Fan, and Chen (2020) to better understand the underlying properties of each convergence club identified in this paper.

[1] There are only a few published articles using J-F human capital accounts for China (e.g., Fraumeni et al., 2019; Golley & Wei, 2015; Holz & Sun, 2018; Li, Liang, Fraumeni, Liu, & Wang, 2013; Li et al., 2014; Li & Wang, 2018; Zhang & Wang, 2021), three of which, are technical papers detailing the constructs of said measures. Additionally, there exist four publications in Chinese journals mentioned in Li (2018), which also focus on measurements and methods.

[2] A growing literature employs the J-F method to study a nation's total human capital stock (see, e.g., Li et al., 2014, and references therein). In addition, the most recent World Bank Changing Wealth of Nations publication uses Jorgenson–Fraumeni and provides comparable measures for 141 countries' human capital wealth over two decades, from 1995 to 2014 (Lange et al., 2018).

[3] There is a burgeoning of studies on a broad range of topics that test the convergence hypothesis using the methodology introduced by Phillips and Sul (2007). See, for instance, Panopoulou and Pantelidis (2009), Fischer (2012), and Borsi and Metiu (2015), for convergence in carbon dioxide emissions, product prices, and per capita real income in the European Union, respectively.

[4] β-convergence refers to the process in which poor economies tend to grow faster than rich ones (Barro & Sala-i-Martin, 1992; Baumol, 1986; Mankiw, Romer, & Weil, 1992), whereas σ-convergence measures the reduction in the dispersion of the cross-sectional distribution of the variable of interest over time (Barro & Sala-i-Martin, 1990). Panel convergence in the Phillips and Sul (2007) framework is analogous to the notion of σ-convergence, conditional on a set of region-specific characteristics.

[5] The Phillips and Sul (2007) convergence test, as well as other club convergence techniques, have been applied to a variety of different subjects for the Chinese economy, including regional economic growth (see Cheong & Wu, 2013; Tian et al., 2016; Xiao, Wang, & Zhou, 2021; Zhang, Xu, & Wang, 2019, and references therein), internet finance (Bai, Yan, Yin, Feng, & Wei, 2021), productivity in the airline industry (Chen, Tzeremes, & Tzeremes, 2018), tourism industry (Tang, 2021), house price dynamics (Meng, Xie, & Zhou, 2015), as well as ecological, environmental, and energy economics (see, among others, Bai, Feng, Du, Wang, & Gong, 2020; Chen, Xu, Managi, & Song, 2019; Cheong, Li, & Shi, 2019; Herrerias, Aller, & Ordonez, 2017; Herrerias & Liu, 2013; Liu, Hong, Li, & Wang, 2018; Pu, 2017; Qiao & Chen, 2020; Wang, Zhang, Huang, & Cai, 2014; Zhu & Lin, 2020). This is the first study, however, to analyze human capital convergence in China from a club convergence perspective.

Finally, while the literature (Fleisher et al., 2010; Fraumeni et al., 2019; Li et al., 2014) has focused mainly on the differences between regional aggregates, such as coastal vs. western regions, and urban vs. rural regions, this study also examines within-region heterogeneity by looking at the disparities in human capital accumulation at the provincial level. Moreover, human capital convergence is also tested for disaggregated data based on urban and rural areas of Chinese provinces separately. Analyzing only regional aggregates could be misleading, as it may mask the true process of convergence of individual provinces, which may either be converging, or possibly diverging, with their regional neighbors.

The findings of the paper suggest that there is no overall convergence in per capita human capital and labor force human capital among the 31 provinces of China, however, there exist multiple subgroups that converge to different equilibria. In particular, while a small number of regions, including the highly urbanized municipalities of Beijing, Shanghai, and Tianjin, have accumulated human capital stocks that are up to three times the national level, the majority of the other provinces are significantly lagging behind. Most alarming, are the provinces at the lower bound, which are even diverging away from the rest of the panel and show no signs of catching up. These results are aligned with current policies that promote human capital growth nationwide, especially in the western provinces and rural areas. Nevertheless, the diverging patterns identified in this study indicate that the most recent and ongoing policy targets may be out of reach, posing further threats to China's development path.

The remainder of the paper is structured as follows. Section 2 summarizes global trends in human capital research, with a particular focus on China. Section 3 introduces the data and presents the descriptive statistics. Section 4 describes the methodology, followed by the corresponding analyses and empirical findings in Section 5. Section 6 offers a complementary exercise that compares the results to those obtained from education-based human capital measures, and Section 7 extends the convergence analysis from the perspectives of human capital polarization and imbalances. Finally, Section 8 provides a discussion of the results and concludes.

2. Human capital

The concept and definition of human capital has evolved over time. Early contemporary references to human capital can be dated back to Schultz (1961) who introduced knowledge as a key distinguishing element between skilled and unskilled labor. The World Bank has expanded this earlier definition, focused on the productive capacity of individuals (World Bank, 2006), to one that encompasses the combination of skills, dexterity, judgment, and labor of people (Lange et al., 2018). Broader definitions include the physical, emotional and mental health, as well as the innate abilities, attributes, motivations and behaviors of individuals as human capital which can be used not only for economic production, but also for the creation of personal and social well-being (UNECE, 2016). The following subsections explore the relevance of human capital accumulation for economic growth and human development, with some additional insights on its evolution in China. Afterwards, a variety of human capital measures, including the approach used in this paper, are discussed.

2.1. The importance of human capital accumulation for economic growth

The creation of human capital has been acknowledged as a development objective, which acts as a main contributor to economic growth, poverty alleviation, and other development goals (Baldacci, Clements, Gupta, & Cui, 2008; Benos & Zotou, 2014; Cunha & Heckman, 2007; Dreze & Sen, 2013; Kosack & Tobin, 2015; Manca, 2012; Mannasoo, Hein, & Ruubel, 2018; Poelhekke, 2013; Ramos, Surinach, & Artís, 2012; Ravallion & Chen, 1997; Romer, 1986).[6] Both neoclassical and endogenous growth theories recognize the importance of human capital, albeit via different channels (Aghion & Howitt, 1998; Benos & Zotou, 2014; Hanushek & Woessmann, 2008; Lucas, 1988; Mankiw et al., 1992; Mannasoo et al., 2018; Romer, 1990). The former emphasizes how an increase in the human capital of the labor force results in a rise in labor productivity, leading to transitional growth toward a new higher steady state; while the latter argues that an increase in education raises innovation in products, processes and technologies, leading to higher growth. Furthermore, increasing human capital leads to greater social benefits at both the firm and regional levels which may not only affect local consumption, productivity and wages (Broersma, Edzes, & Dijk, 2016; Czaller, 2017), but also increase public awareness and the capacity of families to address their own needs (Baldacci et al., 2008). In addition, Cunha and Heckman (2007) and Dreze and Sen (2013) show the intrinsic importance of human capital to human development at the individual level.

Human capital accumulation and development may result in a synchronized growth cycle whereby human capital investment generates more productive industries, which increases the demand for human capital, whose investment is funded by the returns of the previous human capital investments (Birdsall, Ross, & Sabot, 1997; Mayer-Foulkes, 2008). Additionally, higher economic growth may provide the conditions for higher investment per pupil, higher educational quality, and lower levels of poverty and inequality. On the other hand, an undersupply of human capital may lead to a poverty, and human development trap, resulting in further underinvestment in human capital (Mayer-Foulkes, 2008). Furthermore, while countries with high human capital are able to experience improved welfare with increasing international trade, in countries with lower human capital, international trade is associated with overall slower human development (Kosack & Tobin, 2015).

Given the economic and social benefits of increasing human capital, as well as the risks caused by an undersupply of it, identifying determinants, or factors, of human capital accumulation is important not only to better understand what drives economic growth, but to evaluate the long-term sustainability of a country's development path and the outcomes and productivity performance of the educational sector (UNECE, 2016). These factors can range from investments in education and health, to

[6] For a detailed review of 57 studies on the effects of human capital on economic growth, see Benos and Zotou (2014).

demographic and labor market elements (Fraumeni et al., 2019; Lange et al., 2018), with a clear impact on countries' level of social cohesion. Investments in education could be formed through parenting, formal education services, on-the-job training, informal learning, among others (UNECE, 2016). In addition, a large and growing body of evidence suggests that health, cognition, and socioemotional development affect the accumulation of human capital (Attanasio, 2015; Heckman, 2010). With regard to demographic changes, human capital is affected by family and community well-being, as well as population aging and migration and human mobility (Arntz, Gregory, & Lehmer, 2014; Beine, Docquier, & Oden-Defoort, 2011; Chand & Clemens, 2019; Clemens, 2014; Clemens, Graham, & Howes, 2015; Ghosh & Mastromarco, 2018; UNECE, 2016). The migration of skilled workers to regions with higher wages and better employment opportunities can lead to increases in human capital in these regions, while those with lower wages and employment may result in human capital depletion (Arntz et al., 2014). However, the prospects of emigration may also induce human capital investment in the regions of origin (Beine et al., 2011; Chand & Clemens, 2019). Preventing the loss of human capital through the flow of skilled workers can be attempted via different policy approaches (Clemens, 2014; Clemens et al., 2015). Nonetheless, migrants embodied with high human capital can interact with the host region's accumulated human capital and improve efficiency and productivity (Ghosh & Mastromarco, 2018). Moreover, human capital is higher in regions with greater market access and lower remoteness (López-Rodríguez, Faína, & López-Rodríguez, 2007). To conclude, given the strategic importance of human capital formation for sustainable development, it deserves further scrutiny.

2.2. Human capital in China

Over the last seventy years, China has undergone several stages of political and economic reforms which have increased its capacity for human capital accumulation (Hu & Hibel, 2014; Qian & Smyth, 2011; Valerio Mendoza, 2018; Zhang, 2017).

From 1949 to 1977, China's reforms were focused on egalitarianism, communism, redistribution of assets, and a state-managed economy. During this period, private enterprises, financial markets, and foreign-investment were abolished. China became isolated from the rest of the world economy and in an effort to become self-sustainable, all economic activity was centrally-planned by the state, which assigned resources and production using fixed prices with no regard to monetary and market mechanisms. In the 1950s, the Hukou System, the national household registration system, was established. The Hukou System acts as an internal passport which is used to control and restrict the flow of people from rural to urban regions. An individual's hukou determines where they have access to public services, including health and education. Also in the 1950s, the Gaokao, or National Higher Education Entrance Examination, was established. The Gaokao is a requisite for admission into higher education institutions. During the Cultural Revolution, from 1966 to 1976, tertiary education was suspended, and the country underwent an extreme social equalizing period (Qian & Smyth, 2011).

In 1977, the Chinese government decided to promote a transition from a state-managed economy toward a market-oriented system. The subsequent structural and economic reforms have focused on economic development. In 1979, the one-child policy was introduced in an effort to control population growth by reducing fertility rates, which also allowed low-income households to concentrate their educational spending on a single child (Zhang, 2017). In the 1980s, the country embarked on gradual economic reform, beginning with the creation of four special economic zones which were given the autonomy to experiment with market policies, such as pricing mechanisms, labor mobility, private ownership, social welfare systems, compensation packages, and foreign direct investment, that were otherwise unavailable in the rest of the country (Valerio Mendoza, 2016; Zeng, 2010). The preferential policies were later extended to several key coastal cities in 1984, and later to all provincial capitals. Successful market policies from these zones are later implemented nationwide, making them serve as the mechanism for subsequent reforms. As the Chinese economy opened up, low-wage labor fueled manufacturing and exports, allowing the coastal regions and their periphery to become substantially richer than the central and western regions. The preferential policies shifted from low-grade manufacturing to high-tech manufacturing during the 1990s, and to research and development in the 2000s. Concurrently, equalizing policies aimed at reducing inter-regional inequality were created such as the "China Western Development Strategy" and "Central China Plan". During the first three decades of gradual reform, China grew at an average of 10% annually, incomes doubling every seven years, heralding a period of prosperity for many.

Additionally, the supply and demand for education were gradually stimulated. The nine-year compulsory education policy was established in 1986. Consequently, primary and junior high school enrollment rates increased, and the demand for senior high schools and tertiary education also grew rapidly. The expansion of vocational schools in the 1980s served as an instrument to channel junior high graduates toward the labor force instead of tertiary education (Valerio Mendoza, 2018). Furthermore, a large-scale expansion of higher education institutions was initiated in 1999 to meet the elevated demand (Hu & Hibel, 2014). This was complemented by policies promoting high-quality universities such as the "211 and 985 Projects" (Zhang, Patton, & Kenney, 2013). The establishment of the 2006 Free Compulsory Education Law has further solidified China's investment in human capital creation.

As a consequence, acceptance rates for tertiary education have increased from 5% in 1977 to 75% in 2016 (Ministry of Education, 2018a). Moreover, gross enrollment rates for junior high school, senior high school, and higher education have increased from 97%, 59.8%, and 22%, respectively, in 2006, to 103.5%, 88.3%, and 45.7% in 2017 (Ministry of Education, 2007, 2018a).[7] Amidst these rising educational attainment levels, the current decade has also been characterized by slower and uneven economic growth and

[7] According to the UNESCO Institute of Statistics, the gross enrollment rate is defined as the total enrollment in a specific level of education, regardless of age, expressed as the share of the population of the age group that officially corresponds to the same level of education. As over- and under-aged students are also included, this ratio can exceed 100%.

the intention of supply-side reforms aimed at transitioning from an economy led by industry and investment to one led by service and consumption. In light of these ongoing reforms, the Chinese government has reaffirmed its public commitment to invest in education. Polices such as the "Central and Western Higher Education Revitalization Plan" (Ministry of Education, 2016) and the "High School Education Popularization Plan (2017–2020)" (Ministry of Education, 2017) have been targeted at improving the levels and quality of secondary and tertiary education, and are meant to be drivers of convergence. Most recently, the "China Education Modernization 2035 Plan" aims to achieve educational attainment levels comparable to high-income, developed nations by the 2030s (Ministry of Education, 2018b).

Human capital in China has increased considerably since 1985 (Li et al., 2013, 2014). The dramatic rise in educational attainment over the last four decades has been acknowledged as an important driver of economic growth and development. For instance, human capital growth has been linked to an increase in worker productivity and total factor productivity on the firm and provincial levels by Fleisher, Hu, Li, and Kim (2011), Fleisher, McGuire, Smith, and Zhou (2015), and Li and Wang (2018). However, in spite of these advances, China's economic growth has not been equally distributed among all provinces, and a burgeoning of studies provide evidence that differences in human capital play an important role in explaining income inequality among Chinese regions (Chen & Fleisher, 1996; Fleisher & Chen, 1997; Fleisher et al., 2010). Moreover, certain provinces may have benefited substantially more than others in terms of human capital, primarily due to rapid urbanization, improvements in educational attainment, and the disproportionate impact of economic reforms over the last decades (Fraumeni et al., 2019).

On a related theme, a number of works have studied differences in the distribution of human capital across China. Qian and Smyth (2011) show that despite the disparities observed in educational attainment between urban vs. rural and coastal vs. inland regions, the gaps within coastal regions have decreased from 1990 to 2000. Similarly, Yang, Huang, and Liu (2014) provide evidence that educational attainment and its distribution between provinces have continued to improve, however, differences across regions have still remained apparent by 2008. Furthermore, Valerio Mendoza (2018) demonstrates that disparities in educational attainment and inequality are far greater when analyzed at the provincial and city levels, than what regional and national level analyses would otherwise suggest. Factors affecting the underlying differences include, but are not limited to, educational development policies, geographic location, quality of schooling institutions, and socioeconomic characteristics. In addition, Ratigan (2017) reveals differences in educational and other social expenditure between provinces, which could help explain the dispersion in educational and human capital outcomes.

Even though human capital is increasing, the stock of human capital in China remains low compared to other middle-income countries (Khor et al., 2016). Whether China will acquire not only the sufficient level, but distribution of human capital stock required to transition toward a developed, high-income nation or remain in a possible "middle-income trap" is a pertinent concern (Zhang, Li, Wang, & Fleisher, 2019). For this reason, studying the evolution of human capital accumulation between all 31 Chinese provinces in a club convergence testing framework has powerful implications for China's future prosperity as it continues to grow and develop.

2.3. Alternative measures of human capital

Measuring human capital trends, or differences in human capital stock, can help explain per capita income disparities, the accumulation of physical capital, and overall growth convergence between and within regions (see, e.g., Coulombe, 2003; Coulombe & Tremblay, 2001; Villarroya, 2007).

The complexity and difficulty of measuring human capital is reflected by the variety of variables used in previous studies, which range from literacy rates (Ranis, Stewart, & Ramirez, 2000; Romer, 1986), enrollment figures (Baldacci et al., 2008; Barro, 1991; Chakraborty, 2004), and schooling years (Barro, 2001; Collins & Bosworth, 1996; Hanushek & Woessmann, 2008; Papageorgiou, 2003; Wang, 2013) as proxies for human capital quantity, to student–teacher ratios (Barro, 1991), educational expenditure (Bose, Haque, & Osborn, 2007; Daniels, 1996), and scores (Bosworth & Collins, 2003), as proxies for human capital quality. Yet, as Benos and Zotou (2014) argue, these variables suffer from a number of weaknesses making them imperfect proxies for human capital. For instance, literacy rates suffer from consistent definitions across countries and omit components of human capital, while enrollment rates and expenditures may reflect future human capital stock, but not the present human capital stock (Benos & Zotou, 2014). In addition, enrollment rates do not reflect attendance nor the quality of education, as argued by UNDP (2010), and, moreover, the effects of schooling years may weaken considerably, or even become insignificant, when controlling for quality indicators (Barro, 2001; Barro & Lee, 1993; Barro & Sala-i-Martin, 2004). Finally, these measures fail to consider the human capital acquired outside school, such as on-the-job training (Cunha & Heckman, 2007).

More comprehensive estimation methods of human capital have been proposed following a cost-based approach (Kendrick, 1976), which values investment in human capital, adjusted for depreciation over time, and an income-based approach that looks at the present value of the income generated by an individual's human capital over their lifetime (Fraumeni, Christian, & Samuels, 2017; Jorgenson & Fraumeni, 1989, 1992a, 1992b). This paper employs the latter, which is considered one of the most precise and widely used methods in constructing human capital accounts to date (Lange et al., 2018; Li et al., 2014). Additionally, for comparative purposes, this study also examines three more conventional human capital measures: average years of schooling of the labor force, the proportion of the labor force with secondary education and above, and the proportion of the labor force with tertiary education and above.

2.4. Jorgenson–Fraumeni lifetime income approach

Under the J-F approach, human capital stock is estimated as the net present value of the expected future lifetime income of all individuals. Expected future lifetime incomes are imputed from the incomes of individuals who are older than a given cohort, for every population subgroup, at the time of observation.[8] The projected future incomes are then estimated with an expected labor income growth rate and discounted to the present with a constant discount rate in a recursive manner for every cohort from oldest to youngest. Additionally, depending on the current stage in an individual's life cycle (pre-school, school-only, work-school, work-only, and retirement) the probabilities of continuing education or employment, as well as survival, are used to calculate the nominal expected lifetime income.[9] For example, nominal expected lifetime income for an individual aged 20 could be calculated as:

$$mi_{y,s,a,e,r} = ymi_{y,s,a,e,r} \cdot ep_{y,s,a,e,r} + sr_{y+1,s,a+1,r} \cdot [er_{y+1,s,a+1,e+1,r} \cdot mi_{y,s,a+1,e+1,r} + (1 - er_{y+1,s,a+1,e+1,r}) \cdot mi_{y,s,a+1,e,r}] \cdot \frac{1+G}{1+R}, \tag{1}$$

where mi represents the average lifetime income for individuals in the work-school group (similar equations are created for other groups), the subscripts y, s, a, e, and r indicate year, sex, age, educational attainment, and region (urban and rural), respectively, ymi signifies average annual market labor income, ep represents the employment rate or the probability of being employed, er denotes the school enrollment rate or the probability of an individual with educational attainment e to enroll in education level $e+1$, sr is the survival rate (the probability of surviving for another year), G is the real income growth rate, and R is the discount rate.[10] Eq. (1) means that the lifetime income of an individual at age a is the life-time income of an individual at age $a+1$ plus his/her income in the current year, after accounting for the probabilities of entering the labor market or continuing schooling, the survival rate, and income growth.

Subsequently, the total nominal human capital stock for each population subgroup $L_{y,s,a,e}$ can be estimated as follows:

$$HC_y = \sum_s \sum_a \sum_e \sum_r mi_{y,s,a,e,r} \cdot L_{y,s,a,e,r}. \tag{2}$$

The total human capital stock HC_y represents the complete human capital wealth, which is composed of two groups: the human capital reserve and the labor force human capital (LFHC). The former includes the young population which has not entered the labor market, i.e., those under the age of 16, and full-time students who are 16 years of age or above, while the latter refers to the human capital of the labor force. The human capital reserve can be understood as the human capital that will be used for productive purposes in the future. On the other hand, labor force human capital is defined as the human capital active in economic activities related to production in the present. Hence, the labor force human capital is particularly useful in reflecting the current human capital used in production. Finally, the total human capital includes the economy's actual, or potential, human capital stock (Li et al., 2013). Given these differences, it is important to look at each measure of human capital stock separately. Overall, these measures provide a more accurate and comprehensive picture of human capital formation.

3. Data

J-F lifetime income-based per capita human capital (PCHC) and per capita labor force human capital (PCLFHC) stock values are from the China Center for Human Capital and Labor Market Research (CHLR). Both CHLR human capital measures are calculated for a panel of 31 provinces spanning from 1985 to 2016 at the provincial level, including urban and rural areas.[11] Furthermore, because nominal human capital stocks are based on earnings, their values are adjusted for the evolution of prices both temporally and spatially. First, using consumer price indices (CPI) to adjust for inflation over time, which are available for each province for both urban and rural areas with a base year of 1985. In addition, convergence in human capital may be affected by the evolution of the cost of living across Chinese provinces, affecting wages as well. Thus, human capital and labor force human capital stocks are also deflated using a living cost index (LCI), a spatial price index adjusted for provincial purchasing power parity (PPP), where

[8] The application of the J-F framework for China requires the use of the Mincer (1974) model because earnings data for individuals who differ in education, age, gender, and location are not easily available for China. In particular, the China Center for Human Capital and Labor Market Research (CHLR) use an augmented version of the Mincer (1974) model, still commonly employed by many, including the World Bank (Lange et al., 2018). More specifically, Fraumeni et al. (2019) estimate individual earnings at the province level by incorporating province-specific aggregates, using multiple waves of the Urban Household Survey (UHS), the China Health and Nutrition Survey (CHNS), the Chinese Household Income Project (CHIP), the China Household Finance Survey (CHFS), and the Chinese Family Panel Studies (CFPS). A detailed description of the methodology can be found in Li et al. (2013, 2014) and Fraumeni et al. (2019), and references within.

[9] Based on the Chinese education system and retirement ages, children under six years old are assumed to be not in school and not working; children aged six to 15 are assumed to be only in school; those aged 16–24 are in the both school and work stage; males aged 25–59 and females aged 25–54 are assumed to be only working; and females and males older than 54 and 59, respectively are assumed to be retired (Li et al., 2013, 2014).

[10] The present value of future income is sensitive to the choice of discount rate. The J-F approach uses a discount rate of 4.58%, which was adopted by the OECD Human Capital Consortium (Liu, 2011; OECD, 2010). This rate falls between two China-specific discount rates of 3.14%, from ten-year government bond interest rates, and 5.43%, from bank lending rates (Li et al., 2013).

[11] There are 31 province-level administrative units in China, which include 22 provinces, four municipalities, and five autonomous regions.

Table 1
Descriptive statistics of Human Capital for 31 provinces (selected years).

	1985				2016			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
	CPI							
PCHC	38.01	18.60	22.93	107.30	261.04	131.25	105.96	665.31
Urban	66.75	21.76	22.97	153.62	336.04	113.33	153.45	728.16
Rural	24.79	7.35	14.64	42.92	117.08	45.01	55.35	213.24
PCLFHC	25.21	10.13	17.00	63.64	143.86	66.08	72.09	373.69
Urban	40.85	8.57	18.20	67.82	174.45	57.25	102.60	407.63
Rural	17.78	4.92	11.92	30.15	88.58	30.37	45.16	160.17
	LCI							
PCHC	43.96	16.34	29.41	100.73	286.41	121.60	131.49	668.27
Urban	72.15	25.06	24.88	184.10	360.21	112.14	184.15	728.16
Rural	31.76	8.45	16.50	54.24	149.89	55.15	63.74	269.47
PCLFHC	29.35	8.63	19.59	59.74	160.46	60.55	83.81	376.75
Urban	44.85	9.34	19.71	81.28	186.58	54.78	123.13	407.63
Rural	22.82	6.46	14.66	38.41	112.26	36.96	54.57	218.31

Note: Summary statistics for per capita human capital (PCHC) and per capita labor force human capital (PCLFHC), deflated using the consumer price index (CPI) and the living cost index (LCI). All values are in thousand RMB Yuan. Urban and rural statistics do not include Shanghai, and are reported separately. Source: CHLR (2018).

urban Beijing is set as the reference area and 1985 is the base year (Brandt & Holz, 2006; Holz, 2006).[12] Since living costs vary across provinces, using the LCI based on a basket of goods and services with different prices across provinces to deflate human capital stocks provides estimates that are even more comparable across regions (Li et al., 2014).

3.1. Descriptive statistics

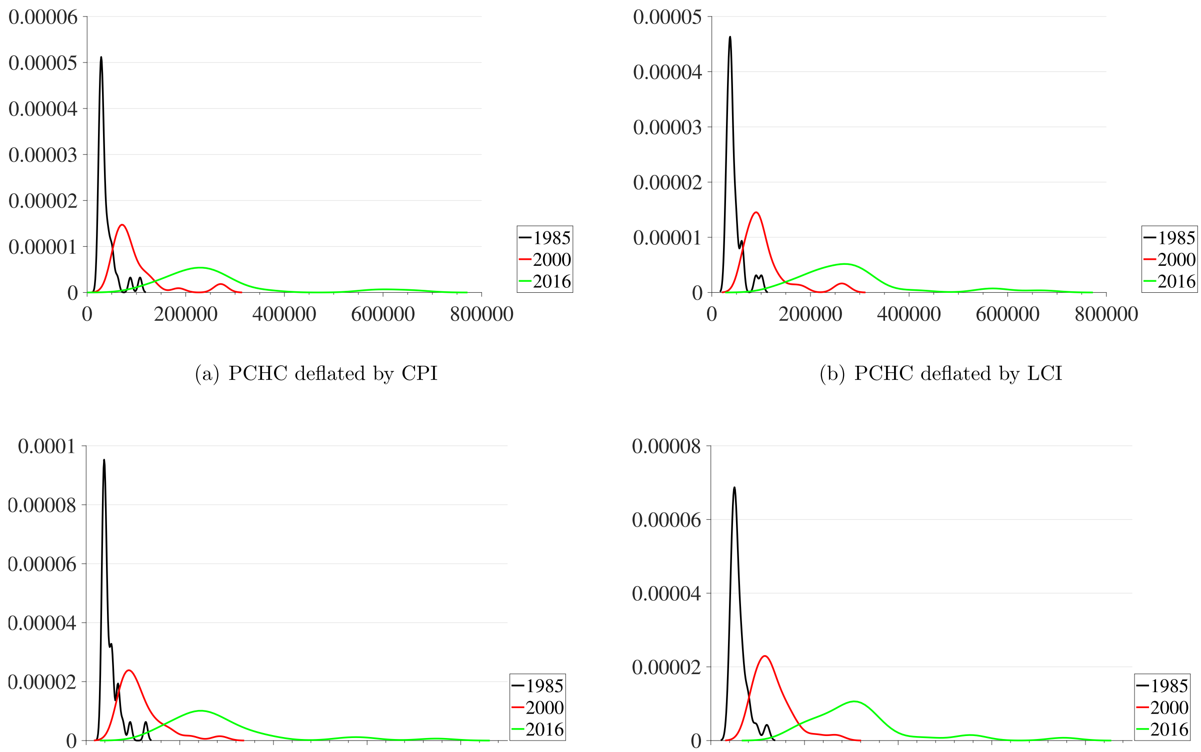
Table 1 shows the descriptive statistics for per capita human capital (PCHC) and per capita labor force human capital (PCLFHC) for the initial and final years in the panel. The table is divided by the type of deflator, i.e., CPI and LCI, for both PCHC and PCLFHC. Additionally, each PCHC and PCLFHC measure is decomposed into urban and rural areas. The data shows that mean values for PCHC have increased more than sixfold from 1985 to 2016, in both CPI and LCI measures. Similarly, PCLFHC has increased more than fivefold from 1985 to 2016, using both deflators. The differences between CPI and LCI seem clear when comparing means, standard deviations and minima. Namely, both PCHC and PCLFHC have higher means and minima, and smaller standard deviations, when using the LCI instead of CPI, suggesting that the disparities between provinces diminish on average when controlling for their respective price levels and purchasing power.

The provinces with the least and the largest human capital stock vary by year and indicator. For example, Qinghai exhibited the lowest PCHC for both CPI and LCI in 1985, whereas Tibet had the lowest PCLFHC when using both deflators. In contrast, the highest PCHC as well as PCLFHC belonged to Shanghai in the same year, irrespective of the type of deflator. According to the last year observations in the panel, Qinghai's lowest position remains largely unchanged, whereas the highest human capital stock values correspond to Beijing, Shanghai, and Tianjin, which also have the highest urbanization rates in the country. Finally, it should be noticed that the standard deviation of each type of J-F human capital stock has significantly increased from 1985 to 2016, indicating that human capital accumulation within China has become much more dispersed.

3.2. Kernel density estimation

This subsection presents a distribution dynamics approach that enables to further explore the spatiotemporal variation in human capital across the 31 provinces. Specifically, following Yang and Pan (2020), kernel density estimation is used to examine the shape of the distribution of human capital and how it evolved from 1985 to 2016. The estimates are based on the normal kernel function with equal weights and optimal bandwidth, and the distribution of human capital is studied for three periods: 1985 and 2016, i.e., the initial and final year, and 2000, which follows the beginning of the large-scale higher education expansion in China. Fig. 1 displays the kernel density curves for PCHC and PCLFHC, deflated by CPI and LCI, respectively. The figures show that the distribution of human capital is largely unimodal and positively skewed for all three years, with some bumps representing a few

[12] As Brandt and Holz (2006) point out, their spatial deflators have a number of weaknesses. Due to data limitations, the Brandt and Holz (2006) LCI measure was created for the base year 1990 and the provincial consumer basket has not been priced at absolute prices each year. Still, the LCI follows the Chinese consumption patterns in line with the National Bureau of Statistics's changing nationwide basket over time. Moreover, their calculations are based on limiting assumptions related to price specifications, pricing methods, and missing data. For instance, they use provincial capital city prices for approximately 40% of the rural budget. In addition, construction costs for rural dwellings are used instead of rent, land, real estate or housing prices as a proxy, which could under- or overestimate the cost of housing. Notwithstanding its limitations, the deflators constructed by Brandt and Holz (2006) are the most widely used spatial price indices for China.



(a) PCHC deflated by CPI

(b) PCHC deflated by LCI

(c) PCLFHC deflated by CPI

(d) PCLFHC deflated by LCI

Fig. 1. Kernel density estimation of the distribution of human capital in China. Authors' calculations using CHLR (2018). Per capita human capital (PCHC) and per capita labor force human capital (PCLFHC) deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

provinces towards the higher human capital ranges. In addition, the mode for each type of human capital series becomes gradually higher, whereas the peaks get significantly lower from 1985 to 2016. These results imply that while the majority of provinces have relatively lower levels of human capital stock, its accumulation improved in all regions over time. Moreover, the flattening curves suggest that human capital accumulation has become more dispersed during the period in question, indicating the emergence of diverging patterns and a more unequal distribution of human capital within China. In what follows, these stylized facts as well as the descriptive results are formally tested.

4. Methodology

This paper employs a regression-based panel convergence test and clustering algorithm developed by Phillips and Sul (2007) to study the evolution and transitional dynamics of human capital among Chinese provinces over the last thirty years. The underlying method suggests that any panel data set X_{it} can have a time-varying latent factor representation as follows:

$$X_{it} = \delta_{it}\mu_t, \tag{3}$$

where X_{it} denotes log per capita human capital for province i at year t, μ_t is a steady-state growth component that is common across individual regions, and δ_{it} represents time-varying factor loadings that capture the deviation of the transition path of each province i from the common trend μ_t. The loading coefficients δ_{it} absorb any idiosyncratic movements in X_{it}. Eq. (3) implies that the transition path of each region toward a steady-state level of human capital depends on province-specific determinants of the evolution of human capital stock, including investment in education and health, urbanization, population aging, gender composition, among other economic and demographic factors. The simple formulation enables testing for convergence by examining whether the factor loadings δ_{it} converge to some common constant δ as $t \to \infty$, in which case the province-specific differences are eliminated over time. To this end, Phillips and Sul (2007) propose the following semiparametric form to model the non-stationary transitional behavior of the factor loadings δ_{it}:

$$\delta_{it} = \delta_i + \frac{\sigma_i}{\log(t)t^{\alpha}}\xi_{it}, \tag{4}$$

where ξ_{it} are $i.i.d.(0,1)$ across i, but weakly dependent over t, σ_i are idiosyncratic scale parameters, and the parameter α is the decay rate, i.e., the speed of convergence. Under this specific form, the loadings δ_{it} converge slowly to the constant δ_i as $t \to \infty$ for any $\alpha \geq 0$, and scaling by the slowly varying function $\log(t)$ ensures a smooth transition path.

Given these preliminary considerations, the null hypothesis of convergence can be written as:

$$H_0 : \quad \delta_i = \delta \text{ for all } i \text{ and } \alpha \geq 0,$$

and is tested against the alternative:

$$H_A : \quad \{\delta_i = \delta \text{ for all } i \text{ with } \alpha < 0\} \text{ or } \{\delta_i \neq \delta \text{ for some } i \text{ with } \alpha \geq 0, \text{ or } \alpha < 0\}.$$

The null hypothesis implies overall convergence for all provinces, pointing to a kind of sustainable human development that is more equally distributed and more inclusive. In contrast, the alternative hypothesis can accommodate overall divergence (i.e., divergence of all provinces in the panel) or club convergence (i.e., a situation in which subgroups converge to different steady state equilibria, with possibly one or more diverging units), suggesting that there are different kinds of unequal development in terms of human capital in China.

4.1. The log(t) test

Testing the hypothesis of interest requires the estimation of the factor loadings δ_{it}, which is impossible without imposing additional structure on δ_{it} and μ_t. Alternatively, Phillips and Sul (2007) define the following relative transition coefficient h_{it} to extract information about δ_{it}:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}}, \tag{5}$$

which measures the loadings δ_{it} in relation to the panel average at time t, while eliminating the common growth component μ_t. The parameter h_{it} traces out a transition path over time for each province i in relation to the panel average. If the factor loading coefficients δ_{it} converge to some constant δ within the limit, the relative transition paths h_{it} converge to unity, and the cross-sectional variance of h_{it} converges to zero asymptotically:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \to 0 \qquad \text{as} \qquad t \to \infty, \tag{6}$$

where H_t measures the distance of province i from the common limit. Hence, when convergence applies, the distance $H_t \to 0$ as $t \to \infty$. If convergence fails to hold, the distance remains positive as $t \to \infty$. This statistical property is exploited in order to test the null hypothesis of human capital convergence between the 31 Chinese provinces in the panel. Specifically, the following 'log(t)' regression is performed:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log(\log(t)) = a + b\log(t) + u_t, \tag{7}$$

for $t = [rT], [rT]+1, \ldots, T$, with some fraction $r > 0$. Phillips and Sul (2007) recommend setting $r = 0.3$ for sample sizes $T \leq 50$. The regression coefficient b converges in probability to a scaled estimate of the speed of convergence 2α under the null. Thus, the convergence hypothesis can be tested by a one-sided t-test for $\alpha \geq 0$ using the estimate $\hat{b} = 2\hat{\alpha}$ and heteroscedasticity and autocorrelation consistent (HAC) standard errors.[13] The null hypothesis is rejected at the 5% significance level if $t_{\hat{b}} < -1.65$.

The methodological framework outlined in this section has several advantages over existing ones. Most importantly, since convergence is treated as an asymptotic property, the nonlinear time-varying factor model accommodates a variety of region-specific transition dynamics, captured by h_{it}, toward the steady state. Specifically, provinces may exhibit periods of transitional heterogeneity or even transitional divergence before convergence ultimately occurs in the long run. Furthermore, as opposed to standard unit root and cointegration techniques, the Phillips and Sul (2007) convergence test does not rely on any limiting assumptions regarding trend stationarity or stochastic non-stationarity of the series studied. Finally, if convergence is rejected for the overall sample, an empirical clustering algorithm based on repeated $\log(t)$ tests is employed to identify convergence clubs and diverging provinces in the panel.

4.2. Convergence club identification

Phillips and Sul (2007) developed a stepwise clustering algorithm to detect both converging subgroups and diverging regions within the panel. The procedure can be summarized as follows:

Step 1: *Last observation ordering*: The N provinces in the panel are sorted in descending order according to the last observation X_{iT}.

[13] The null hypothesis implies convergence in growth rates (relative convergence) rather than level convergence (absolute convergence). However, Phillips and Sul (2007, 2009) show that a sufficiently large convergence speed, i.e., $\hat{\alpha} \geq 1$, which is equivalent to $\hat{\beta} \geq 2$, yields convergence in the absolute sense within the panel.

Step 2: *Core group formation*: The first k highest units are selected from the panel to form all possible subgroups G_k for $2 \leq k < N$. Next, a $\log(t)$ regression is conducted and the convergence test statistic $t_{\hat{b}}$ is calculated for each subgroup k. The core group of size k^* is determined by maximizing $t_{\hat{b}}(k)$ over k subject to $\min\{t_{\hat{b}}(k)\} > -1.65$. Choosing the core group size based on this criterion reduces the overall type II error probability. If $k^* = N$, all provinces converge, and thus, there is overall convergence in the panel. If the condition $\min\{t_{\hat{b}}(k)\} > -1.65$ does not hold for $k = 2$, the first unit in G_k is dropped and the same procedure is performed for the remaining provinces. The loop is repeated until a pair of units is detected with $t_{\hat{b}} > -1.65$ and a core group G_k^* can be formed. If the condition $t_{\hat{b}} > -1.65$ fails to hold for all such subsequent pairs, then there are no convergence clubs in the panel, in which case the entire panel diverges.

Step 3: *Sieve individuals for club membership*: After the core group G_k^* is formed, the remaining provinces are added one by one and the $\log(t)$ test is performed for each. If the corresponding test statistic $t_{\hat{b}}$ exceeds some critical value c^*, the province can be included in G_k^*. Phillips and Sul (2007, 2009) suggest to set a highly conservative critical value to minimize the probability of sieving a false unit into a convergence subgroup. Specifically, a sieve criterion $c^* = 0$, recommended for sample sizes of $T \leq 50$, is used in this paper. Once all provinces satisfying the criterion c^* are included in the core club, the $\log(t)$ test is repeated for the whole subgroup. If the associated t-statistic is greater than -1.65, the first convergence club is formed. Otherwise, the critical value has to be raised in order to increase the degree of conservativeness of the test and the procedure is repeated until $t_{\hat{b}} > -1.65$ for the entire group. If no additional provinces can be sieved to the initial core group, one may conclude that G_k^* itself constitutes a convergence club.

Step 4: *Recursion and stopping rule*: A second subgroup is formed consisting of all units that could not be included in the convergence club identified in Step 3. If there is only one province left at this point, that province diverges. Otherwise, the $\log(t)$ test is run for all remaining units. If the entire subgroup converges, i.e., $t_{\hat{b}} > -1.65$, the remaining provinces form a second convergence club. If not, Steps 1–3 are repeated to detect any smaller subgroups that form convergence clubs within the panel. If no further clubs can be found, it can be concluded that the remaining provinces diverge.

Step 5: *Club merging*: Given the high value of the sieve criterion c^* set in Step 2, the clustering algorithm becomes very conservative. While a conservative choice of the critical value c^* reduces the risk of erroneously including a province into a convergence club, it also tends to raise the probability of detecting more convergent subgroups than the actual number. To overcome this problem, Phillips and Sul (2009) propose to run a series of $\log(t)$ regressions to test for convergence across adjacent clubs identified in the panel. If the t-statistic is greater than -1.65, the corresponding subgroups can be merged into a larger convergence club. Finally, the $\log(t)$ test can be performed again to see whether the formerly diverging provinces can be added to these larger clubs.

5. Empirical results

The following subsections present a series of convergence test and clustering outcomes for each different type of J-F human capital stock accumulation considered. The empirical findings are structured into per capita human capital (PCHC) and per capita labor force human capital (PCLFHC), followed by the estimation results based on the urban and rural dimensions.

5.1. Per capita human capital

Table 2 reports the club convergence classification results for all 31 provinces from 1985 to 2016. The results are organized by deflator: CPI followed by LCI. Fig. 2 offers a visual inspection of the corresponding relative transition path of each province, h_{it}, obtained from Eq. (5) for both samples. In addition, Fig. A.1 provides subplots of transition paths for each convergence club, separately (Appendix A). Finally, as an extension to the individual trajectories, Fig. 3 displays the average transition curves for all clubs identified in the two panels ($\bar{h}_{clubt}$), together with the diverging regions ($h_{divergingt}$).

The null hypothesis of overall human capital per capita convergence is rejected at the 5% level for both CPI and LCI samples. Furthermore, the clustering algorithm identifies three clubs and a few diverging provinces in each. Clubs are ordered according to the accumulation of human capital stock, with the highest corresponding to Club 1. This first club, consisting of Beijing, Tianjin, Shanghai, Chongqing, and Anhui, is consistent in both samples, with estimated speeds of convergence of $\hat{\alpha} = 0.033$ and $\hat{\alpha} = 0.035$ in the LCI and CPI samples, respectively. Interestingly, three of the five provinces in Club 1 – three of the four municipalities under direct administration of the central government of China – manifest the highest PCHC throughout the entire sample period considered (Fig. 2), whereas all other provinces are persistently lagging behind. Moreover, while the initial stock of human capital was significantly lower in all regions compared with Beijing and Shanghai, Tianjin is the only region that was able to catch up with them since 1985. Tianjin's rise may coincide with successful efforts in developing its prestigious universities, higher education internationalization, and its high economic development. Additionally, Chongqing and Anhui are the only other provinces that are accumulating human capital at a rate that would allow them to catch up and converge with the top three provinces, as illustrated in Fig. 2. Club 2 comprises the largest, yet weakest convergence club in the CPI sample, including a total of 19 provinces. Even though the province-specific trajectories within this subgroup indicate transitional divergence and heterogeneity to a significant degree, convergence could not be rejected at the 5% level.

The last club detected in the PCHC (CPI) sample, Club 3, contains Yunnan, Tibet, Gansu, Hunan, Heilongjiang, and Xinjiang, all of them failing to converge toward the rest of the panel. This result is not surprising since the most western provinces are the least developed, however, it is alarming that the club also includes Hunan and Heilongjiang, and that they are moving away from all the other regions (Fig. 3/(a)). Part of these results might be driven by the flow of migrants from these provinces to more prosperous

Table 2
Convergence club classification: PCHC.

PCHC (CPI) Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−10.232	−0.550 (0.054)	−0.275
Club 1	Beijing, Tianjin, Shanghai, Anhui, Chongqing	0.587	0.070 (0.120)	0.035
Club 2	Hebei, Shanxi, I. Mongolia, Liaoning, Jilin, Jiangsu, Zhejiang, Fujian, Jiangxi, Shandong, Henan, Hubei, Guangdong, Guangxi, Hainan, Sichuan, Guizhou, Shaanxi, Ningxia	0.037	0.004 (0.121)	0.002
Club 3	Heilongjiang, Hunan, Yunnan, Tibet, Gansu, Xinjiang	1.123	0.074 (0.066)	0.037
Diverging	Qinghai			
PCHC (LCI) Clubs	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−13.802	−0.652 (0.047)	−0.326
Club 1	Beijing, Tianjin, Shanghai, Anhui, Chongqing	0.465	0.066 (0.142)	0.033
Club 2	Hebei, Shanxi, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Sichuan, Guizhou, Shaanxi, Ningxia	0.087	0.006 (0.070)	0.003
Club 3	Yunnan, Tibet, Gansu, Xinjiang	2.786	0.170 (0.061)	0.085
Diverging	Zhejiang, Qinghai			

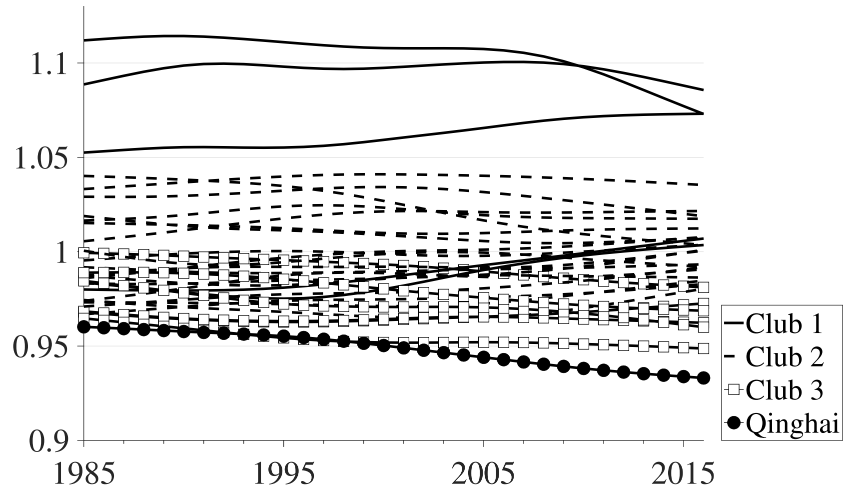
Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita human capital (PCHC) for 31 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI) and living cost index (LCI). The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Merging of the neighboring clubs is rejected in both samples considered.

ones, contributing to the accumulation of human capital stocks of the destination. Finally, Qinghai is classified as a diverging unit since it exhibits distinct PCHC growth dynamics from the three clubs and is diverging away from the lowest club. The convergence test results for the PCHC (LCI) are nearly identical to the classification obtained for PCHC (CPI). In terms of differences, Club 2 includes 18 of the same provinces as in the CPI sample, with the inclusion of Hunan and Heilongjiang, which used to belong to Club 3, alongside Yunnan, Tibet, Gansu, and Xinjiang. This suggests that without adjusting for their lower cost of living, the PCHC of Hunan and Heilongjiang converges to the least-performing subgroup. This distortion, however, is corrected once deflating by LCI. Furthermore, since the value of PCHC in Zhejiang becomes higher relative to that of provinces in Club 2 on average after adjusting for the cost of living, it does not converge with the second club in the LCI sample, but diverges on a path between Clubs 1 and 2 (Fig. 3/(b)).

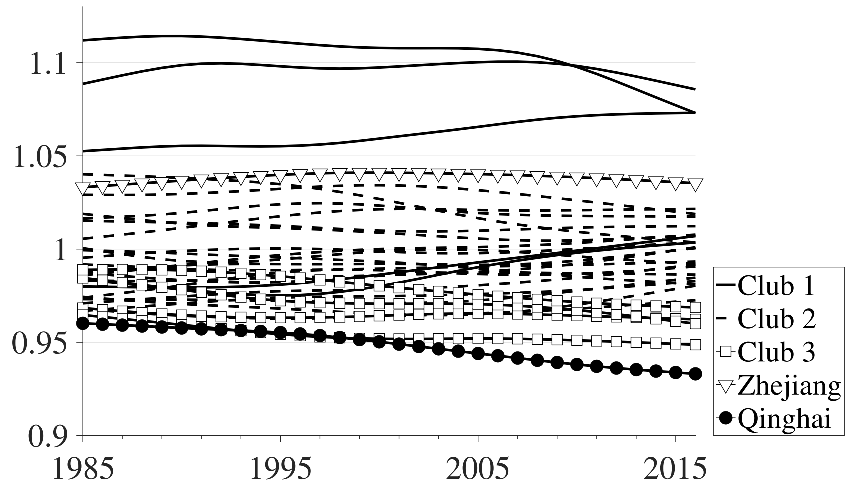
To complement the analysis, Fig. 4 illustrates the regional components behind each club. The club classification results highly reflect the regional disparities between the east and west. The three best-performing municipalities, which are all coastal cities, together with Chongqing and Anhui form Club 1, while every province in the far west is in Club 3.[14] The East–West dimension is also evident in the diverging provinces detected in the samples. In the case of Zhejiang, a coastal province, its divergent status in the LCI sample does not carry a negative connotation, as it exhibits a human capital accumulation above all provinces that are not in Club 1, once controlling for differences in the cost of living. Zhejiang's divergent path may be further explained by its within-province inequality, where the northern area, close to Shanghai, may be catching up with Club 1, while the southern part is lagging behind (Wei & Ye, 2004). On the other hand, Qinghai in the western interior part of China, diverges in a negative way, and appears to be falling into a serious human capital growth, and hence, development trap. The figure also shows that geographical location and income do not fully explain human capital accumulation since the coastal provinces are not converging to a single club, and Club 2 includes western, central and coastal provinces. Furthermore, the results differ from the convergence clubs in terms of provincial income in Tian et al. (2016), where seven coastal provinces as well as Inner Mongolia converge to the highest income club. On the other hand, the fact that several central and western provinces converge to some coastal ones, may be due to the policy initiatives aimed at revitalizing these regions, mentioned in Section 2.2.

It is important to reiterate that the total per capita human capital stock employed in this subsection considers the entire human capital wealth, including both the labor force human capital and the reserve human capital, which will be used for future production. Thus, the estimation results presented here incorporate the province-specific human potential of the younger generations who have not yet entered the labor market. Alternatively, focusing solely on the human capital of the labor force may yield a better approximation of the productive capacity of those who are currently part of the labor force, and therefore, it is explored next.

[14] Chongqing is the fourth municipality under the direct administration of the central government, which is the only such municipality located in the interior of China.



(a) PCHC deflated by CPI



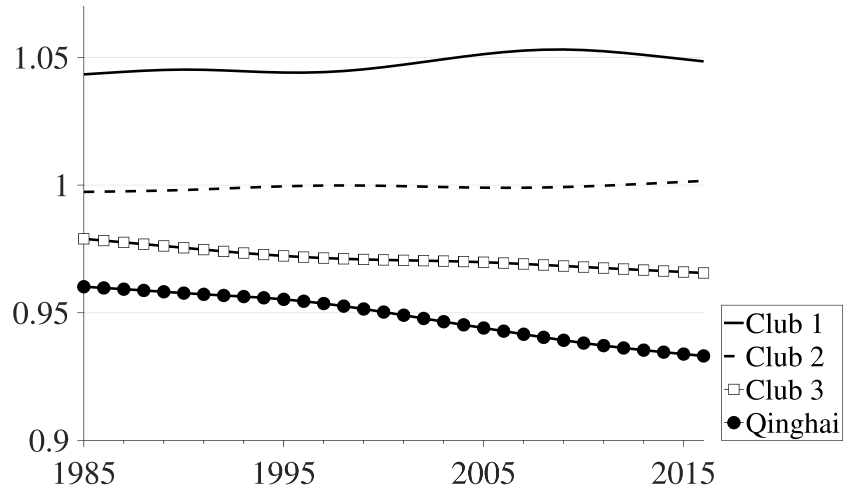
(b) PCHC deflated by LCI

Fig. 2. Relative transition paths of all provinces in China: PCHC. Authors' calculations using CHLR (2018). Relative transition paths of per capita human capital (PCHC) deflated by (a) consumer price index (CPI) and (b) living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

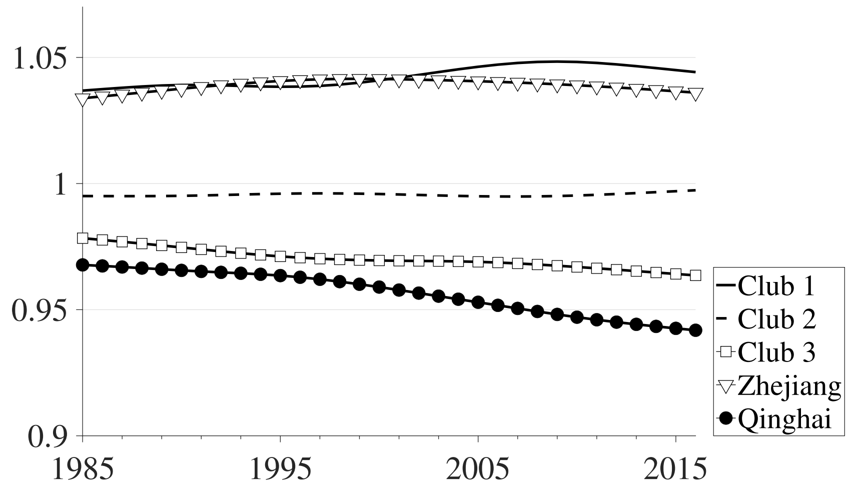
5.2. Per capita labor force human capital

Table 3 shows the convergence test results for PCLFHC deflated by CPI and LCI. Even though the clustering patterns in the PCLFHC samples resemble important similarities with the club classification results obtained for PCHC, the differences between the two samples suggest that for some provinces the actual reserve human capital included in the total stock, which will be used for productive purposes in the future, will alter the pace of human capital accumulation, and thus, human development.

Six convergence clubs are identified in the CPI sample. Not surprisingly, the three coastal municipalities – Beijing, Tianjin, and Shanghai – occupy the best performing club, showing distinct human capital growth dynamics, being on transition paths permanently above all other provinces during the sample period considered (Fig. 5/(a)). A notable difference with the PCHC sample, however, is that the first subgroup does not include Anhui and Chongqing. This result suggests that while the human capital of these two provinces used for productive purposes at the present (LFPCHC) does not converge to that of the top three, their human capital reserves will allow them to catch up in the future, as reflected in the PCHC classification outcomes. Going further, the clustering



(a) PCHC deflated by CPI



(b) PCHC deflated by LCI

Fig. 3. Average relative transition paths for convergence clubs and diverging provinces: PCHC. Authors' calculations using CHLR (2018). Average relative transition paths of per capita human capital (PCHC) deflated by (a) consumer price index (CPI) and (b) living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

results in Table 3 shed light on a number of smaller subgroups within the second, largest club identified in both PCHC samples.[15] In particular, Club 2 consists of three provinces surrounding the Yangtze River Delta – Jiangsu, Zhejiang, and Anhui –, as well as Henan, Guangdong, Chongqing, and Shaanxi. The Yangtze River Delta is one the richest areas in China, with 20% of national GDP. While the average relative transition path of this second club shows little evidence of catching up toward the highest club, it clearly diverges from the rest of the provinces with lower human capital levels. In the middle, Club 3 is the largest club with eight provinces, and Club 4 consists of Jilin, Hunan, Guangxi, Hainan, Sichuan, and Ningxia. In addition, Club 5 comprises the remaining northeastern and southeastern provinces, namely, Guizhou, Yunnan, Gansu, and Xinjiang. At the lower bound, Tibet and Qinghai constitute the least performing club, converging in the absolute sense, at an estimated speed of $\hat{\alpha} = 1.266$. Finally, while Heilongjiang diverges from the rest of the provinces, performing Step 5 of the clustering algorithm (see Section 4.2) enables to merge this province with Club 4. This finding is also consistent with the transition paths observed in (Fig. 5/(a)).

[15] Note that Clubs 2–4 identified in the PCLFHC (CPI) panel largely correspond to the provinces in Club 2 in the PCHC samples (Table 2).

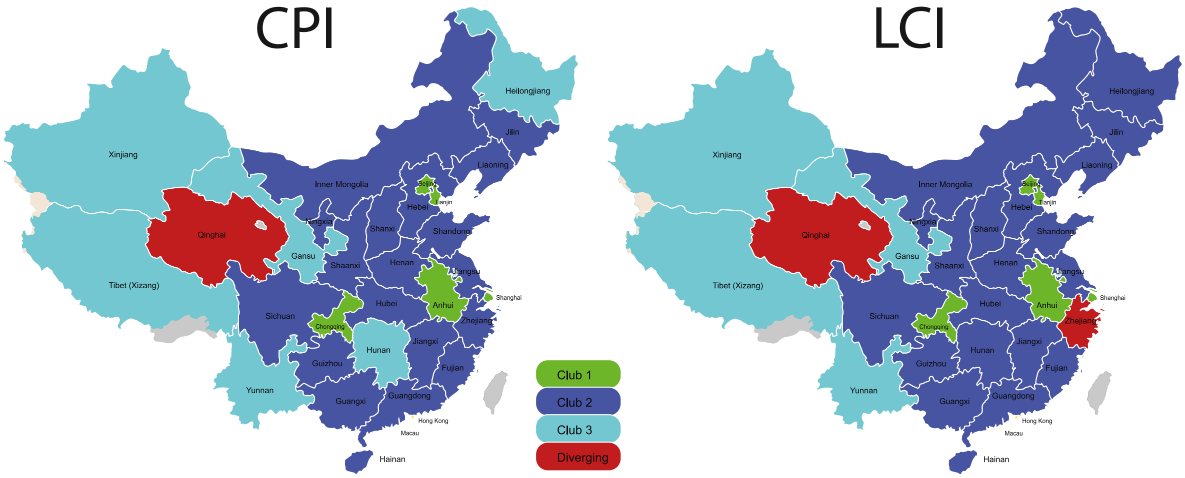


Fig. 4. Convergence club classification: PCHC. Authors' creation using Wikimedia Commons. Convergence club classification results for per capita human capital (PCHC) deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

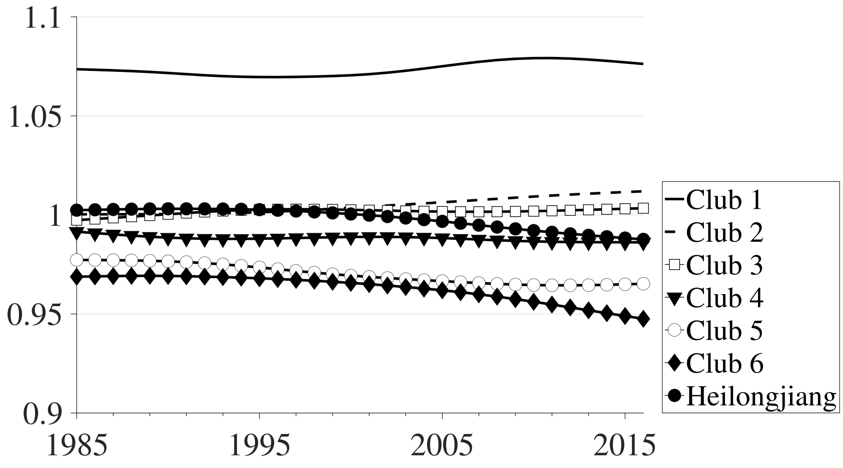
Table 3
Convergence club classification: PCLFHC.

PCLFHC (CPI) Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−26.317	−0.826 (0.031)	−0.413
Club 1	Beijing, Tianjin, Shanghai	1.504	0.242 (0.161)	0.121
Club 2	Jiangsu, Zhejiang, Anhui, Henan, Guangdong, Chongqing, Shaanxi	0.521	0.106 (0.203)	0.053
Club 3	Hebei, Shanxi, I. Mongolia, Liaoning, Fujian, Jiangxi, Shandong, Hubei	1.538	0.212 (0.138)	0.106
Club 4	Jilin, Hunan, Guangxi, Hainan, Sichuan, Ningxia	1.108	0.241 (0.217)	0.120
Club 5	Guizhou, Yunnan, Gansu, Xinjiang	1.684	0.514 (0.305)	0.257
Club 6	Tibet, Qinghai	3.193	2.532 (0.793)	1.266
Diverging	Heilongjiang			
PCLFHC (LCI) Clubs	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−53.152	−0.974 (0.018)	−0.487
Club 1	Beijing, Shanghai	−0.713	−0.791 (1.109)	−0.396
Club 2	Hebei, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Guangdong, Guangxi, Chongqing, Shaanxi, Ningxia	0.885	0.098 (0.111)	0.049
Club 3	Shanxi, Hunan, Hainan, Sichuan, Xinjiang	0.739	0.345 (0.466)	0.172
Club 4	Guizhou, Yunnan, Gansu, Qinghai	0.712	0.318 (0.447)	0.159
Diverging	Tianjin, Zhejiang, Tibet			

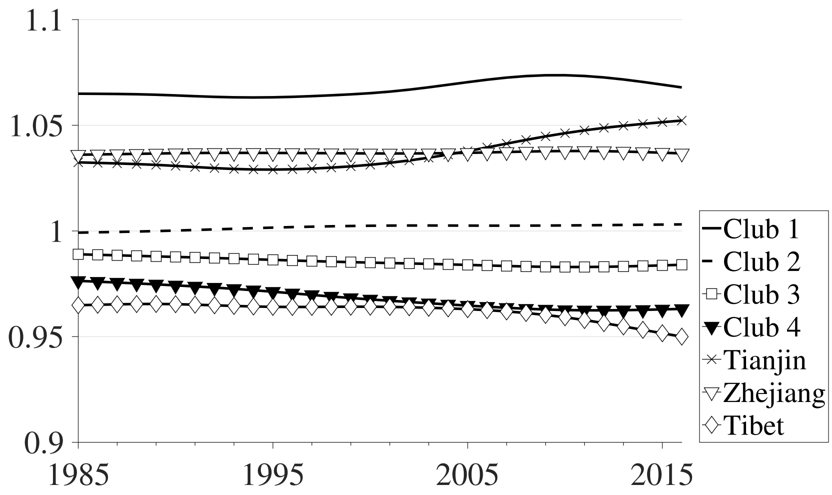
Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita labor force human capital (PCLFHC) for 31 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI) and living cost index (LCI). The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Clubs 2 and 3 in the CPI sample could be merged into an aggregate club that converges at a rate of $\hat{\alpha} = 0.030$. Similarly, the diverging province in the CPI sample, Heilongjiang, could be merged with Club 4 to form an aggregate club that converges at a rate of $\hat{\alpha} = 0.171$.

The regional patterns illustrated in Fig. 6 reveal within-region heterogeneity to a significant degree. Most strikingly, while the recent literature provides evidence that coastal provinces, on average, tend to converge to the highest income levels in China (see, e.g., Tian et al., 2016), not all of these provinces have experienced uniform accumulation of human capital. In fact, relatively high income provinces on the east coast, including Shandong and Liaoning, fall below the panel average and form part of Club 3. Still, however, one may conclude that there is a remarkable division along the East–West dimension.

The results for the PCLFHC sample deflated by LCI are broadly consistent with the CPI sample classifications, and yet, a number of differences emerge. For instance, two less convergence clubs are identified, and there are three divergent provinces detected in the LCI panel. Most noteworthy, is the separation of Tianjin from the highest club (Beijing and Shanghai), which, along with Zhejiang, could not be sieved to any of the subgroups, and they are following their individual transition paths between the first and second clubs (Fig. 5/(b)). This finding suggests that when controlling for disparities in the cost of living, Beijing and Shanghai



(a) PCLFHC deflated by CPI



(b) PCLFHC deflated by LCI

Fig. 5. Average relative transition paths for convergence clubs and diverging provinces: PCLFHC. Authors' calculations using CHLR (2018). Average relative transition paths of per capita labor force human capital (PCLFHC) deflated by (a) consumer price index (CPI) and (b) living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

form a separate club remaining above the rest of the provinces, whereas Tianjin diverges away, because it is no longer consistently above the other regions. In fact, its relative transition path was below that of Zhejiang up until the mid-2000s (Fig. 5/(b)). Even so, Tianjin is evidently catching up with the provinces of Club 1, diverging away from Zhejiang. Similarly, Zhejiang displays a higher rate of human capital accumulation, once adjusting for the purchasing power, diverging above Club 2. Interestingly, after accounting for differences in living costs, many provinces from Clubs 3 and 4 of the CPI sample converge to the second highest club, which is also the largest and includes most of the coastal and central provinces. Similarly, other provinces in the lowest clubs converge towards higher clubs in the LCI sample since their costs of living are lower: Club 3 consists of Shanxi, Hunan, Hainan, Sichuan, Xinjiang, whereas the lowest convergence club, Club 4, is formed by Guizhou, Yunnan, Gansu, Qinghai. Surprisingly, Qinghai's PCLFHC converges to the lowest club once adjusting for the purchasing power, separating from Tibet. Despite having a lower cost of living, Tibet does not accumulate enough PCLFHC and diverges away and below the rest of the provinces. The corresponding visual evidence in Fig. 6 lends further support to the similarities and differences between the CPI and LCI sample results.

Lastly, regarding the differences in the convergence patterns between PCHC and PCLFHC, the LCI deflated results reveal that in the former, Qinghai is falling away from the lowest club, while Tibet is the lowest province in the latter. These patterns can be partly explained by the evolution of the provinces' future labor force, i.e., the reserve human capital (potential lifetime income) embodied in their children. Specifically, the transition path for Qinghai's reserve PCHC exhibits a relatively low and continued

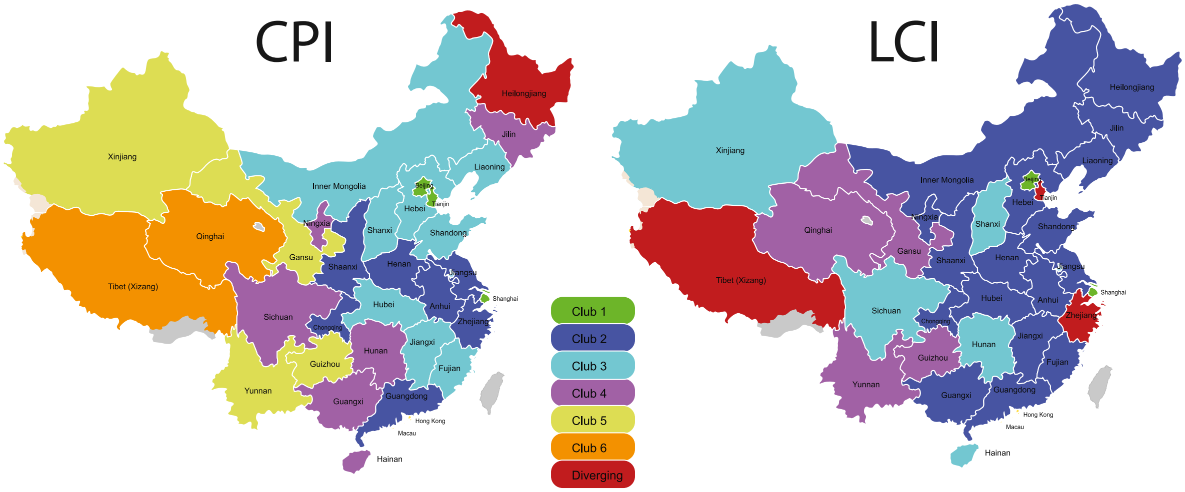


Fig. 6. Convergence club classification: PCLFHC. Authors' creation using Wikimedia Commons. Convergence club classification results for per capita labor force human capital (PCLFHC) deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

drop throughout the entire sample period (See Fig. B.1/(a) in Appendix B). In fact, it diverges below and away from all provinces, including Tibet. This declining trend is even more pronounced starting from the turn of the century, which signals an upcoming decline in its future PCLFHC transition path. In other words, Qinghai's present productive capacity is likely to be replaced by a labor force with a weaker human capital relative to other provinces in subsequent years.[16] On the other hand, the transition path of Tibet's reserve PCHC reveals a sharp decline only during the period between 1985 to 2000 (Fig. B.1/(b)). As its young population gradually enters the labor force, Tibet's per capita reserve human capital should translate into a decreasing PCLFHC relative to the panel average. This downward tendency is already reflected in Fig. 5/(b) from 2001 onwards. Nevertheless, Tibet's reserve is relatively higher than that of Yunnan, Gansu, and Qinghai over the entire period studied, which explains why its total PCHC is not the lowest. Instead its overall PCHC is higher than that of the aforementioned three provinces, which implies that its labor force may be more productive in the future (see Figs. 2 and A.1).

Given the different samples, indicators, and deflators used throughout the analysis, it is important to emphasize which results merit greater attention than others. It can be argued that the LCI, which adjusts nominal human capital by each province's purchasing power, is a more reliable deflator, since it controls for the evolution of province-specific differences in the cost of living that may affect convergence outcomes. For this reason, while attention should be given to what bias, if any, appears between the results using the two deflators, major implications should be drawn from the LCI results. Similarly, since labor human capital stock is a part of total human capital stock, PCLFHC reflects the productive capacity of a population's labor force, while PCHC includes the reserve human capital, that which will be used for production in the future. Given this relationship, PCLFHC may better reflect the actual human capital employed in a province's economy while the PCHC encompasses the human potential in the upcoming generations that will enter the labor force in the future.

5.3. Urban and rural per capita human capital

Evidence in the literature suggests that the urban–rural gap in China has been rising over time (see, e.g., Li et al., 2013). Consequently, the preceding analyses of province level aggregates may not reflect intra-provincial human capital dynamics driven by disparities in urbanization and rural-to-urban migration. For this reason, human capital convergence is also tested for the urban and rural areas separately. Following the arguments presented in Section 5.2, the subsequent discussion focuses on PCHC deflated using the LCI, yet, the club classification outcomes as well as the corresponding figures for PCLFHC and the CPI samples are included in Appendix C.

Convergence classifications for PCHC by urban and rural regions of 30 provinces are reported in Table 4 and illustrated in Fig. 7.[17] While the null hypothesis of overall convergence is rejected at the 5% confidence level for both subsamples considered, the results display substantial differences. Consistent with the clustering patterns presented in Section 5.1, the highest of the four clubs detected in the urban sample includes Beijing and Tianjin, whereas Qinghai is diverging below and away from all other provinces. Most notably, however, the highest club also includes Tibet, which is among the least performing regions in the provincial aggregates. Of the remaining 26 provinces, nine of them, including the majority of coastal areas, some central, and even western provinces are

[16] Note that besides the transition from reserve to labor force human capital, migratory inflows and outflows may also affect the dynamics of the present human capital stock (PCLFHC).

[17] Shanghai is omitted from the analyses in this subsection since there is no urban and rural disaggregation of human capital stock for this province.

Table 4
Convergence club classification: Urban vs. Rural PCHC (LCI).

Urban sample Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−52.853	−0.540 (0.010)	−0.270
Club 1	Beijing, Tianjin, Tibet	3.958	0.362 (0.091)	0.181
Club 2	Hebei, Jilin, Jiangsu, Zhejiang, Anhui, Jiangxi, Shandong, Chongqing, Guizhou	2.569	0.401 (0.156)	0.200
Club 3	Shanxi, I. Mongolia, Liaoning, Fujian, Henan, Hubei, Guangxi, Sichuan, Shaanxi, Ningxia, Xinjiang	3.784	0.352 (0.093)	0.176
Club 4	Heilongjiang, Hunan, Guangdong, Hainan, Yunnan	6.264	1.876 (0.299)	0.938
Diverging	Gansu, Qinghai			
Rural sample Clubs	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (s.e.)	$\hat{\alpha}$
Full Sample	No overall convergence	−13.927	−0.695 (0.050)	−0.348
Club 1	Hebei, Zhejiang, Fujian, Henan	3.516	1.022 (0.291)	0.511
Club 2	Beijing, Tianjin, Shanxi, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Hubei, Guangdong, Guangxi, Chongqing, Sichuan, Ningxia	−1.424	−0.127 (0.089)	−0.063
Club 3	Hunan, Hainan, Shaanxi	3.077	3.920 (1.274)	1.960
Club 4	Guizhou, Yunnan, Tibet, Gansu, Qinghai, Xinjiang	−0.887	−0.119 (0.134)	−0.059
Diverging	–			

Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita human capital (PCHC) for urban and rural regions in 30 Chinese provinces between 1985 and 2016, deflated by living cost index (LCI). Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province. The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Clubs 2 and 3 in the urban sample could be merged into an aggregate club that converges at a rate of $\hat{\alpha} = 0.147$.

converging into Club 2, while 11 mostly interior provinces converge into Club 3 (see Fig. 8). Turning to Fig. 7, Clubs 2 and 3 are the only subgroups that have managed to boost their performance and exhibit a catching-up process, especially since 2005. Notwithstanding these improvements, both Clubs 2 and 3 are still far from approaching Club 1 in terms of PCHC accumulation. The urban areas of Heilongjiang, Hunan, Guangdong, Hainan, and Yunnan form Club 4 with the relatively lowest human capital level per person, displaying a trajectory diverging below the other three clubs. Finally, Gansu follows its own transition path, diverging below Clubs 1–4, yet above Qinghai.

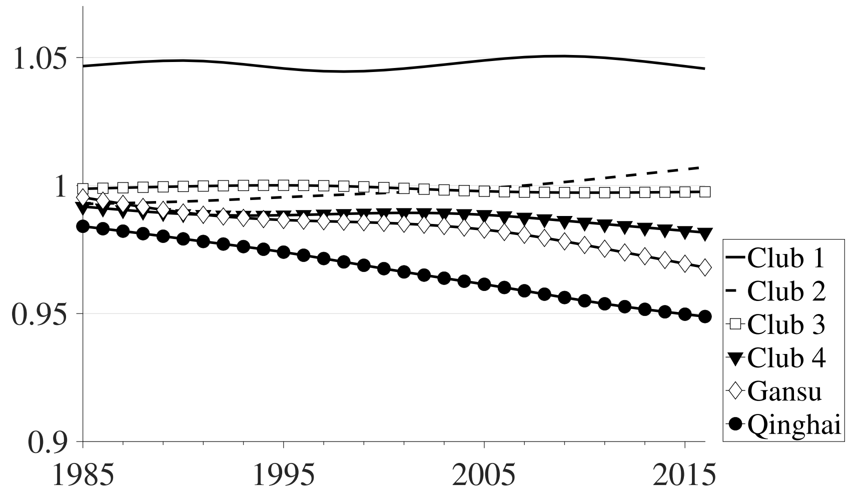
In contrast, Club 1 in the rural sample includes Hebei, Henan, Fujian, and Zhejiang; the first two and the last two are geographically connected (see Fig. 8). A notable absence from the top group is Beijing and Tianjin, which, along with 17 other provinces, converge into the second highest rural club. Clubs 3 and 4 display transition paths below unity, and show little, if any, evidence of catching up with Clubs 1 and 2. The lowest clubs includes the rural regions of Guizhou, Yunnan, Tibet, Gansu, Qinghai, and Xinjiang, which have also been identified as the least performing ones in the province level analyses.

Discrepancies between the urban and rural subsample results are indicative of the influence of the heterogeneous urbanization process on the club formation of provincial aggregates. For instance, the urban area in Tibet forms part of the highest club, together with Beijing and Tianjin. However, Tibet is the province with the largest share of rural population, and thus, its insufficient rural human capital accumulation explains why its overall performance at the province level is particularly low. Finally, it is not always straightforward to compare the highly urbanized municipalities of Beijing, Tianjin, and Shanghai with other provinces, as was done in the previous sections. However, this section compared only the urban areas in each province, and the significant gap between the highest club remains evident when comparing the transition paths for provincial PCHC (Fig. 3/(b)) and urban PCHC (Fig. 7/(a)).

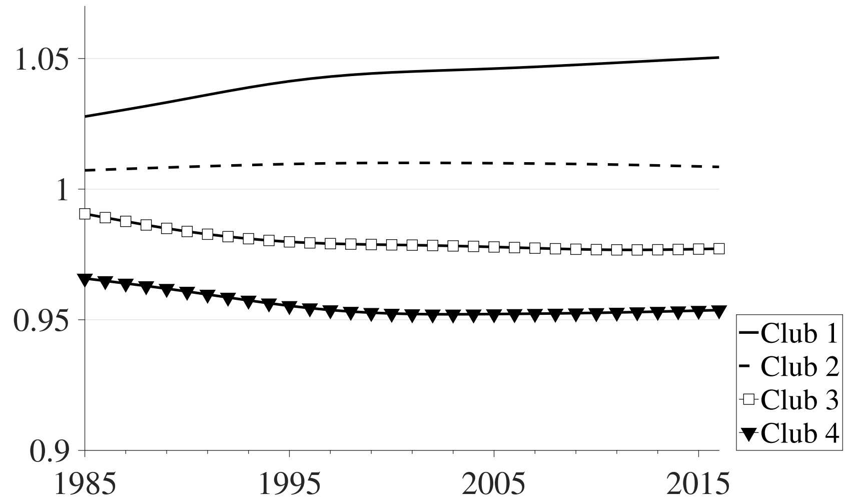
6. Comparison with education-based measures of human capital

Quantifying human capital is a complex task, which is why there exists an ongoing debate about the choice of proxies to measure human capital. Despite its limitations, this paper considers the J-F human capital approach that provides a more comprehensive view than traditional measures of educational quantity or quality, as discussed in Section 2.3. Not only are the J-F estimates better predictors of GDP growth than conventional measures of human capital (Zhang, Li, Wang, & Fleisher, 2019; Zhang & Wang, 2021), but most importantly, they consider other elements besides education, including on-the-job training, health, abilities, and unobserved school quality, that may significantly affect the accumulation of human capital over time.[18]

[18] Following Hanushek and Woessmann (2007), Appendix D presents estimates for GDP growth using J-F human capital and three education-based measures discussed in this section. Figs. D.1 and D.2 confirm that the variation in J-F human capital estimates explain variations in GDP growth rates better than the other indicators considered.



(a) Urban PCHC deflated by LCI



(b) Rural PCHC deflated by LCI

Fig. 7. Average relative transition paths for convergence clubs and diverging provinces: Urban vs. Rural PCHC (LCI). Authors' calculations using CHLR (2018). Average relative transition paths of (a) urban and (b) rural per capita human capital (PCHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

Without comparing the results of J-F human capital to those of education-based indicators, one cannot identify the value-added of including these missing elements. Hence, for the sake of comparison, this section repeats the convergence test by Phillips and Sul (2007) for (1) the average years of schooling of the labor force, (2) the proportion of the labor force with secondary educational attainment levels and above, and (3) the proportion of the labor force with tertiary educational attainment levels and above for all 31 provinces between 1985 and 2016. These educational proxies are calculated using the annual publications of the China Statistical Yearbook for the years 1995–2017 following Fraumeni et al. (2019).

The descriptive statistics for these alternative measures displayed in Table 5 indicate that mean values for the average years of schooling of the labor force (AYS), the proportion of the labor force with secondary education and above (PLFS), and the proportion with tertiary education and above (PLFT), have all increased substantially from 1985 to 2016. Additionally, the rankings based on the last observation of the sample period for all provinces for each of the three measures are shown in Table 6. In line with the J-F human capital series, Beijing, Shanghai and Tianjin are at the highest levels in terms of average years of schooling and educational attainment. Moreover, the provinces with the lowest alternative human capital measures also bear some similarities with the J-F club classifications previously obtained.

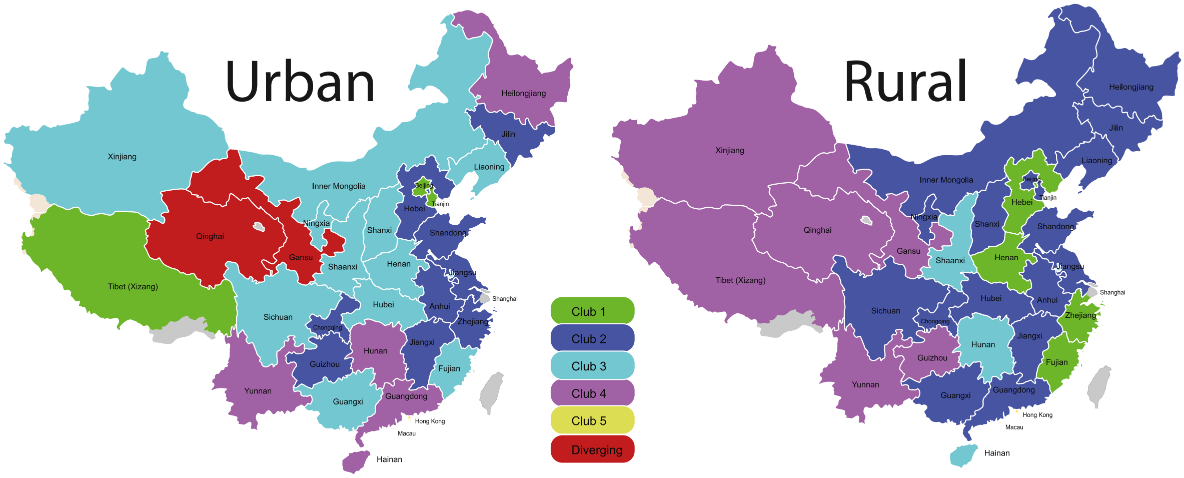


Fig. 8. Convergence club classification: Urban vs. Rural PCHC (LCI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita human capital (PCHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

Table 5
Descriptive statistics of education-based human capital measures for 31 provinces (selected years).

	1985				2016			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
AYS	6.18	1.43	2.08	9.22	9.93	1.13	5.75	12.89
PLFS	0.14	0.07	0.03	0.36	0.35	0.10	0.13	0.72
PLFT	0.02	0.02	0.01	0.10	0.17	0.08	0.07	0.51

Note: Summary statistics for education-based human capital measures refer to average years of schooling of the labor force (AYS), proportion of the labor force with secondary education and above (PLFS), and proportion of the labor force with tertiary education and above (PLFT). Authors' calculations using the China Statistics Year Books 1995–2017.

The results of the convergence tests for all three human capital proxies are reported in Table 7 with their corresponding transitional paths displayed in Fig. 9. These findings reveal a striking difference to the J-F club convergence classifications, since for all three indicators, overall convergence could not be rejected. The corresponding transitional paths in Fig. 9 are labeled "Full Sample" because all 31 provinces in each sample converge towards unique equilibria. These findings are robust to using more conservative sieve criteria for club membership. The results further illustrate that despite the existing gaps, the provinces with the lowest levels of schooling and educational attainment are catching up with the rest.

Education-based variables can only partially measure the human capital of an individual because they omit different aspects of human capital accumulation that are captured by the J-F approach. The results presented here demonstrate that overlooking such missing elements paints a different picture of human capital dynamics in China. In particular, education-based measures underestimate interprovincial human capital disparities in China, while the J-F estimates uncover the differences caused by the omitted factors. The findings also suggest that the gains in educational attainment are not equally rewarded across provinces in monetary value, reflected by the J-F approach.

In sum, convergence in terms of average years of schooling or levels of educational attainment does not imply convergence in other forms of human capital accumulation, represented by the J-F approach, therefore, it would be misleading to extrapolate education convergence to human capital convergence.

7. Club convergence, polarization, and imbalances in human capital in China

The Phillips and Sul (2007) convergence test and clustering algorithm employed in this paper is based on a non-linear factor model representation that is comparable to the concept of conditional σ-convergence, which measures the reduction of dispersion of human capital among the 31 provinces over time. Alternative methods to evaluate and better understand the subgroup convergence of human capital in China include (i) the application of the Esteban et al. (2007) index (hereafter EGR index) to measure the polarization in human capital, and (ii) the decomposition of human capital into its contributing factors using the Kaya-Zenga index proposed by Wang et al. (2020).

Table 6
Provincial ranking of education-based human capital measures for 31 provinces (2016).

Rank	AYS	PLFS	PLFT
1	Beijing	Beijing	Beijing
2	Shanghai	Shanghai	Shanghai
3	Tianjin	Tianjin	Tianjin
4	Jiangsu	Jiangsu	Jiangsu
5	Liaoning	Shaanxi	Shaanxi
6	Shaanxi	Guangdong	Liaoning
7	Hubei	Hubei	Zhejiang
8	Guangdong	Liaoning	Xinjiang
9	Shanxi	Chongqing	Ningxia
10	Jilin	Zhejiang	Hubei
11	Hunan	Shanxi	Jilin
12	Shandong	Jilin	Fujian
13	Heilongjiang	Ningxia	Heilongjiang
14	Zhejiang	Hunan	Shanxi
15	Hainan	Fujian	Shandong
16	Chongqing	Inner Mongolia	Gansu
17	Hebei	Hainan	Chongqing
18	Henan	Henan	Inner Mongolia
19	Inner Mongolia	Xinjiang	Guangdong
20	Xinjiang	Shandong	Hunan
21	Fujian	Heilongjiang	Anhui
22	Anhui	Gansu	Qinghai
23	Jiangxi	Hebei	Sichuan
24	Guangxi	Jiangxi	Hainan
25	Ningxia	Anhui	Hebei
26	Sichuan	Qinghai	Yunnan
27	Gansu	Sichuan	Guangxi
28	Guizhou	Guangxi	Henan
29	Yunnan	Yunnan	Jiangxi
30	Qinghai	Guizhou	Guizhou
31	Tibet	Tibet	Tibet

Note: Provinces are ranked in descending order based on the average years of schooling of the labor force (AYS), proportion of the labor force with secondary education and above (PLFS), and proportion of the labor force with tertiary education and above (PLFT). Authors' calculations using the China Statistics Year Books 1995–2017.

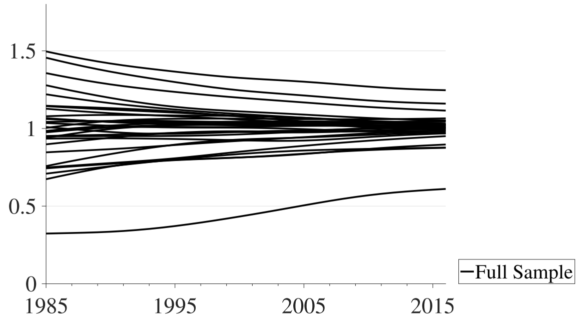
Table 7
Convergence club classification: Education-based human capital measures.

AYS Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ $(s.e.)$	$\hat{\alpha}$
Full Sample Diverging	Overall convergence –	5.773	0.376 (0.065)	0.188
PLFS Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ $(s.e.)$	$\hat{\alpha}$
Full Sample Diverging	Overall convergence –	5.061	0.508 (0.100)	0.254
PLFT Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ $(s.e.)$	$\hat{\alpha}$
Full Sample Diverging	Overall convergence –	11.368	0.766 (0.067)	0.383

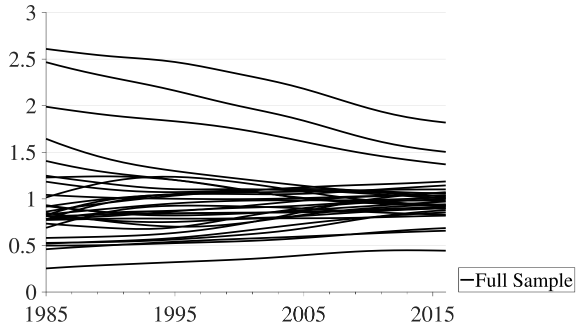
Note: Authors' calculations using the China Statistics Year Books 1995–2017. Log(t) test results for convergence in average years of schooling of the labor force (AYS), proportion of the labor force with secondary education and above (PLFS), and proportion of the labor force with tertiary education and above (PLFT). The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$.

7.1. Measuring polarization in human capital with the EGR index

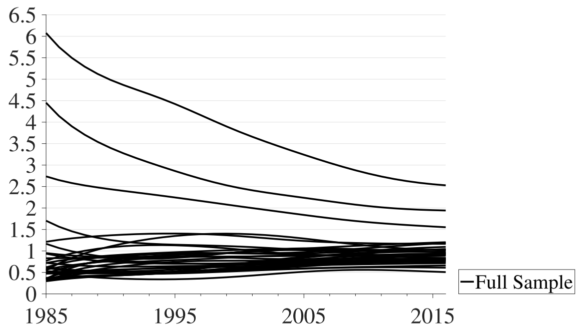
This first approach follows the endogenous grouping algorithm proposed by Aghevli and Mehran (1981) and Davies and Shorrocks (1989) to identify an optimal distribution partition for any number of groups specified within the panel. Esteban et al. (2007) extend this methodology to select the partition that minimizes the within-group inequality of the variable of interest and thereby demarcating different groups. The number of groups for the partitions here have been exogenously set to match the number of convergence clubs identified previously in each sample. Accordingly, the generalized EGR polarization index for human capital



(a) Average years of schooling of the labor force



(b) Proportion of the labor force with secondary education and above



(c) Proportion of the labor force with tertiary education and above

Fig. 9. Relative transition paths of all provinces in China: Education-based human capital measures. Authors' calculations using the China Statistics Year Books 1995–2017. Relative transition paths of (a) average years of schooling of the labor force, (b) proportion of the labor force with secondary education and above, and (c) proportion of the labor force with tertiary education and above. Sample: 31 Chinese provinces, 1985–2016.

is defined as:

$$EGR(\alpha, \beta) = \sum_{j=1} \sum_{k=1} \pi_j^{1+\alpha} \pi_k |\mu_j - \mu_k| - \beta(G - G_b), \tag{8}$$

where π represents a partition, or EGR group, measured as an interval that should not have a large dispersion relative to the dispersion of the entire distribution, α is a positive constant capturing the sensitivity of the index to polarization, μ_j and μ_k are the average human capital stocks of groups j and k, G and G_b are the dispersion of human capital for the observation sample and between each group, respectively, measured by the Gini coefficient, and β is the weight attached to the measurement error that is used to minimize the within-group inequality $G - G_b$. The optimal lower and upper limits, or bounds, of human capital that define each EGR group are computed using an iterative procedure introduced by Aghevli and Mehran (1981) and refined by Davies and

Table 8
EGR index within China (1985–2016).

	PCHC (CPI)		PCHC (LCI)		PCLFHC (CPI)		PCLFHC (LCI)	
1985	0.1091		0.0769		0.0539		0.0575	
1986–2000	0.1282		0.1075		0.0649		0.0755	
2000–2016	0.1351		0.1184		0.0769		0.0912	
Optimal partition of groups in 2016: Lower (LB) and Upper (UB) Bounds								
	LB	UB	LB	UB	LB	UB	LB	UB
EGR 1	318.39	665.31	338.96	668.27	237.82	373.69	211.39	376.75
EGR 2	217.69	318.39	246.63	338.96	166.9	237.82	158.28	211.39
EGR 3	105.96	217.69	131.49	246.63	136.24	166.9	128.3	158.28
EGR 4					123.97	136.24	83.81	128.3
EGR 5					99.73	123.97		
EGR 6					72.09	99.73		

Note: Authors' calculations using CHLR (2018). The EGR index is calculated with parameters $\alpha = 1$ and $\beta = 1$ with a maximum number of iterations for convergence to the optimal partitioning of groups equal to 16 and the level of precision for convergence to the optimal partition of groups is equal to 0.000001. The lower and upper bounds of human capital stock are in thousand RMB Yuan.

Shorrocks (1989). In what follows, these EGR groups are compared with the convergence clubs identified by the Phillips and Sul (2007) method in Section 5.

Table 8 reports the resulting EGR indices calculated for each of the human capital stocks for the periods 1985, 1986–2000, and 2000–2016. The results indicate that the polarization of human capital has increased from 1985 to 2016. This increase is more pronounced after controlling for the differences in the cost of living. Furthermore, Table 8 shows the lower and upper bounds of human capital stock for the optimal partitions estimated by the EGR index in 2016.[19] These optimal partitions are highly corroborative of the club classifications generated using the Phillips and Sul (2007) technique, as shown in the Chi-squared and Fisher's exact tests reported in Tables E.2–E.5 in Appendix E. The tests confirm that there is a statistically significant relationship between the EGR groups and the convergence clubs at the 1% confidence level for every human capital measure studied. The frequency distributions shown in Tables E.2–E.5 further illustrate the extent of similitude between each classification. For example, in the PCHC (CPI) sample, all but one of the provinces in the highest EGR group also belong to Club 1. Similarly, 13 of the 15 provinces (87%) in the second highest EGR group are also in Club 2. Finally, the lowest EGR group contains all the provinces in the least-performing Club 3. The results are similar for the PCHC (LCI) sample, where three of the five provinces in Club 1 are also in EGR 1, EGR 2 contains 86% of provinces in Club 2, and once more, all provinces from Club 3 are in EGR 3. In the case of PCLFHC, all provinces in the two highest EGR groups are in their corresponding convergence clusters, Clubs 1 and 2. Moreover, all of the members of the lowest convergence subgroups, Clubs 5 and 6, are in groups EGR 5 and 6, respectively. Finally, considering PCLFHC (LCI), all provinces in Club 1 are in EGR 1. The latter also includes the two diverging regions Tianjin and Zhejiang, which, as explained in Section 5.2, are above the rest of the other provinces, but not catching up to the top club, and therefore diverge in between the two highest clubs. In addition, all provinces in EGR 2 are also in Club 2, while the four provinces in the lowest subgroup, Club 4, are all in EGR 4.

The results from the EGR grouping algorithm presented in this subsection are consistent with the main findings of the club convergence analysis, thereby serving as a robustness exercise for the Phillips and Sul (2007) approach.

7.2. Examining human capital imbalances with the Kaya-Zenga index

Imbalance analysis is frequently used when analyzing regional differences in the variable of interest. In order to understand the mechanisms for the convergence clubs identified in this paper, this subsection explores imbalances in human capital and its contributing factors. Inspired by Wang et al. (2020), human capital can be decomposed into the product of human capital per average years of schooling (human capital return), average years of schooling per unit GDP (education intensity), GDP per capita, and population as follows:

$$HC_i = \frac{HC_i}{E_i} \cdot \frac{E_i}{Y_i} \cdot \frac{Y_i}{P_i} \cdot P_i = hce_i e_h y_i P_i, \tag{9}$$

where HC_i, E_i, and Y_i refer to human capital, average years of schooling, and GDP of province i, respectively, and hce_i, e_i, y_i, and P_i are human capital return, education intensity, GDP per capita, and population of province i.[20] Accordingly, the Kaya-Zenga index, which calculates the imbalance in human capital contributed by each province, can also be decomposed into the imbalances in the different contributing factors. Specifically, the imbalance in human capital contributed by province i is defined as:

$$I_i(HC) = I_i^{hce}(HC) + I_i^{e}(HC) + I_i^{y}(HC) + I_i^{P}(HC) - I_i^{int}(HC), \tag{10}$$

[19] The EGR group classification for each type of human capital stock is reported in Table E.1 in Appendix E.

[20] Data for GDP, average years of schooling of the labor force, and population are from the China Statistical Yearbooks 1995–2017.

where human capital return, education intensity, GDP per capita, population, and their interaction term are denoted as $I_i^{hce}(HC)$, $I_i^{e}(HC)$, $I_i^{y}(HC)$, $I_i^{P}(HC)$, and $I_i^{int}(HC)$, respectively.[21] Next, the overall imbalance in human capital (or its driving factors) can be calculated as the average imbalance contributed by each province i:

$$I(HC) = \frac{\sum I_i(HC)}{N}, \tag{11}$$

and finally, the average imbalance contributed by each club to the total imbalance in human capital (or its driving factors) is given by:

$$I_c(HC) = \frac{\sum I_i^c(HC)}{N^c}, \tag{12}$$

where I_i^c is the imbalance contributed by province i in club c and N^c refers to the number of provinces in club c.

Fig. 10 shows the imbalance in the contributing factors of human capital computed using Eq. (11) for each of the samples included in the study. The results indicate that for each of the samples, the education intensity has been a driving factor in reducing the overall human capital imbalance throughout the panels. On the other hand, GDP per capita and the human capital return have contributed to increasing the imbalance of human capital, although the magnitudes of their contribution have been decreasing over the last decade. In addition, the contribution of population has been increasing in recent years. In all of the samples, however, the role of the interaction term appears to be negligible. Fig. 11 further illustrates the contributions to the overall imbalance of human capital by each club of the PCHC samples, computed using Eq. (12).[22] The differences between the contributions to the imbalances of the driving factors provide important insights into the dynamics of each club. For instance, Club 1 contributes negatively to the population imbalance, whereas the opposite can be said of Clubs 2 and 3, which contribute to increasing it. Although GDP per capita and the human capital return in each club contributes positively to the overall imbalance, their contribution is the lowest in Club 3. In contrast, education intensity in Clubs 2 and 3 is more prominent in reducing the overall imbalance, yet is a minor contributing factor in Club 1.

The differences in the contributing factors between each club suggests that the provinces in the top club have accumulated disproportionately high levels of human capital despite their relatively small populations, especially in the case of Beijing, Shanghai, and Tianjin. These regions also have some of the highest concentrations of China's higher education institutions (Borsi, Valerio Mendoza, & Comim, 2022). On the other hand, the members of Club 3 likewise have small population shares, yet their returns to human capital and education intensities are among the lowest of the entire panel. Lastly, while the interaction term is mostly negligible for Clubs 1 and 2, it is the largest for Club 3, with a negative effect on the overall imbalance, suggesting these regions have the largest potential gains, or will benefit the most, from increases to their human capital factors.

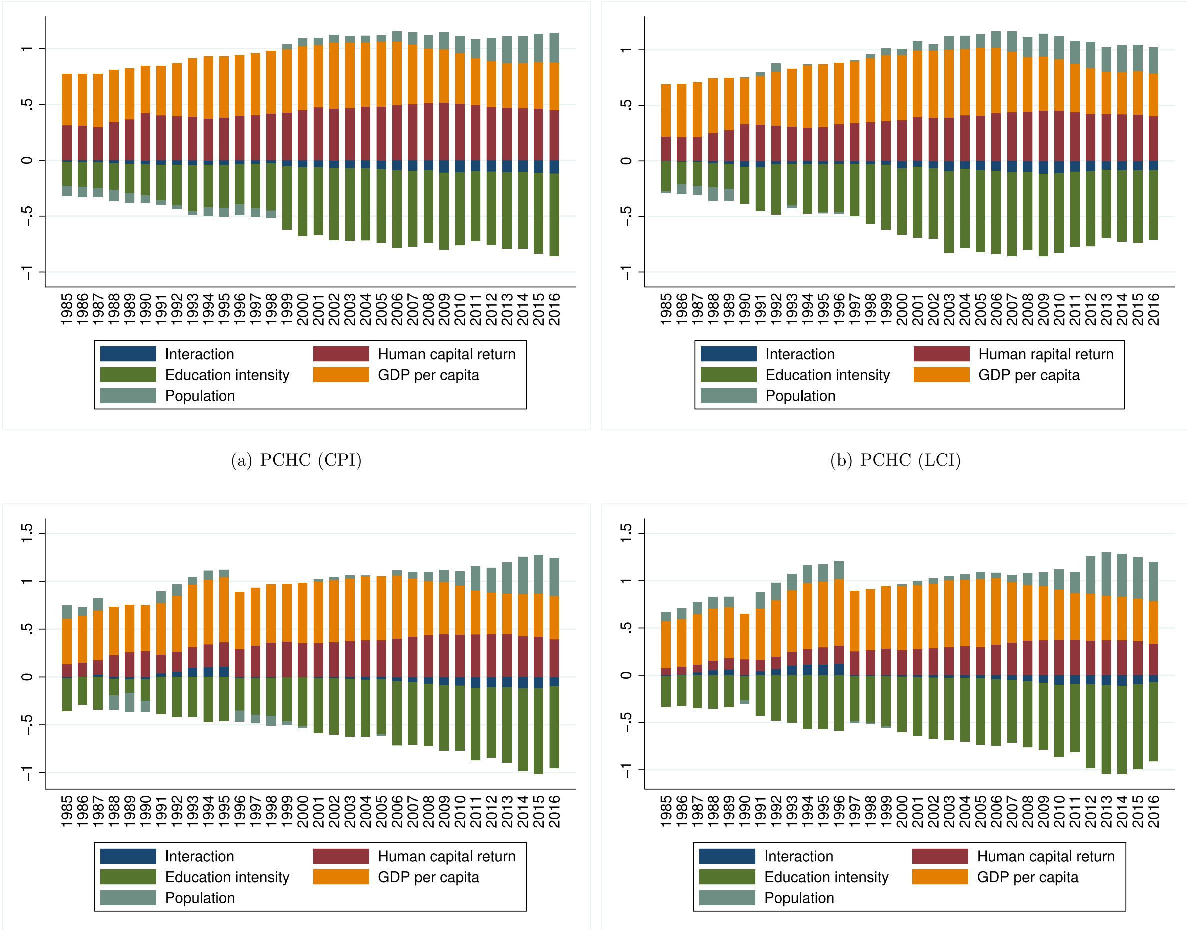
8. Discussion and concluding remarks

The purpose of this paper was to analyze the evolution of human capital accumulation across and within 31 Chinese provinces between 1985 and 2016 from a club convergence perspective. A convergence test and clustering algorithm proposed by Phillips and Sul (2007) was applied for the first time in a human capital context to identify converging subgroups and diverging provinces within the panel. Human capital stock accounts based on the Jorgenson–Fraumeni lifetime income approach were used for per capita human capital (PCHC) and per capita labor force human capital (PCLFHC). In addition, real values for both PCHC and PCLFHC were deflated using CPI and LCI in order to account for inflation and differences in the cost of living between provinces, respectively. Furthermore, urban and rural human capital accumulation across provinces were also examined. To complement the analysis, the convergence test was repeated for three well-established education-based human capital measures that consider average years of schooling and levels of educational attainment of the labor force. Moreover, the distribution of human capital was also assessed in terms of polarization and imbalances, using the EGR and Kaya-Zenga indices, respectively.

The main results indicate that there is no overall convergence in human capital growth for any of the J-F samples. However, several convergence clubs were identified within each panel considered. Specifically, three clubs were detected in the PCHC panel. The first club consists of the provinces exhibiting the highest human capital accumulation, namely, Beijing, Shanghai, and Tianjin, together with Anhui and Chongqing. The latter two, despite still being below a number of provinces in Club 2, are accumulating PCHC at a faster pace, enabling them to catch up with the top three. Zhejiang leads the largest subgroup, Club 2, and even diverges away from it when adjusting for the differences in the cost of living, following its own human capital growth path. Most worrying are the provinces at the lower bound, including the western-border members of Club 3, as well as the divergent Qinghai. They are not only failing to catch up to Clubs 1 and 2, but are even straying away from them. These findings are broadly consistent in both CPI and LCI samples. The outcomes for the PCLFHC panel provide further insights into the club classification, pointing to the existence of even greater heterogeneity among the 31 provinces in China. The first subgroup does not include Anhui and Chongqing, suggesting that their catching-up behavior reflected in the PCHC results is largely explained by their reserve human capital. In addition, the western-most provinces are consistently located in the lower clubs. Moreover, the PCLFHC (LCI) outcomes emphasize how differences in the cost of living may distort the convergence club classifications. Lastly, the results from the urban and rural samples further reinforce the large gap between the urban regions of the top three municipalities and those of other

[21] Appendix F provides a detailed description of the components of the imbalances in human capital and its contributing factors.

[22] Contributions of the PCLFHC samples are shown in Appendix G.



(a) PCHC (CPI)

(b) PCHC (LCI)

(c) PCLFHC (CPI)

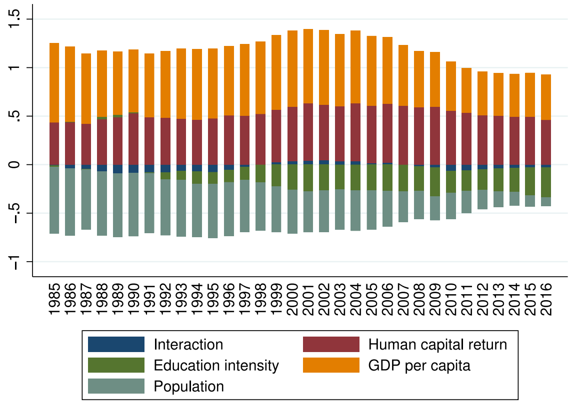
(d) PCLFHC (LCI)

Fig. 10. Imbalance in the contributing factors of human capital: human capital return, education intensity, GDP per capita, population, and their interaction term. Authors' calculations using CHLR (2018). PCHC and PCLFHC deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

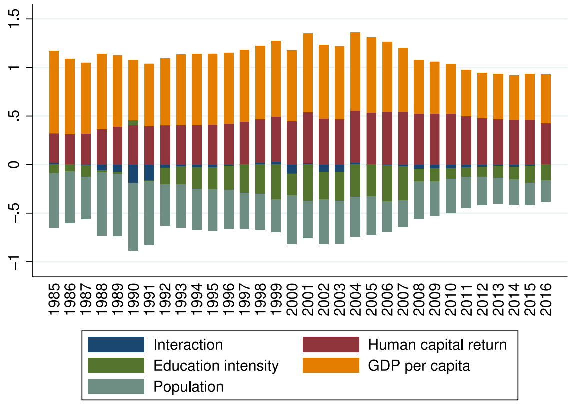
provinces. They also indicate that the club classification may be driven by low human capital accumulation in rural areas for some provinces. Overall, the lower divergence in PCHC compared to PCLFHC foreshadows a lower degree of divergence in the human capital of China's future labor force. This is because total human capital can be inferred as a predictor of future labor force human capital, since it includes the reserve human capital, which will be used by the labor force in the future. To further strengthen the analysis, the EGR optimal groups validate the convergence club classification results and the Kaya-Zenga decomposition of human capital reveal differences in the contributing factors of each club.

Some of the empirical evidence presented here deserves particular attention. Most importantly, the results for each of the education-based measures considered point to overall convergence, suggesting that average years of schooling as well as educational attainment levels of the labor force tend to underestimate interprovincial human capital disparities in China. Thus, focusing only on education and ignoring other elements such as on-the-job training, health, abilities, and unobserved school quality may be misleading. In fact, despite the increasing stock of human capital on average in China, the province-specific differences in the rate of accumulation indicate that the provinces are far from an overall convergence of human capital defined by the J-F approach. More specifically, the majority of the provinces are notably falling behind Beijing, Shanghai, Tianjin, and even Zhejiang, and are therefore at risk of entering a development trap. Furthermore, Yunnan, Gansu, Qinghai, and Tibet are consistently at the bottom, indicating the greatest concern in this regard. These provinces are not accumulating neither PCLFHC nor PCHC at a pace that would enable them to catch up to any other province in China. Policies aimed at reducing the rate of skilled worker movement from these regions might ameliorate the situation. Additionally, the case of Tibet suggests that its poor performance at the province level seems to be driven by the low human capital of its dominantly rural population. In fact, its urban PCHC is converging with the best-performing urban areas, yet its rural territory is in the lowest convergence club.

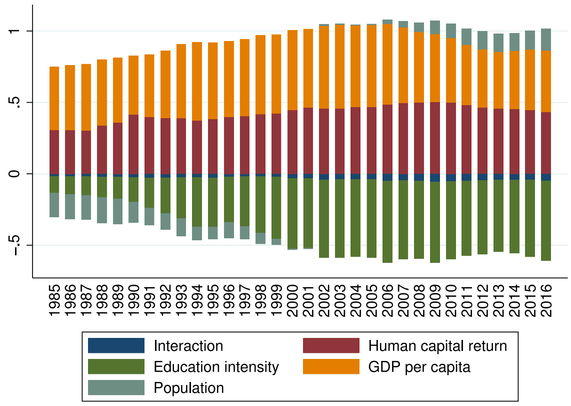
An in-depth analysis of interprovincial migration and its impact on human capital accumulation is beyond the scope of this article and is not explored here because of data limitations. Nevertheless, the composition of population within each province hints



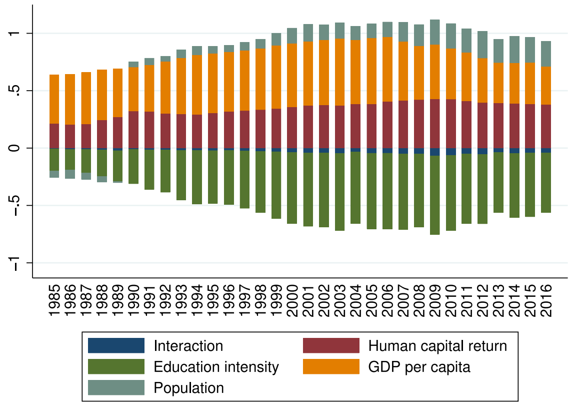
(a) Club 1 - PCHC (CPI)



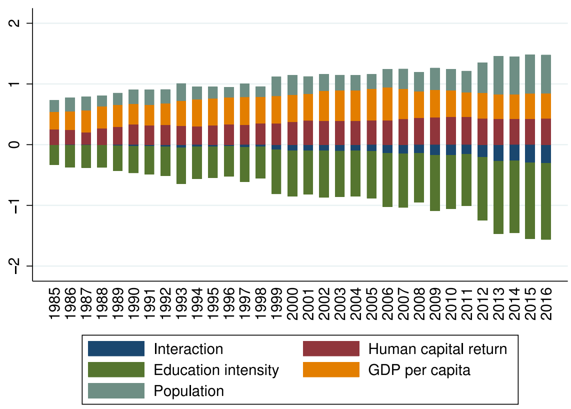
(b) Club 1 - PCHC (LCI)



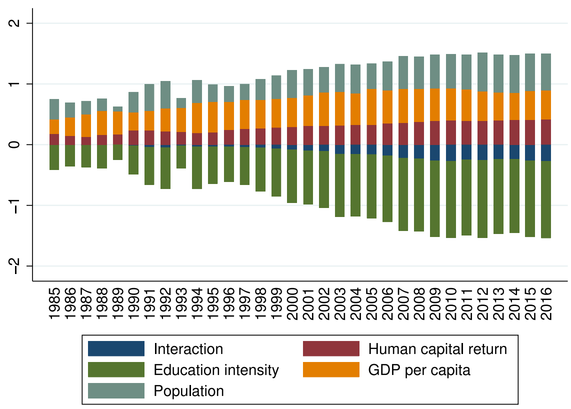
(c) Club 2 - PCHC (CPI)



(d) Club 2 - PCHC (LCI)



(e) Club 3 - PCHC (CPI)



(f) Club 3 - PCHC (LCI)

Fig. 11. Imbalance in the contributing factors of human capital by convergence club: human capital return, education intensity, GDP per capita, population, and their interaction term. Authors' calculations using CHLR (2018). PCHC deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

at the potential role of internal movements in explaining the heterogeneity in human capital dynamics in China. In particular the labor force to reserve population ratio, i.e., how the labor force compares to the young population which has not entered the labor market, reveals some interesting patterns (Appendix H). The ratio displays an upward trend for all of the provinces due to the negative impact of the one-child policy on the children's share in the population. Coastal and northern provinces with higher human capital accumulation, including Beijing, Tianjin, Shanghai, Liaoning, or Jilin, however, have a significantly larger labor force relative to the young population, especially towards the end of the sample period. Such regional disparities in the labor force to reserve population ratio suggest that some provinces may provide better life opportunities and are therefore more likely to attract migrants who leave their children behind, especially in the urban areas (see, e.g., Yang & Bansak, 2020). Moreover, the disproportionate share of the labor force in terms of the young population in some provinces could also explain the differences in the total vs. labor force human capital convergence test results and should be further studied.

The findings of the paper contribute to the existing research on human capital evolution, educational attainment, and overall development in China. While previous studies have analyzed differences in human capital among regional aggregates based on geographic location (Fleisher et al., 2010) or economic development (Fraumeni et al., 2019), this study reveals province-specific heterogeneity in human capital accumulation within these regions. For example, some coastal provinces are converging with central and northeastern provinces in human capital accumulation, whereas others are diverging away toward higher levels. Therefore, while geography explains convergence in GDP (Tian et al., 2016), this is not the case with human capital. Additionally, even though human capital is known to be a key driver of income growth, the results provide evidence that human capital convergence does not follow the patterns of income convergence, as suggested by Tian et al. (2016). The findings, however, are more in line with the dispersion in educational attainment levels found by Valerio Mendoza (2018), which suggests province-, or even city-specific causes to the within region disparities, thus advocating for local level solutions and policies. Similarly, the opposing outcomes obtained from the J-F estimates and the education-based human capital measures are consistent with the results of Fraumeni et al. (2019). Finally, the convergence club classification from this paper seems to be fairly consistent with the social policy spending regimes identified by Ratigan (2017), implying that wealth and educational expenditure explain some of the variation in human capital stock growth. For instance, Qinghai was singled out as not following similar social spending patterns than others since its share of social safety net spending was among the highest in China, but it had one of the lowest shares of education investment.

Whatever the most suitable social, economic, or educational policy for human capital formation in China, it is important to remark that it should take into account the results of this investigation, once policies should take into account the distinct contexts and impacts in different provinces. As Khor et al. (2016) points out, in order to avoid the middle-income trap, the Chinese labor force needs to achieve a significantly higher share of upper secondary school attainment level, comparable to the OECD average (80%). This goal is aligned with current educational reforms and policies, such as the "High School Education Popularization Plan (2017–2020)" and the "Education Modernization 2035 Plan" (Ministry of Education, 2017, 2018b, respectively), both of which stipulate increasing the quantity of human capital stock by bridging the compulsory education and higher education, via increased senior high school education. Likewise, reforms aimed at improving compulsory education in rural areas (State Council, 2016) and the "Central and Western Higher Education Revitalization Plan" (Ministry of Education, 2016) seem to recognize the weaknesses in human capital accumulation in rural, less-developed, and poverty-stricken regions.

Finally, the evidence provided by this paper can offer valuable policy insights for China's "14th Five-Year Plan for National Economic and Social Development and Long-Term Objectives for 2035" (National Development and Reform Commission, 2021). First, because it can assist the government in promoting the joint prosperity of developed and less-developed areas, implementing regional coordinated development strategies in an in-depth manner. Secondly, because fostering human capital seems a pre-condition to achieve the Plan's objectives of adhering to innovation-driven development and acceleration of the development of a modern industrial system. Given that 'equal development' is one of the key objectives of the long-term goals for 2035, it needs to be equitable and convergent not simply at the education level but across all the contributing factors to human capital accumulation. Thus, the main policy implication provided by this paper is clear: it is important to recognize the inexistence of overall convergence in human capital for the 31 Chinese provinces, so that efforts in promoting an optimization of regional resources can be furthered. Moreover, evidence about the human capital divide between Beijing, Shanghai and Tianjin *vis-á-vis* the majority of the other provinces can assist the Chinese government in its efforts for promoting equal development and a more cohesive society. Boosting convergence in China's human capital can be instrumentally important to increase competitiveness and construct a higher-level new open economy system, which in turn would allow to take the benefits of a digital economy to a wider sector of the population in the form of economic opportunities and public services.

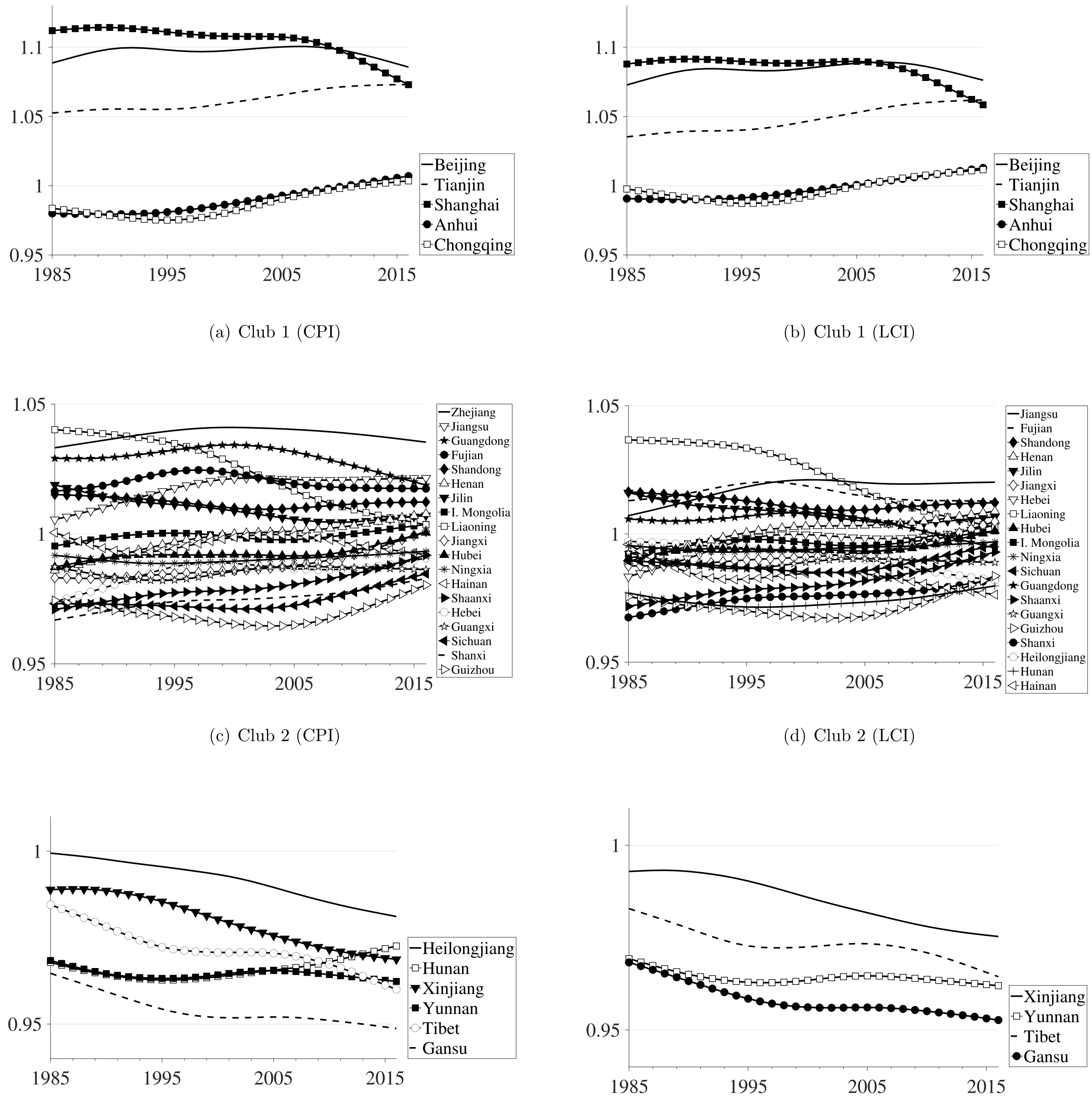
The convergence of human capital between Chinese provinces is an implicit target of the aforementioned policies, as well as priority of the socialist development advocated by the Communist Party of China in order to achieve a harmonious society. While the latest reforms are unarguably heading in the right direction, the findings of this paper highlight the magnitude of the challenge for most provinces in generating the necessary growth in human capital that enables China to continue on a prosperous development path.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.



(a) Club 1 (CPI)

(b) Club 1 (LCI)

(c) Club 2 (CPI)

(d) Club 2 (LCI)

(e) Club 3 (CPI)

(f) Club 3 (LCI)

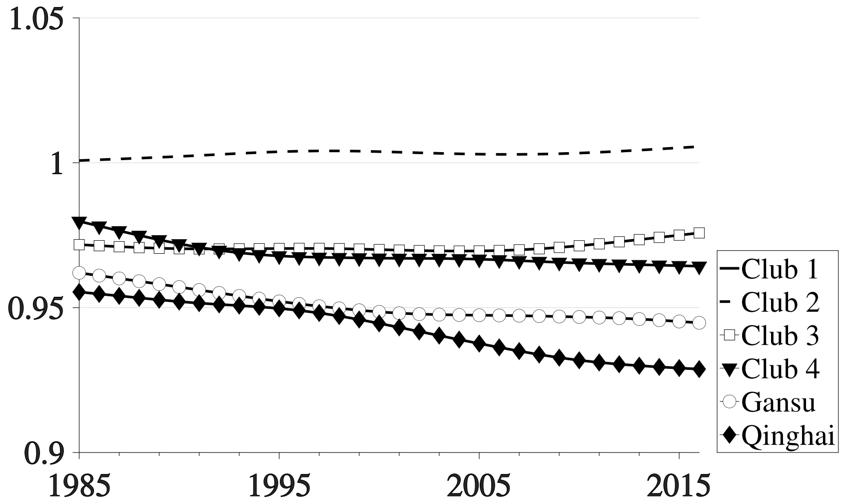
Fig. A.1. Relative transition paths of provinces forming Clubs 1, 2, and 3: PCHC. Authors' calculations using CHLR (2018). Relative transition paths of per capita human capital (PCHC) deflated by (a)–(c)–(e) consumer price index (CPI) and (b)–(d)–(f) living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.

Acknowledgments

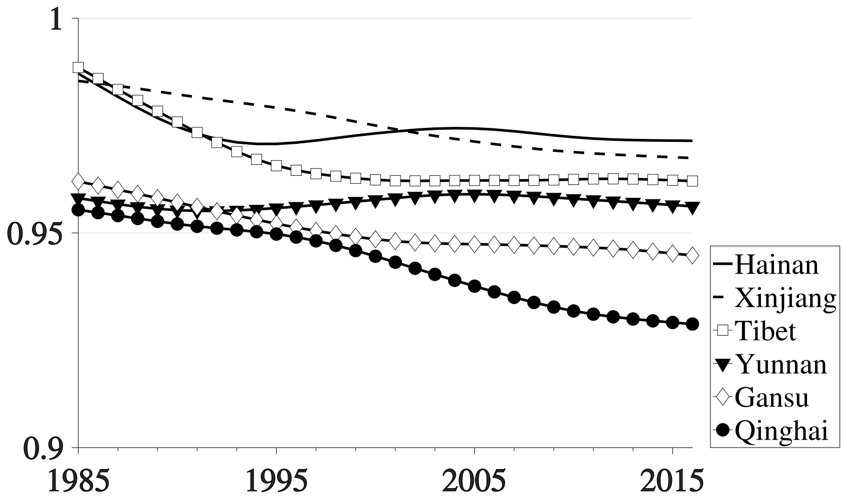
The authors would like to thank seminar participants at the 10th International Symposium on Human Capital and Labor Markets and the WEAI 15th International Conference for helpful discussion and comments. This research has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie grant agreement No. 838534. All remaining errors are our own. Declarations of interest: none.

Appendix A. Relative transition paths of provinces forming clubs 1, 2, and 3: PCHC

See Fig. A.1.



(a) Reserve PCHC deflated by LCI



(b) Club 4 and diverging provinces (LCI)

Fig. B.1. Relative transition paths for convergence clubs and diverging provinces: Reserve PCHC. Authors' calculations using CHLR (2018). (a) Average relative transition paths and diverging provinces and (b) relative transition paths of provinces forming Club 4 together with diverging provinces. Relative transition paths of per capita reserve human capital deflated by living cost index (LCI). Reserve PCHC is the per capita human capital of the young population which has not entered in the labor market, i.e., those under the age of 16 and full-time students who are 16 years of age or above. Sample: 31 Chinese provinces, 1985–2016.

Appendix B. Relative transition paths for convergence clubs and diverging provinces: Reserve PCHC

See Fig. B.1.

Appendix C. Urban and rural club convergence results: PCHC (CPI), PCLFHC (CPI), and PCLFHC (LCI)

See Tables C.1–C.3 and Figs. C.1–C.6.

Appendix D. Estimates for GDP growth using alternative measures of human capital

See Figs. D.1 and D.2.

Table C.1
Convergence club classification: Urban vs. Rural PCHC (CPI).

Urban sample Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−33.638	−0.686 (0.020)	−0.343
Club 1	Beijing, Tianjin	4.085	1.711 (0.419)	0.855
Club 2	Hebei, Shanxi, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Ningxia, Xinjiang	7.052	0.229 (0.032)	0.114
Diverging	Gansu, Qinghai			
Rural sample **Clubs**	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−12.625	−0.646 (0.051)	−0.323
Club 1	Tianjin, Hebei, Zhejiang, Fujian, Henan	4.837	0.776 (0.160)	0.388
Club 2	Beijing, Shanxi, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Hubei, Guangdong, Guangxi, Chongqing, Sichuan, Shaanxi, Ningxia	−0.632	−0.055 (0.087)	−0.028
Club 3	Hunan, Hainan, Guizhou, Yunnan, Gansu, Xinjiang	0.852	0.253 (0.297)	0.126
Club 4	Tibet, Qinghai	3.292	3.966 (1.205)	1.983
Diverging	–			

Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita human capital (PCHC) for urban and rural regions in 30 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI). Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province. The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Merging of the neighboring clubs is rejected in both samples considered.

Table C.2
Convergence club classification: Urban vs. Rural PCLFHC (CPI).

Urban sample Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−21.886	−1.148 (0.052)	−0.574
Club 1	Hebei, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Tibet	6.598	0.607 (0.092)	0.304
Club 2	Shanxi, I. Mongolia, Liaoning, Jilin, Jiangxi, Henan, Hubei, Hainan, Chongqing, Yunnan, Shaanxi, Ningxia	1.661	0.374 (0.225)	0.187
Club 3	Heilongjiang, Hunan, Guangxi, Sichuan, Guizhou, Xinjiang	2.661	0.919 (0.346)	0.460
Diverging	Beijing, Tianjin, Gansu, Qinghai			
Rural sample **Clubs**	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−12.281	−0.702 (0.057)	−0.351
Club 1	Beijing, Tianjin, Jiangsu, Zhejiang, Fujian, Henan	2.053	0.572 (0.278)	0.286
Club 2	Hebei, I. Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Jiangxi, Shandong, Hubei, Guangdong, Guangxi, Chongqing, Shaanxi, Ningxia	0.093	0.015 (0.163)	0.008
Club 3	Shanxi, Hainan, Sichuan	1.534	0.927 (0.604)	0.463
Club 4	Guizhou, Yunnan, Tibet, Gansu, Xinjiang	0.278	0.092 (0.330)	0.046
Diverging	Hunan, Qinghai			

Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita labor force human capital (PCLFHC) for urban and rural regions in 30 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI). Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province. The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Clubs 1 and 2 in the urban sample could be merged into an aggregate club that converges at a rate of $\hat{\alpha} = 0.065$.

Table C.3
Convergence club classification: Urban vs. Rural PCLFHC (LCI).

Urban sample Clubs	Provinces	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−12.770	−0.961 (0.075)	−0.481
Club 1	Hebei, Shanxi, I. Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Ningxia, Xinjiang	2.339	0.100 (0.043)	0.050
Diverging	Beijing, Tianjin, Gansu, Qinghai			
Rural sample Clubs	**Provinces**	$t_{\hat{b}}$	$\hat{b}$ (*s.e.*)	$\hat{\alpha}$
Full Sample	No overall convergence	−10.601	−0.551 (0.052)	−0.275
Club 1	Beijing, Zhejiang, Henan	0.955	0.186 (0.195)	0.093
Club 2	Tianjin, Hebei, Shanxi, I. Mongolia, Jilin, Heilongjiang, Jiangsu, Anhui, Fujian, Jiangxi, Shandong, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Shaanxi	0.088	0.010 (0.110)	0.005
Club 3	Liaoning, Guizhou, Yunnan, Tibet, Gansu, Qinghai, Ningxia, Xinjiang	2.332	0.296 (0.127)	0.148
Diverging	–			

Note: Authors' calculations using CHLR (2018). Log(t) test results for convergence in per capita labor force human capital (PCLFHC) for urban and rural regions in 30 Chinese provinces between 1985 and 2016, deflated by living cost index (LCI). Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province. The table contains the speed of convergence ($\hat{\alpha}$), the corresponding coefficient estimates ($\hat{b}$) and t-statistics. Newey–West standard errors are reported in parentheses. The null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$. Merging of the neighboring clubs is rejected in both samples considered.

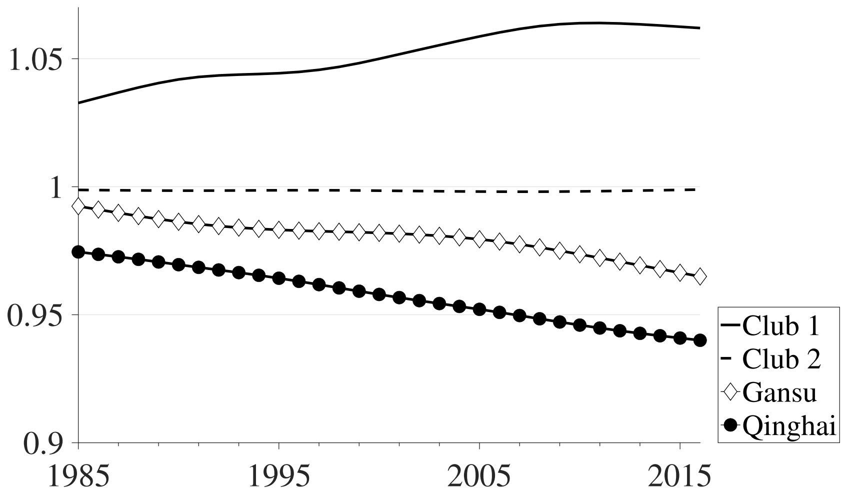
Table E.1
EGR group classification (2016).

PCHC (CPI) Clubs	Provinces
EGR 1	Beijing, Shanghai, Tianjin, Zhejiang
EGR 2	Jiangsu, Shandong, Fujian, Anhui, Liaoning, Henan, Inner Mongolia, Hebei, Jilin, Hubei, Chongqing, Guangdong, Jiangxi, Ningxia, Shaanxi
EGR 3	Sichuan, Shanxi, Heilongjiang, Guangxi, Xinjiang, Hunan, Hainan, Guizhou, Gansu, Yunnan, Qinghai, Tibet
PCHC (LCI) Clubs	**Provinces**
EGR 1	Beijing, Shanghai, Tianjin, Zhejiang, Jiangsu
EGR 2	Shandong, Fujian, Anhui, Liaoning, Henan, Inner Mongolia, Hebei, Jilin, Hubei, Chongqing, Jiangxi, Ningxia, Shaanxi, Sichuan
EGR 3	Guangdong, Shanxi, Heilongjiang, Guangxi, Xinjiang, Hunan, Hainan, Guizhou, Gansu, Yunnan, Qinghai, Tibet
PCLFHC (CPI) Clubs	**Provinces**
EGR 1	Beijing, Shanghai, Tianjin
EGR 2	Zhejiang, Jiangsu, Guangdong
EGR 3	Shandong, Fujian, Anhui, Liaoning, Henan, Inner Mongolia
EGR 4	Jilin, Hubei, Jiangxi
EGR 5	Hebei, Chongqing, Ningxia, Shaanxi, Sichuan, Shanxi, Heilongjiang, Guangxi, Hainan
EGR 6	Xinjiang, Hunan, Guizhou, Gansu, Yunnan, Qinghai, Tibet
PCLFHC (LCI) Clubs	**Provinces**
EGR 1	Beijing, Shanghai, Tianjin, Zhejiang
EGR 2	Jiangsu, Shandong, Fujian, Anhui, Liaoning, Henan, Inner Mongolia, Hebei
EGR 3	Jilin, Hubei, Chongqing, Jiangxi, Ningxia, Shaanxi, Sichuan, Guangdong, Shanxi, Heilongjiang
EGR 4	Guangxi, Xinjiang, Hunan, Hainan, Guizhou, Gansu, Yunnan, Qinghai, Tibet

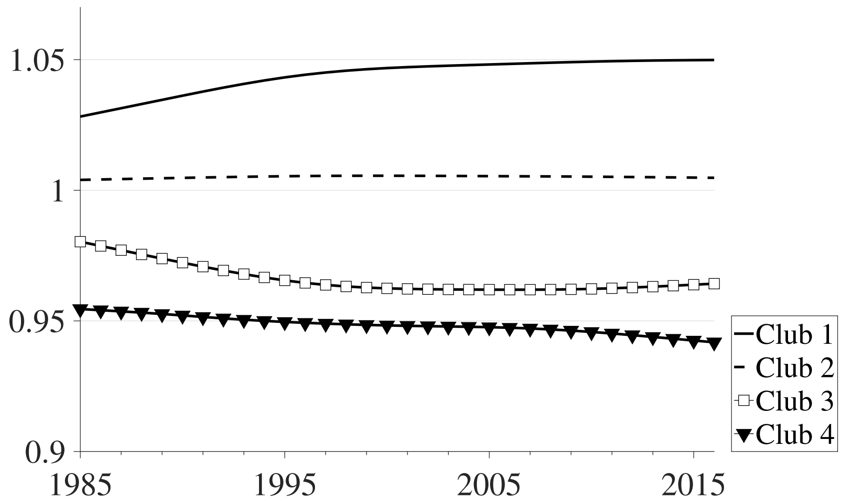
Note: Authors' calculations using CHLR (2018).

Appendix E. Chi-squared and Fisher's exact tests: EGR groups vs. convergence clubs

See Tables E.1 and E.5.



(a) Urban PCHC deflated by CPI



(b) Rural PCHC deflated by CPI

Fig. C.1. Average relative transition paths for convergence clubs and diverging provinces: Urban vs. Rural PCHC (CPI). Authors' calculations using CHLR (2018). Average relative transition paths of (a) urban and (b) rural per capita human capital (PCHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

Table E.2
Chi-squared and Fisher's exact tests: PCHC (CPI).

PCHC (CPI)					
	Club 1	Club 2	Club 3	Diverging	Total
EGR 1	3	1	0	0	4
	(0.6)	(2.5)	(0.8)	(0.1)	
EGR 2	2	13	0	0	15
	(2.4)	(9.2)	(2.9)	(0.5)	
EGR 3	0	5	6	1	12
	(1.9)	(7.4)	(2.3)	(0.4)	
Total	5	19	6	1	31
			Pearson Chi-squared		24.8761***
			Fisher's exact		0.000

Note: Authors' calculations using CHLR (2018). Frequencies are reported along with their corresponding expected values in parenthesis.
***Indicates significance at 1% confidence level.

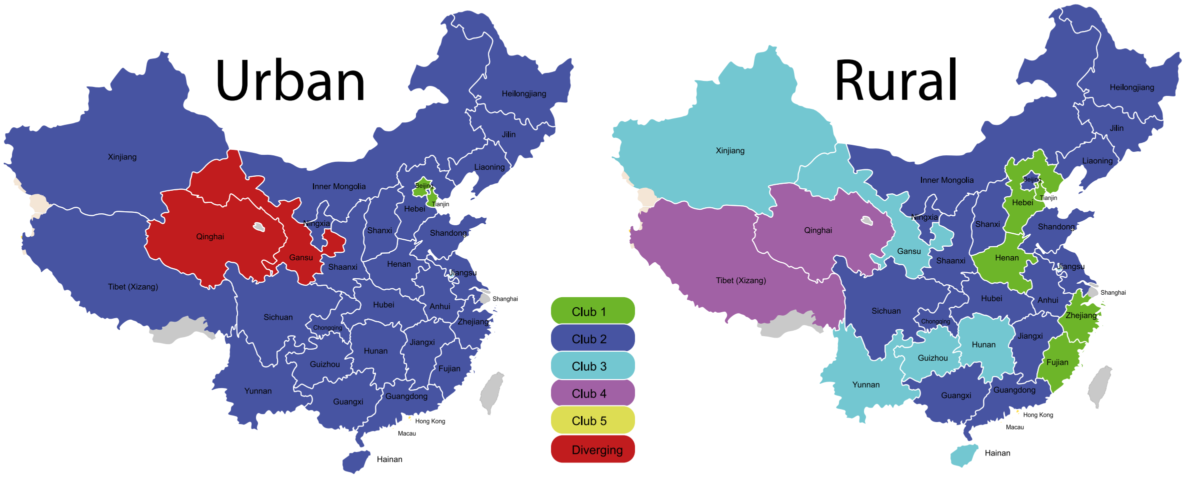


Fig. C.2. Convergence club classification: Urban vs. Rural PCHC (CPI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita human capital (PCHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

Table E.3
Chi-squared and Fisher's exact tests: PCHC (LCI).

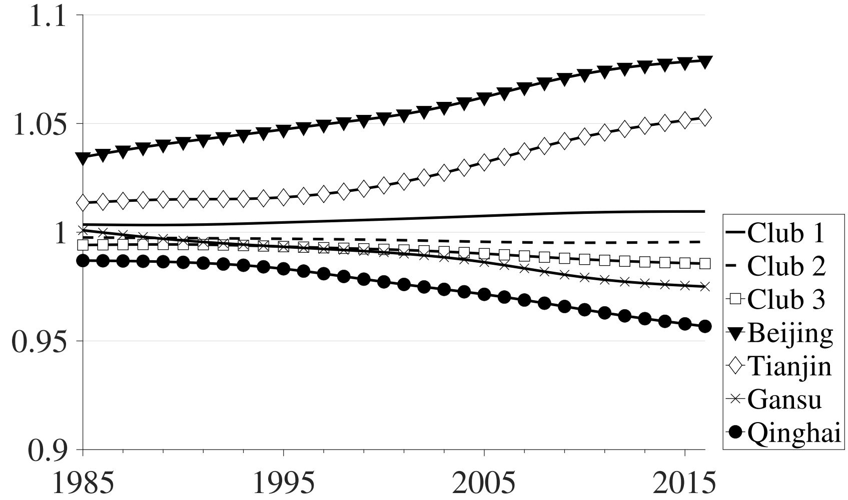
PCHC (LCI)	Club 1	Club 2	Club 3	Diverging	Total
EGR 1	3	1	0	1	5
	(0.8)	(3.2)	(0.6)	(0.3)	
EGR 2	2	12	0	0	14
	(2.3)	(9)	(1.8)	(0.9)	
EGR 3	0	7	4	1	12
	(1.9)	(7.7)	(1.5)	(0.8)	
Total	5	20	4	2	31
			Pearson Chi-squared		19.2385***
			Fisher's exact		0.001

Note: Authors' calculations using CHLR (2018). Frequencies are reported along with their corresponding expected values in parenthesis.
***Indicates significance at 1% confidence level.

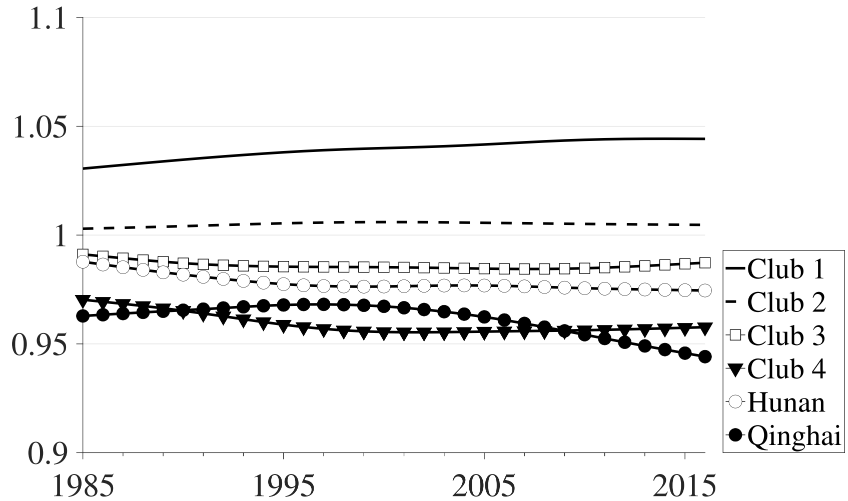
Table E.4
Chi-squared and Fisher's exact tests: PCLFHC (CPI).

PCLFHC (CPI)	Club 1	Club 2	Club 3	Club 4	Club 5	Club 6	Diverging	Total
EGR 1	3	0	0	0	0	0	0	3
	(0.3)	(0.7)	(0.8)	(0.6)	(0.4)	(0.2)	(0.1)	
EGR 2	0	3	0	0	0	0	0	3
	(0.3)	(0.7)	(0.8)	(0.6)	(0.4)	(0.2)	(0.1)	
EGR 3	0	2	4	0	0	0	0	6
	(0.6)	(1.4)	(1.5)	(1.2)	(0.8)	(0.4)	(0.2)	
EGR 4	0	0	2	1	0	0	0	3
	(0.3)	(0.7)	(0.8)	(0.6)	(0.4)	(0.2)	(0.1)	
EGR 5	0	2	2	4	0	0	1	9
	(0.9)	(2)	(2.3)	(1.7)	(1.2)	(0.6)	(0.3)	
EGR 6	0	0	0	1	4	2	0	7
	(0.7)	(1.6)	(1.8)	(1.4)	(0.9)	(0.5)	(0.2)	
Total	3	7	8	6	4	2	1	31
					Pearson Chi-squared			77.0899***
					Fisher's exact			0.000

Note: Authors' calculations using CHLR (2018). Frequencies are reported along with their corresponding expected values in parenthesis.
***Indicates significance at 1% confidence level.



(a) Urban PCLFHC deflated by CPI



(b) Rural PCLFHC deflated by CPI

Fig. C.3. Average relative transition paths for convergence clubs and diverging provinces: Urban vs. Rural PCLFHC (CPI). Authors' calculations using CHLR (2018). Average relative transition paths of (a) urban and (b) rural per capita human capital (PCLFHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

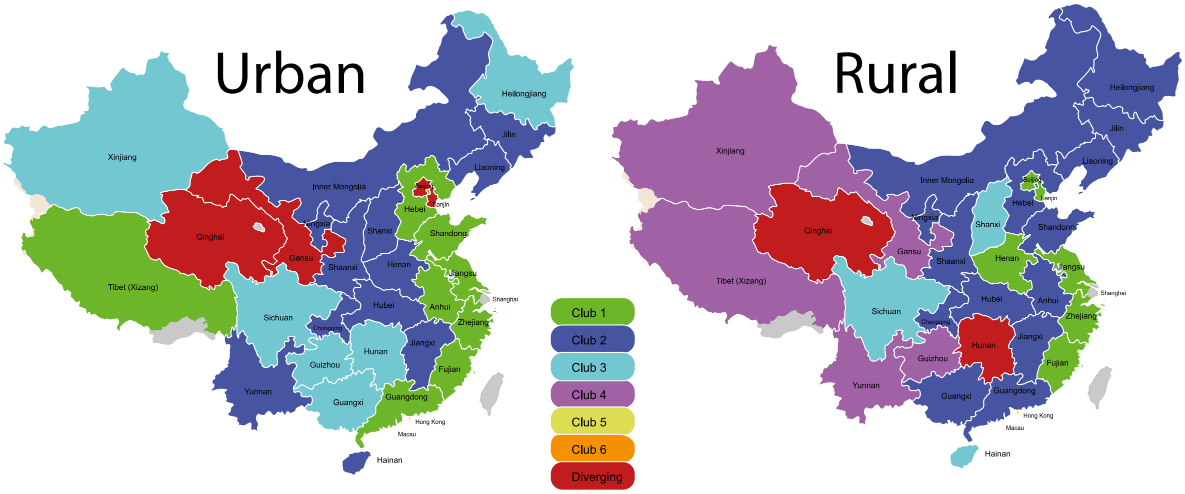
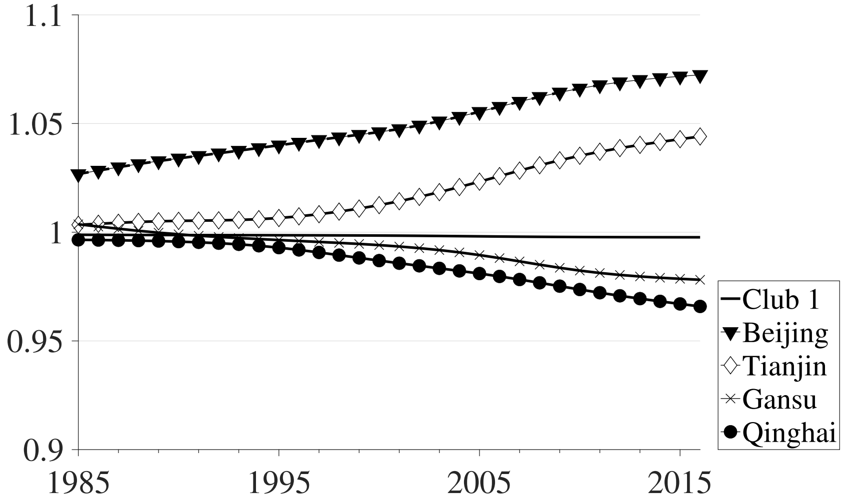


Fig. C.4. Convergence club classification: Urban vs. Rural PCLFHC (CPI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita labor force human capital (PCLFHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

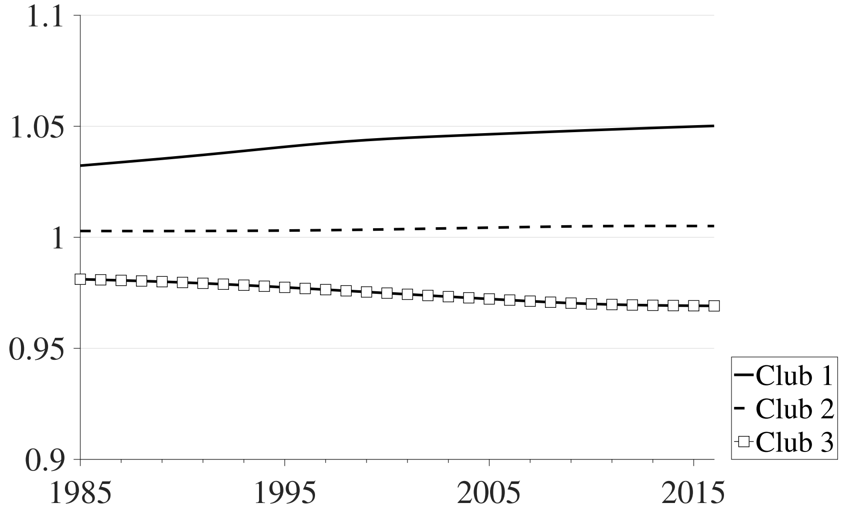
Table E.5
Chi-squared and Fisher's exact tests: PCLFHC (LCI).

PCLFHC (LCI)	Club 1	Club 2	Club 3	Club 4	Diverging	Total
EGR 1	2	0	0	0	2	4
	(0.3)	(2.2)	(0.6)	(0.5)	(0.4)	
EGR 2	0	8	0	0	0	8
	(0.5)	(4.4)	(1.3)	(1)	(0.8)	
EGR 3	0	8	2	0	0	10
	(0.6)	(5.5)	(1.6)	(1.3)	(1)	
EGR 4	0	1	3	4	1	9
	(0.6)	(4.9)	(1.5)	(1.2)	(0.9)	
Total	2	17	5	4	3	31
				Pearson Chi-squared		44.9007***
				Fisher's exact		0.000

Note: Authors' calculations using CHLR (2018). Frequencies are reported along with their corresponding expected values in parenthesis.
***Indicates significance at 1% confidence level.



(a) Urban PCLFHC deflated by LCI



(b) Rural PCLFHC deflated by LCI

Fig. C.5. Average relative transition paths for convergence clubs and diverging provinces: Urban vs. Rural PCLFHC (LCI). Authors' calculations using CHLR (2018). Average relative transition paths of (a) urban and (b) rural per capita human capital (PCLFHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

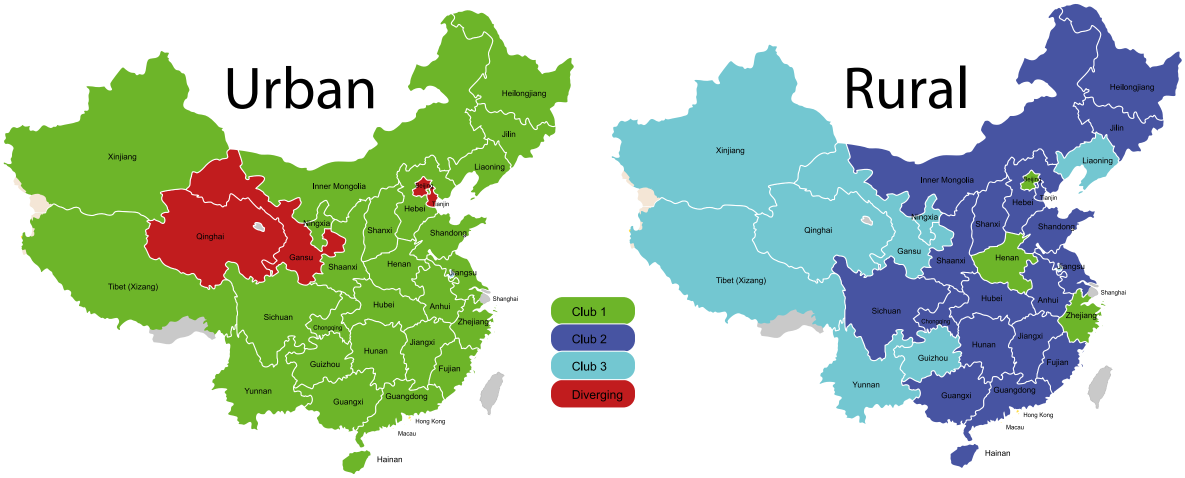
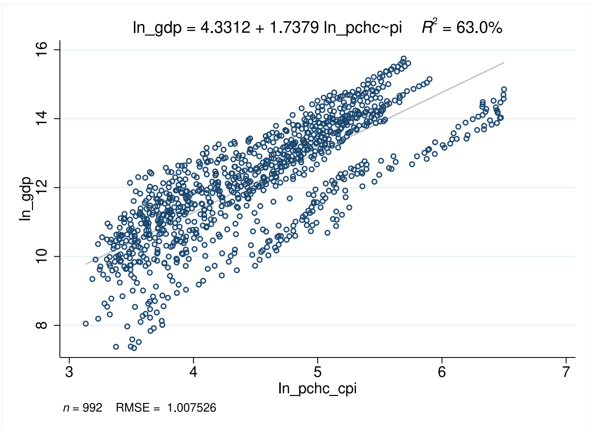
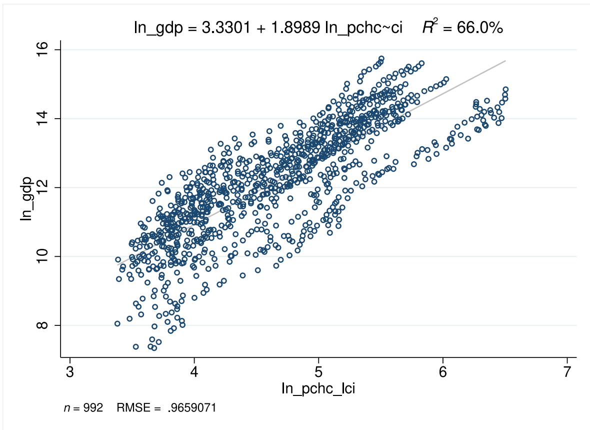


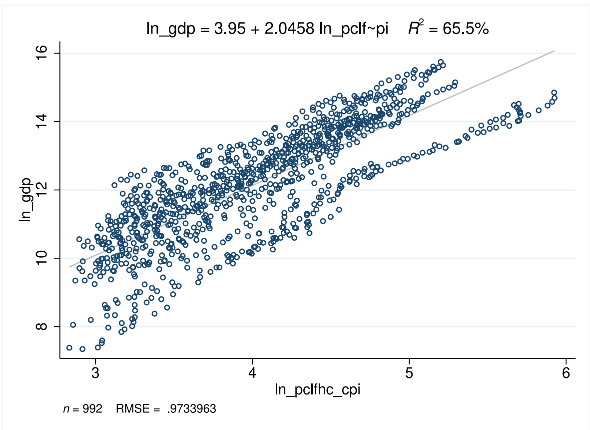
Fig. C.6. Convergence club classification: Urban vs. Rural PCLFHC (LCI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita labor force human capital (PCLFHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985–2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.



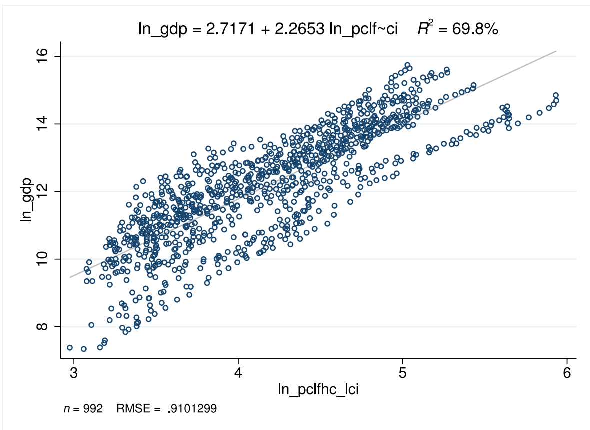
(a) GDP and PCHC (CPI)



(b) GDP and PCHC (LCI)

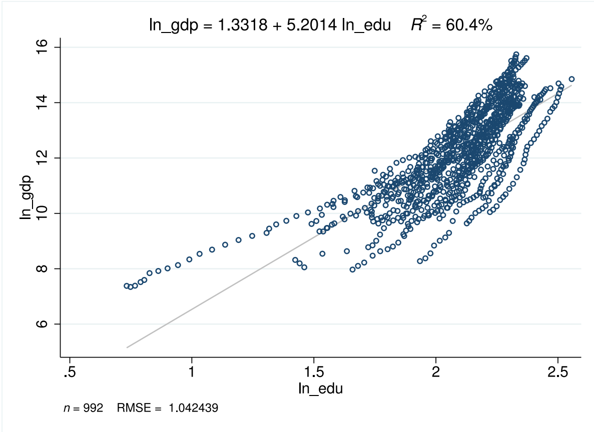


(c) GDP and PCLFHC (CPI)

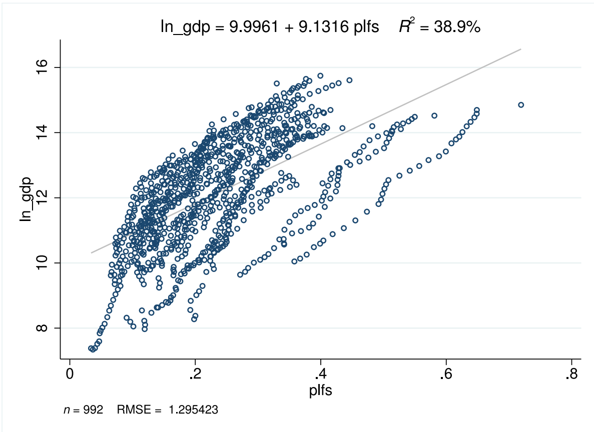


(d) GDP and PCLFHC (LCI)

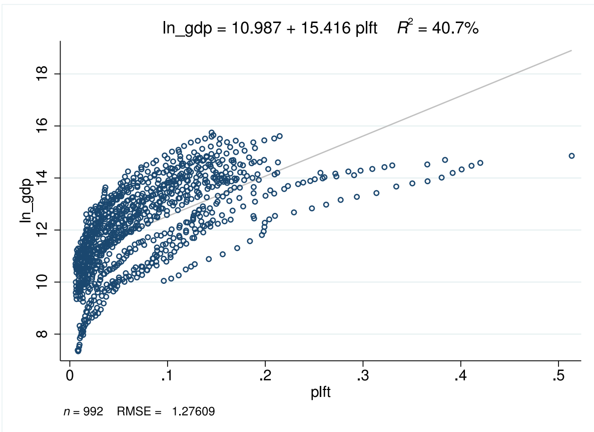
Fig. D.1. GDP vs. PCHC and PCLFHC. Authors' calculations using CHLR (2018) and the China Statistics Year Books 1995–2017. PCHC and PCLFHC deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.



(a) GDP and AYS



(b) GDP and PLFS



(c) GDP and PLFT

Fig. D.2. GDP vs. average years of schooling of the labor force (AYS), proportion of the labor force with secondary education and above (PLFS), and proportion of the labor force with tertiary education and above (PLFT). Authors' calculations using the China Statistics Year Books 1995–2017. Sample: 31 Chinese provinces, 1985–2016.

Appendix F. Kaya-Zenga decomposition of human capital

The imbalance in human capital contributed by province i can be measured as the relative gap between the upper average of human capital $M_i^+(HC)$, and the lower average of human capital $M_i^-(HC)$ as following Wang et al. (2020):

$$\begin{aligned} I_i(HC) &= \frac{M_i^+(HC) - M_i^-(HC)}{M_i^+(HC)} \\ &= \frac{M_i^+(hce)M_i^+(e)M_i^+(y)M_i^+(P) - M_i^-(hce)M_i^-(e)M_i^-(y)M_i^-(P)}{M_i^+(HC)} \\ &= \frac{M_i^+(hce) - M_i^-(hce)\cdot K_h(hce)}{M_i^+(HC)} + \frac{M_i^+(e) - M_i^-(e)\cdot K_h(e)}{M_i^+(HC)} \\ &+ \frac{M_i^+(y) - M_i^-(y)\cdot K_h(y)}{M_i^+(HC)} + \frac{M_i^+(P) - M_i^-(P)\cdot K_h(P)}{M_i^+(HC)} - I_i^{int}(HC) \\ &= I_i^{hce}(HC) + I_i^{e}(HC) + I_i^{y}(HC) + I_i^{P}(HC) - I_i^{int}(HC). \end{aligned} \tag{F.1}$$

This variable can be decomposed into the imbalances in human capital return, education intensity, GDP per capita, population, and their interaction term, denoted as $I_i^{hce}(HC)$, $I_i^{e}(HC)$, $I_i^{y}(HC)$, $I_i^{P}(HC)$, and $I_i^{int}(HC)$, respectively. To measure the imbalance, the 31 provinces are sorted by human capital stock in ascending order ($i = 1, 2, \ldots, 31$). The province with the highest human capital is denoted as province r ($r = 31$). The lower averages of human capital $M_i^-(HC)$, and its contributing factors $M_i^-(hce)$, $M_i^-(e)$, $M_i^-(y)$, and $M_i^-(P)$ are calculated as the averages of all provinces whose values are lower or equal to province i, as follows:

$$\begin{aligned} M_i^-(HC) &= \frac{\sum_{h=1}^{i} HC_h}{i} = \frac{\sum_{h=1}^{i} HC_h}{\sum_{h=1}^{i} E_h}\cdot\frac{\sum_{h=1}^{i} E_h}{\sum_{h=1}^{i} Y_h}\cdot\frac{\sum_{h=1}^{i} Y_h}{\sum_{h=1}^{i} P_h}\cdot\frac{\sum_{h=1}^{i} P_h}{i} = \\ &= M_i^-(hce)M_i^-(e)M_i^-(y)M_i^-(P). \end{aligned} \tag{F.2}$$

Similarly, $M_i^+(HC)$, $M_i^+(hce)$, $M_i^+(e)$, $M_i^+(y)$, and $M_i^+(P)$ denote the upper averages, calculated as the mean of all provinces whose values are higher than province i, while $M_r^+(HC)$, $M_r^+(hce)$, $M_r^+(e)$, $M_r^+(y)$, and $M_r^+(P)$ are human capital stock, human capital return, education intensity, GDP per capita, and population of province r, respectively:

$$M_i^+(HC) = \begin{cases} \frac{\sum_{h=i+1}^{r} HC_h}{r-i} = \frac{\sum_{h=i+1}^{r} HC_h}{\sum_{h=i+1}^{r} E_h}\cdot\frac{\sum_{h=i+1}^{r} E_h}{\sum_{h=i+1}^{r} Y_h}\cdot\frac{\sum_{h=i+1}^{r} Y_h}{\sum_{h=i+1}^{r} P_h}\cdot\frac{\sum_{h=i+1}^{r} P_h}{r-i} \\ = M_i^+(hce)M_i^+(e)M_i^+(y)M_i^+(P), i \le r-1 \\ HC_r = \frac{HC_r}{E_r}\cdot\frac{E_r}{Y_r}\cdot\frac{Y_r}{P_r}\cdot P_r = M_r^+(hce)M_r^+(e)M_r^+(y)M_r^+(P), i = r. \end{cases} \tag{F.3}$$

Moreover, $K_i(hce)$, $K_i(e)$, $K_i(y)$, and $K_i(P)$ are polynomials of the above calculated upper and lower averages. For instance, $K_i(hce)$ contains the upper and lower averages of e, y, and P, and is calculated as follows:

$$\begin{aligned} K_i(hce) = \Bigg(&\frac{M_i^+(e)M_i^+(y)M_i^+(P)}{2} + \frac{M_i^-(e)M_i^-(y)M_i^+(P)}{3} \\ &+ \frac{M_i^-(e)M_i^+(y)M_i^-(P)}{3} + \frac{M_i^+(e)M_i^-(y)M_i^-(P)}{3} - \frac{M_i^-(e)M_i^+(y)M_i^+(P)}{6} \\ &- \frac{M_i^+(e)M_i^-(y)M_i^+(P)}{6} - \frac{M_i^+(e)M_i^+(y)M_i^-(P)}{6} \Bigg). \end{aligned} \tag{F.4}$$

The calculation of $K_i(e)$, $K_i(y)$, and $K_i(P)$ are similar. Finally, variable $I_i^{int}(HC)$ is the interaction term of the difference between the upper and lower averages of human capital return, education intensity, GDP per capita, and population. This variable can be used to reveal the relationship between these four variables taking the following form:

$$I_i^{int}(HC) = \frac{[M_i^+(hce) - M_i^-(hce)][M_i^+(e) - M_i^-(e)][M_i^+(y) - M_i^-(y)][M_i^+(P) - M_i^-(P)]}{M_i^+(HC)}. \tag{F.5}$$

Appendix G. Imbalance in human capital and its contributors of each convergence club: PCLFHC (CPI) and PCLFHC (LCI)

See Fig. G.1.

Appendix H. Labor force to reserve population ratio for 31 provinces (1985–2016)

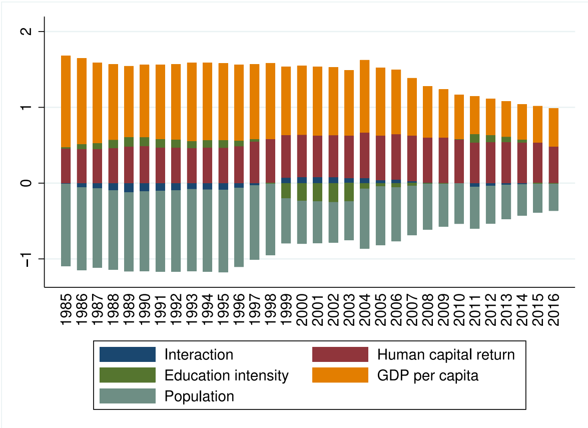
See Table H.1.

Table H.1
Labor force to reserve population ratio for 31 provinces (1985–2016).

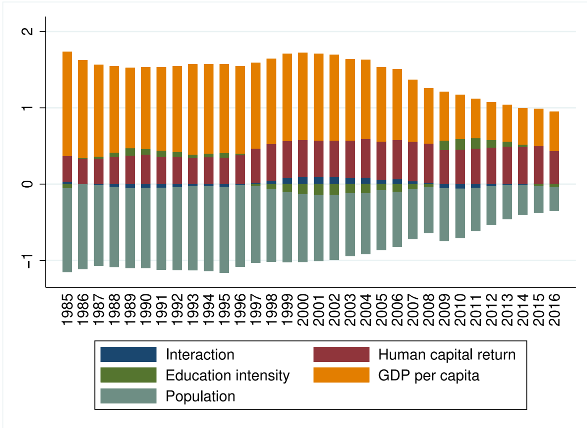
	Beijing	Tianjin	Hebei	Shanxi	I. Mongolia	Liaoning	Jilin	Heilongjiang	Shanghai	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong	Henan
1985	2.087	2.066	1.624	1.459	1.312	1.780	1.490	1.353	2.657	1.945	1.953	1.325	1.222	1.050	1.569	1.279
1986	2.115	2.089	1.643	1.526	1.358	1.814	1.566	1.418	2.605	2.061	2.070	1.400	1.269	1.114	1.659	1.345
1987	2.183	2.122	1.659	1.629	1.409	1.855	1.597	1.507	2.592	2.178	2.164	1.483	1.292	1.180	1.661	1.412
1988	2.232	2.162	1.711	1.670	1.502	1.962	1.649	1.621	2.602	2.221	2.178	1.583	1.378	1.270	1.773	1.492
1989	2.283	2.209	1.730	1.687	1.608	2.048	1.724	1.723	2.665	2.198	2.195	1.660	1.449	1.357	1.808	1.562
1990	2.338	2.261	1.726	1.711	1.680	2.091	1.777	1.806	2.684	2.145	2.201	1.682	1.533	1.413	1.807	1.616
1991	2.336	2.293	1.740	1.734	1.761	2.199	1.846	1.933	2.694	2.153	2.197	1.757	1.564	1.478	1.840	1.609
1992	2.387	2.307	1.733	1.751	1.833	2.252	1.934	2.028	2.693	2.163	2.139	1.824	1.583	1.545	1.880	1.618
1993	2.409	2.284	1.734	1.747	1.885	2.299	2.002	2.119	2.667	2.171	2.088	1.849	1.598	1.599	1.939	1.635
1994	2.435	2.274	1.731	1.734	1.921	2.330	2.070	2.181	2.644	2.203	2.081	1.868	1.596	1.650	1.960	1.657
1995	2.461	2.272	1.747	1.732	1.964	2.389	2.134	2.261	2.661	2.233	2.136	1.847	1.600	1.688	1.981	1.691
1996	2.418	2.269	1.755	1.742	2.016	2.456	2.210	2.344	2.700	2.186	2.092	1.832	1.612	1.728	2.012	1.678
1997	1.723	1.989	1.735	1.679	2.026	2.350	2.093	2.248	2.288	2.090	2.027	1.782	1.587	1.677	1.952	1.658
1998	1.850	2.096	1.785	1.724	2.125	2.472	2.188	2.345	2.499	2.144	2.117	1.775	1.699	1.706	1.988	1.674
1999	1.946	2.183	1.847	1.773	2.229	2.522	2.264	2.422	2.635	2.213	2.220	1.775	1.818	1.745	2.063	1.717
2000	3.257	2.767	2.012	1.901	2.479	2.860	2.567	2.719	3.800	2.464	2.471	1.901	2.026	1.830	2.216	1.808
2001	3.249	2.773	2.042	1.839	2.483	2.840	2.588	2.794	3.778	2.440	2.402	1.808	2.083	1.766	2.182	1.748
2002	3.388	2.854	2.150	1.809	2.494	2.890	2.637	2.951	3.843	2.488	2.377	1.782	2.176	1.751	2.228	1.761
2003	3.434	2.930	2.285	1.819	2.546	2.996	2.765	3.104	4.018	2.533	2.413	1.766	2.250	1.747	2.380	1.800
2004	3.459	2.985	2.402	1.830	2.633	3.038	2.844	3.177	4.077	2.552	2.473	1.749	2.324	1.715	2.512	1.845
2005	3.477	3.057	2.526	1.875	2.764	3.094	3.004	3.282	4.147	2.590	2.565	1.751	2.398	1.727	2.632	1.932
2006	3.411	3.136	2.483	1.917	2.788	3.158	3.119	3.321	4.140	2.593	2.607	1.781	2.476	1.755	2.667	1.866
2007	3.532	3.293	2.477	1.947	2.794	3.207	3.173	3.383	4.293	2.653	2.644	1.866	2.543	1.807	2.684	1.822
2008	3.814	3.538	2.492	2.052	2.870	3.292	3.206	3.452	4.592	2.767	2.748	1.956	2.608	1.859	2.683	1.802
2009	4.153	3.768	2.542	2.225	2.979	3.452	3.339	3.593	4.805	2.952	2.935	2.084	2.706	1.917	2.727	1.794
2010	4.426	4.015	2.603	2.362	3.124	3.642	3.423	3.726	5.006	3.122	3.115	2.172	2.843	1.961	2.729	1.829
2011	4.451	3.762	2.461	2.296	3.008	3.481	3.247	3.591	4.854	2.978	3.016	2.111	2.744	1.836	2.548	1.689
2012	4.574	3.614	2.422	2.241	2.941	3.425	3.186	3.570	4.635	2.853	2.965	2.093	2.660	1.825	2.388	1.634
2013	4.672	3.583	2.401	2.247	2.892	3.319	3.133	3.587	4.370	2.852	2.992	2.058	2.565	1.818	2.303	1.639
2014	4.683	3.538	2.389	2.273	2.823	3.280	3.100	3.672	4.072	2.878	3.014	2.082	2.528	1.863	2.249	1.700
2015	4.557	3.647	2.360	2.310	2.758	3.162	3.037	3.792	3.887	2.962	3.075	2.064	2.490	1.892	2.174	1.797
2016	4.504	3.617	2.222	2.377	2.764	3.145	3.070	3.749	3.308	2.772	2.920	2.041	2.350	1.820	2.112	1.741

	Hubei	Hunan	Guangdong	Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan	Tibet	Shaanxi	Gansu	Qinghai	Ningxia	Xinjiang
1985	1.482	1.446	1.314	1.176	1.090	1.466	1.429	0.965	1.081	1.249	1.510	1.262	1.092	1.020	1.071
1986	1.536	1.497	1.345	1.239	1.175	1.554	1.486	1.025	1.126	1.262	1.518	1.327	1.168	1.067	1.078
1987	1.589	1.540	1.390	1.327	1.290	1.641	1.545	1.086	1.170	1.273	1.509	1.420	1.242	1.134	1.051
1988	1.655	1.617	1.438	1.360	1.294	1.825	1.717	1.141	1.253	1.286	1.575	1.519	1.321	1.186	1.135
1989	1.693	1.672	1.476	1.362	1.299	2.013	1.902	1.206	1.331	1.299	1.636	1.625	1.397	1.216	1.235
1990	1.707	1.715	1.501	1.359	1.302	2.204	2.094	1.273	1.392	1.310	1.709	1.695	1.510	1.230	1.311
1991	1.727	1.761	1.545	1.414	1.330	2.352	2.251	1.374	1.479	1.248	1.729	1.730	1.582	1.294	1.383
1992	1.746	1.796	1.545	1.458	1.330	2.417	2.341	1.455	1.546	1.211	1.709	1.755	1.633	1.376	1.431
1993	1.762	1.818	1.517	1.498	1.322	2.380	2.360	1.506	1.614	1.194	1.704	1.770	1.683	1.429	1.471
1994	1.776	1.810	1.480	1.531	1.327	2.294	2.320	1.531	1.683	1.203	1.687	1.790	1.719	1.485	1.498
1995	1.802	1.819	1.488	1.565	1.333	2.201	2.308	1.534	1.747	1.198	1.671	1.792	1.752	1.531	1.513
1996	1.833	1.812	1.543	1.598	1.378	2.182	2.243	1.514	1.806	1.199	1.651	1.768	1.787	1.570	1.556
1997	1.790	1.799	1.568	1.563	1.358	2.140	2.185	1.486	1.786	1.192	1.558	1.723	1.740	1.532	1.492
1998	1.874	1.884	1.700	1.585	1.418	2.222	2.239	1.473	1.834	1.241	1.586	1.731	1.781	1.582	1.531
1999	1.956	1.977	1.826	1.616	1.489	2.273	2.266	1.465	1.877	1.304	1.623	1.736	1.823	1.619	1.563
2000	2.216	2.164	2.073	1.727	1.641	2.403	2.329	1.496	1.966	1.396	1.787	1.792	1.934	1.737	1.731
2001	2.173	2.116	2.034	1.716	1.641	2.183	2.162	1.466	1.912	1.337	1.773	1.759	1.908	1.673	1.736
2002	2.192	2.108	2.059	1.746	1.667	2.079	2.091	1.481	1.918	1.340	1.824	1.753	1.912	1.657	1.759
2003	2.236	2.140	2.123	1.780	1.690	2.009	2.056	1.502	1.957	1.321	1.913	1.784	1.942	1.671	1.824
2004	2.245	2.153	2.137	1.794	1.749	1.991	1.997	1.518	1.972	1.340	1.995	1.808	1.972	1.692	1.879
2005	2.298	2.208	2.147	1.816	1.811	1.977	1.971	1.533	2.007	1.352	2.099	1.817	1.995	1.725	1.895
2006	2.369	2.314	2.149	1.812	1.776	1.941	1.967	1.520	2.036	1.387	2.140	1.795	1.985	1.700	1.978
2007	2.398	2.355	2.140	1.790	1.767	1.919	1.966	1.507	2.045	1.406	2.237	1.802	2.008	1.700	2.027
2008	2.483	2.397	2.207	1.803	1.811	1.919	2.011	1.516	2.086	1.452	2.336	1.826	2.041	1.744	2.085
2009	2.604	2.449	2.343	1.861	1.919	1.986	2.126	1.549	2.159	1.531	2.438	1.957	2.108	1.844	2.181
2010	2.702	2.475	2.499	1.918	2.040	2.131	2.276	1.594	2.202	1.680	2.595	2.088	2.182	1.961	2.265
2011	2.583	2.311	2.397	1.841	1.977	2.081	2.205	1.554	2.078	1.725	2.429	2.079	2.143	1.864	2.170
2012	2.523	2.170	2.345	1.799	1.984	2.077	2.181	1.528	2.037	1.792	2.403	2.152	2.145	1.875	2.112
2013	2.470	2.077	2.344	1.787	2.013	2.082	2.158	1.504	2.022	1.850	2.399	2.162	2.129	1.901	2.058
2014	2.429	2.017	2.386	1.811	2.061	2.157	2.208	1.550	2.038	1.796	2.478	2.236	2.139	1.996	2.035
2015	2.370	1.955	2.457	1.852	2.154	2.244	2.195	1.570	2.063	1.778	2.605	2.276	2.132	2.119	2.012
2016	2.325	1.901	2.366	1.759	2.012	2.181	2.170	1.561	1.996	1.756	2.448	2.330	2.136	2.033	1.992

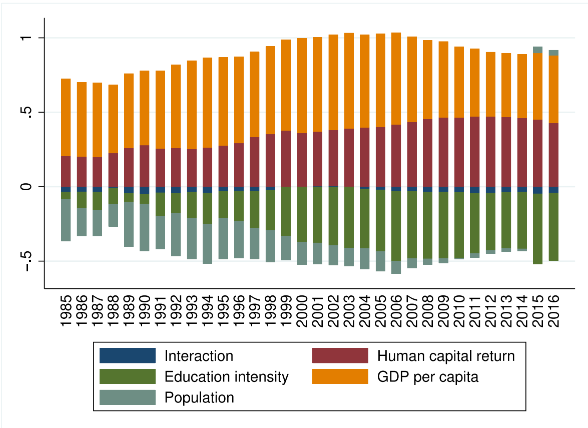
Note: Labor force to reserve population ratio for all provinces in China. Labor force refers to the active population aged 16–59 for males and 16–54 for females, and reserve population is the young population which has not entered in the labor market, i.e., those under the age of 16 and full-time students who are 16 years of age or above. Authors' calculations using CHLR (2018). Sample: 31 Chinese provinces, 1985–2016.



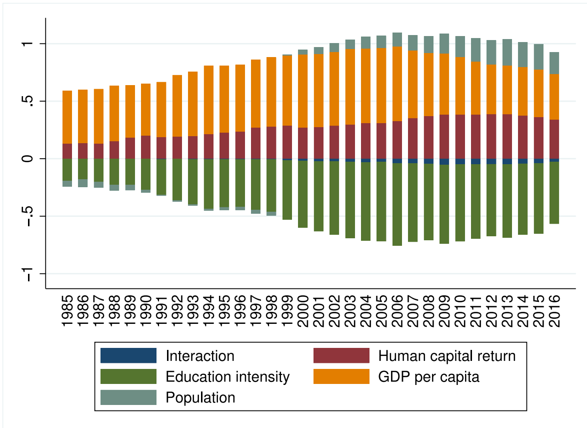
(a) Club 1 - PCLFHC (CPI)



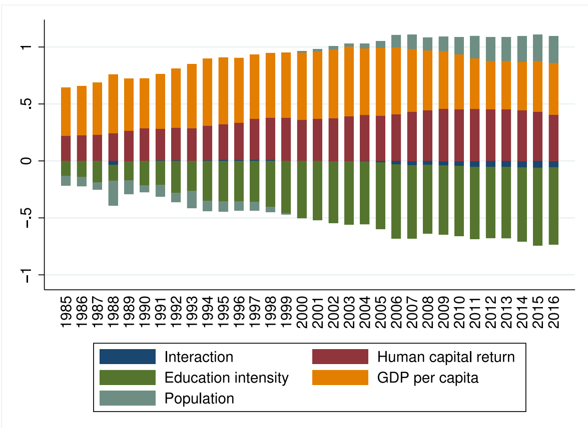
(b) Club 1 - PCLFHC (LCI)



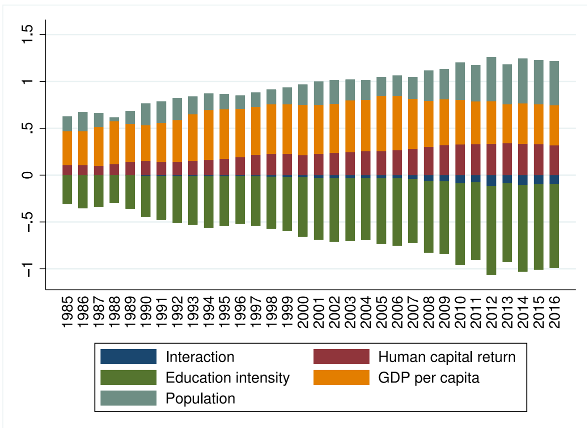
(c) Club 2 - PCLFHC (CPI)



(d) Club 2 - PCLFHC (LCI)

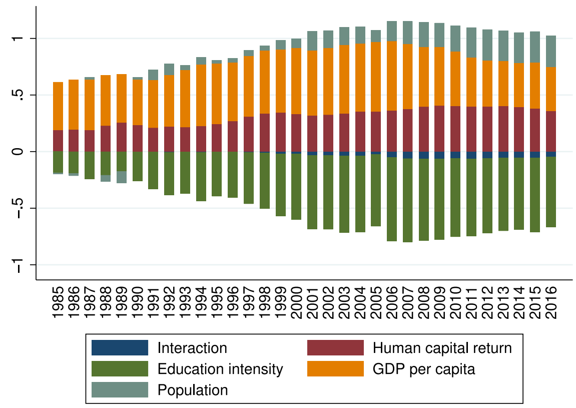


(e) Club 3 - PCLFHC (CPI)

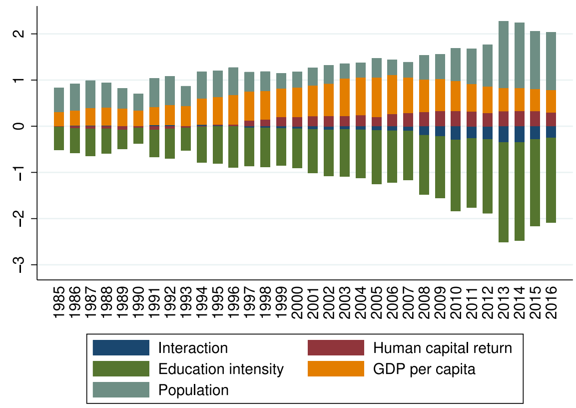


(f) Club 3 - PCLFHC (LCI)

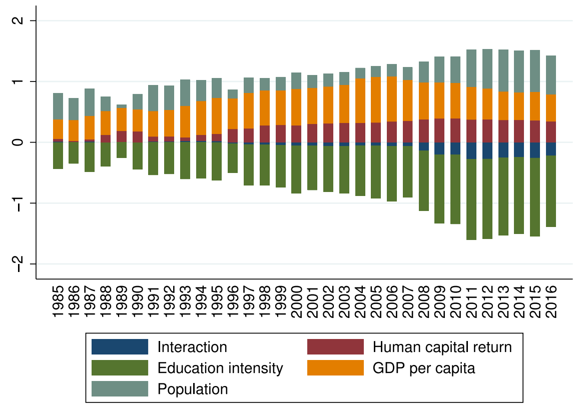
Fig. G.1. Imbalance in the contributing factors of human capital by convergence club: human capital return, education intensity, GDP per capita, population, and their interaction term. Authors' calculations using CHLR (2018). PCLFHC deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985–2016.



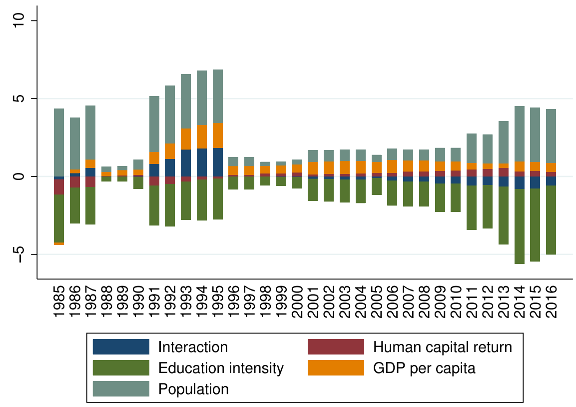
(g) Club 4 - PCLFHC (CPI)



(h) Club 4 - PCLFHC (LCI)



(i) Club 5 - PCLFHC (CPI)



(j) Club 6 - PCLFHC (CPI)

Fig. G.1. (*continued*).

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