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

Valerio Mendoza, Octasiano and Borsi, Mihály Tamás and Comim, Flavio

IQS School of Management, Universitat Ramon Llull, Centre of Development Studies, University of Cambridge

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

Octasiano Miguel VALERIO MENDOZA* Mihály Tamás BORSI†

Flavio COMIM‡,§

**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.

**JEL Classification:** C33; I25; O15; O53; R11

**Keywords:** Human capital; Club convergence; Dynamic factor model; Asia; China

*Corresponding author. Department of Quantitative Methods, IQS School of Management, Universitat Ramon Llull, Via Augusta 390, 08017 Barcelona, Spain. E-mail: octasiano.valerio@iqs.url.edu.

†Department of Economics and Finance, IQS School of Management, Universitat Ramon Llull, Via Augusta 390, 08017 Barcelona, Spain. E-mail: mihaly.borsi@iqs.edu.

‡Department of Economics and Finance, IQS School of Management, Universitat Ramon Llull, Via Augusta 390, 08017 Barcelona, Spain. E-mail: flavio.comim@iqs.url.edu.

§Centre of Development Studies, University of Cambridge, 7 West Road, CB3 9DT Cambridge, UK

# 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 and 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 (Sen, 1999; Benos and Zotou, 2014). 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, and Carey, 2018). This is not a minor issue because economies limited by insufficient supply of human capital may fall into the "middle-income trap" (Mayer-Foulkes, 2008; Glauben, Herzfeld, Rozelle, and Wang, 2012; Khor, Pang, Liu, Chang, Mo, Loyalka, and Rozelle, 2016; Zhang, Li, Wang, and Fleisher, 2019). In addition, given the uneven economic development and income disparities across regions (Pedroni and Yao, 2006; Cheong and Wu, 2013; Westerlund, 2013; Tian, Zhang, Zhou, and Yu, 2016), human capital may not have improved equally among Chinese provinces (see, e.g., Li, Liu, Li, Fraumeni, and Zhang, 2014; Valerio Mendoza, 2018; Fraumeni, He, Li, and Liu, 2019). 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, 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 and Chen, 1997; Fleisher, Li, and Zhao, 2010; Gao, Zhai, and Garfinkel, 2010; Gao, Zhai, Yang, and Li, 2014; Khor et al., 2016; Ratigan, 2017; Golley and Kong, 2018).[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] Even more, distinguishing between the total human capital stock and labor force human capital within this framework enables to study human development

[1]There are only a few published articles using J-F human capital accounts for China (e.g., Li, Liang, Fraumeni, Liu, and Wang, 2013; Li et al., 2014; Golley and Wei, 2015; Holz and Sun, 2018; Li and Wang, 2018; Fraumeni et al., 2019), 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).

according to the future and present productive capacity of Chinese provinces separately.

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 $\beta$-convergence and $\sigma$-convergence (see, e.g., Coulombe and Tremblay, 2001; Coulombe, 2003).[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.

Finally, while the literature (Fleisher et al., 2010; Li et al., 2014; Fraumeni et al., 2019) 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 individ-

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

ual 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 provinces, including 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. The following section offers a complementary exercise that compares the results to those obtained from education-based human capital measures. Finally, Section 7 provides a brief 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 (Romer, 1986; Ravallion and Chen, 1997; Cunha and Heckman, 2007; Baldacci, Clements, Gupta, and Cui, 2008; Manca, 2012; Ramos, Surinach, and Artís, 2012; Dreze and Sen, 2013; Benos and Zotou, 2014; Poelhekke, 2013; Kosack and Tobin, 2015; Mannasoo, Hein, and Ruubel, 2018).[5] Both neoclassical and endogenous growth theories recognize the importance of human capital, albeit via different channels (Lucas, 1988; Romer, 1990; Mankiw et al., 1992; Aghion and Howitt, 1998; Hanushek and Woessmann, 2008; Benos and Zotou, 2014; Mannasoo et al., 2018). 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, and Dijk, 2016; Czaller, 2017), but also in-

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

crease 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, and 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 and 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 demographic and labor market elements (Lange et al., 2018; Fraumeni et al., 2019), 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 (Heckman, 2010; Attanasio, 2015). 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 (Beine, Docquier, and Oden-Defoort, 2011; Arntz, Gregory, and Lehmer, 2014; Clemens, 2014; Clemens, Graham, and Howes, 2015; UNECE, 2016; Ghosh and Mastromarco, 2018; Chand and Clemens, 2019). 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 and 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 and Mastromarco, 2018). Moreover, human capital is higher in regions with greater market access and lower remoteness (López-Rodríguez, Faína, and 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 (Qian and Smyth, 2011; Hu and Hibel, 2014; Zhang, 2017; Valerio Mendoza, 2018).

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 and 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 (Zeng, 2010; Valerio Mendoza, 2016). 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 and Hibel, 2014). This was complemented by policies promoting high-quality universities such as the "211 and 985 Projects" (Zhang, Patton, and 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). Amidst these rising educational attainment levels, the current decade has also been characterized by slower and uneven economic growth and 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 and Fleisher, 1996; Fleisher and 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 et al., 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 and Tremblay, 2001; Coulombe, 2003; 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 (Romer, 1986; Ranis, Stewart, and Ramirez, 2000), enrollment figures (Barro, 1991; Chakraborty, 2004; Baldacci et al., 2008), and schooling years (Collins and Bosworth, 1996; Barro, 2001; Papageorgiou, 2003; Hanushek and Woessmann, 2008) as proxies for human capital quantity, to student-teacher ratios (Barro, 1991), educational expenditure (Daniels, 1996; Bose, Haque, and Osborn, 2007), and scores (Bosworth and 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 and 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 and Lee, 1993; Barro, 2001; Barro and Sala-i-Martin, 2004). Finally, these measures fail to consider the human capital acquired outside school, such as on-the-job training (Cunha and 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 (Jorgenson and Fraumeni, 1989, 1992a, b; Fraumeni, Christian, and Samuels, 2017). This paper employs the latter, which is considered one of the most precise and widely used methods in constructing human capital accounts to date (Li et al., 2014; Lange et al., 2018). 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.[6] 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

[6] Earnings data for individuals who differ in education, age, gender, and location are not available for China. To overcome this problem, CHLR use the Mincer (1974) model, still commonly employed by many, including the World Bank (Lange et al., 2018). More specifically, individual earnings at the province level are estimated from an augmented version of the model, 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), Li et al. (2014) and Fraumeni et al. (2019), and references within.

lifetime income.[7] For example, nominal expected lifetime income for an individual aged 20 could be calculated as:

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

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.[8] Equation 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

[7] 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).

[8] 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 (OECD, 2010; Liu, 2011). 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).

(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

Per capita human capital (PCHC) and per capita labor force human capital (PCLFHC) stock values from the China Human Capital Index Report (2018) are taken 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 using the J-F lifetime income-based approach, at the provincial level, including urban and rural areas.

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 urban Beijing is set as the reference area and 1985 is the base year (Brandt and Holz, 2006; Holz, 2006).[9] 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).

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 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. In what follows, these descriptive results

[9] 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.

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).

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 $t$, $\mu_t$ is a steady-state growth component that is common across individual regions, and $\delta_{it}$ represents time-varying factor loadings that capture the deviation of the transition path of each province $i$ from the common trend $\mu_t$. The loading coefficients $\delta_{it}$ absorb any idiosyncratic movements in $X_{it}$. Equation 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 $\delta_{it}$ converge to some common constant $\delta$ 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 $\delta_{it}$:

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

where $\xi_{it}$ are $i.i.d.(0,1)$ across $i$, but weakly dependent over $t$, $\sigma_i$ are idiosyncratic scale parameters, and the parameter $\alpha$ is the decay rate, i.e., the speed of convergence. Under this specific form, the loadings $\delta_{it}$ converge slowly to the constant $\delta_i$ 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:

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

and is tested against the alternative:

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

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 $\delta_{it}$, which is impossible without imposing additional structure on $\delta_{it}$ and $\mu_t$. Alternatively, Phillips and Sul (2007) define the following relative transition coefficient $h_{it}$ to extract information about $\delta_{it}$:

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

which measures the loadings $\delta_{it}$ in relation to the panel average at time $t$, while eliminating the common growth component $\mu_t$. 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 $\delta_{it}$ converge to some constant $\delta$ 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:

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

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 $2\alpha$ 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.[10] 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 $X_{iT}$.

Step 2 *Core group formation*: The first $k$ highest units are selected from the panel to

[10]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.

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. In addition, Figure 1 offers a visual inspection of the relative transition path of each province, $h_{it}$, obtained

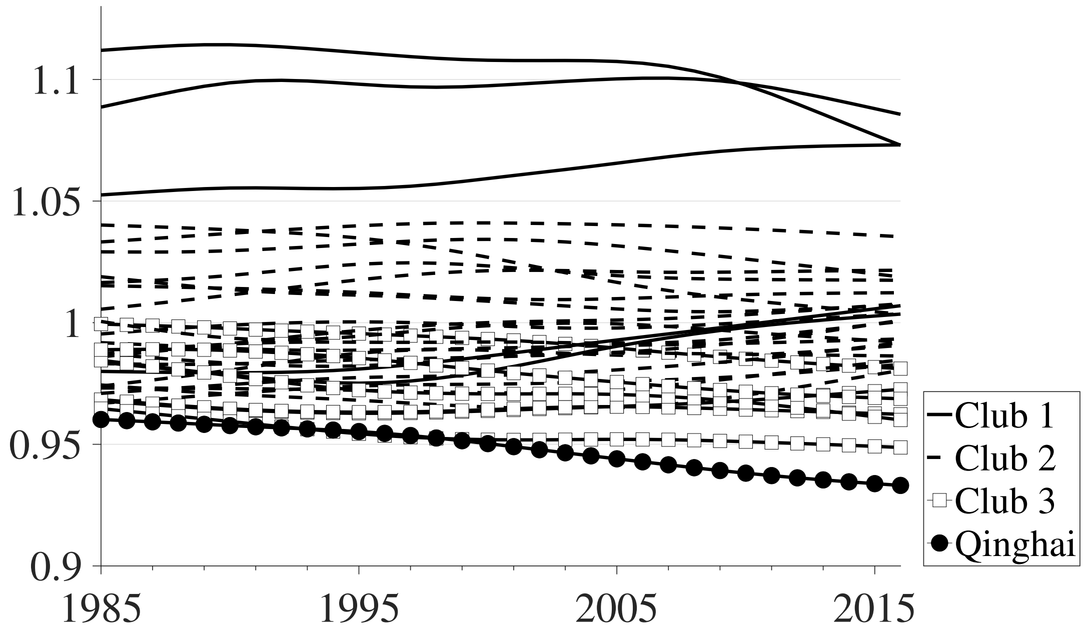
Table 2: Convergence club classification: PCHC

| 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 | | | |

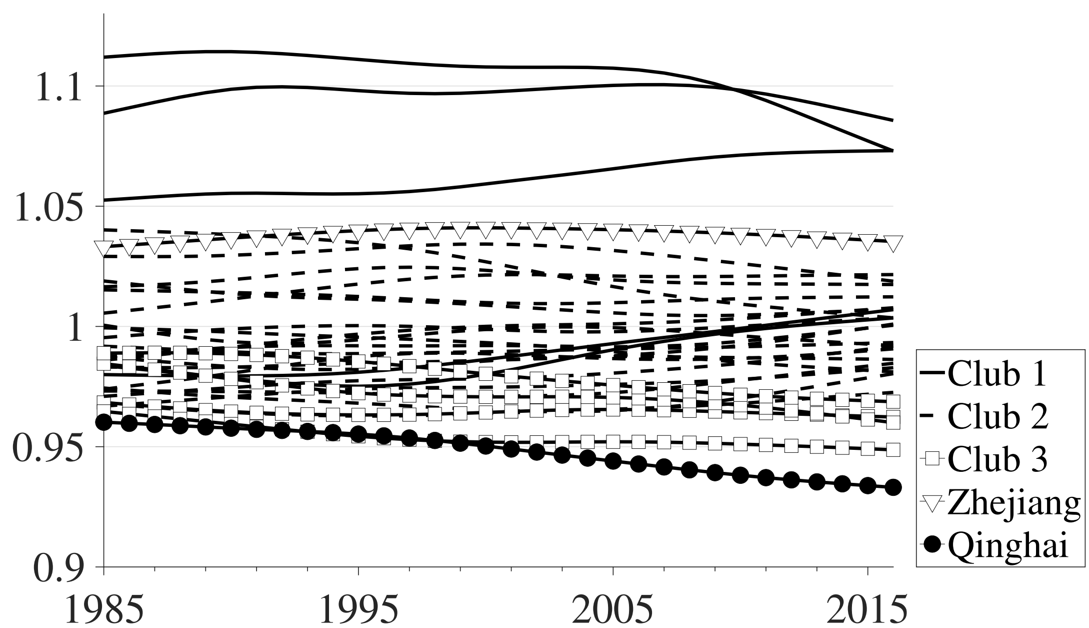
**Note:** Authors' calculations using CHLR (2018). Log($t$) test results for convergence in per capita human capital (PCHC) for 31 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI) and living cost index (LCI). The table contains the speed of convergence ($\hat{\alpha}$), 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.

from Equation 5 for both samples. As an extension to the individual paths, Figure 2 displays the average transition curves for each club identified in the two panels ($\bar{h}_{clubt}$), together with the corresponding 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




(a) PCHC deflated by CPI

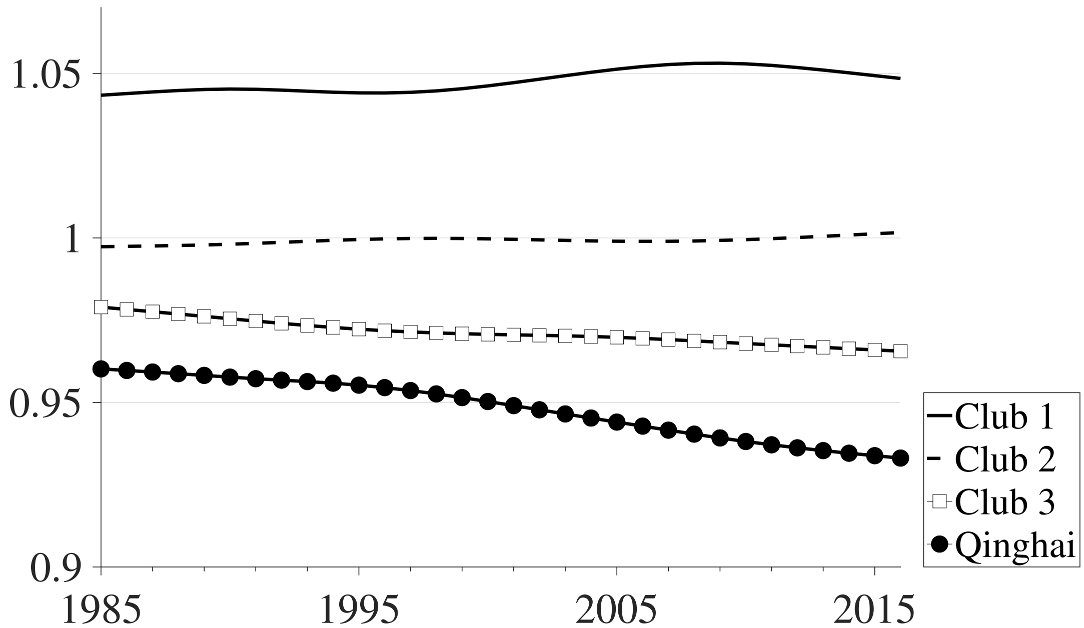



(b) PCHC deflated by LCI

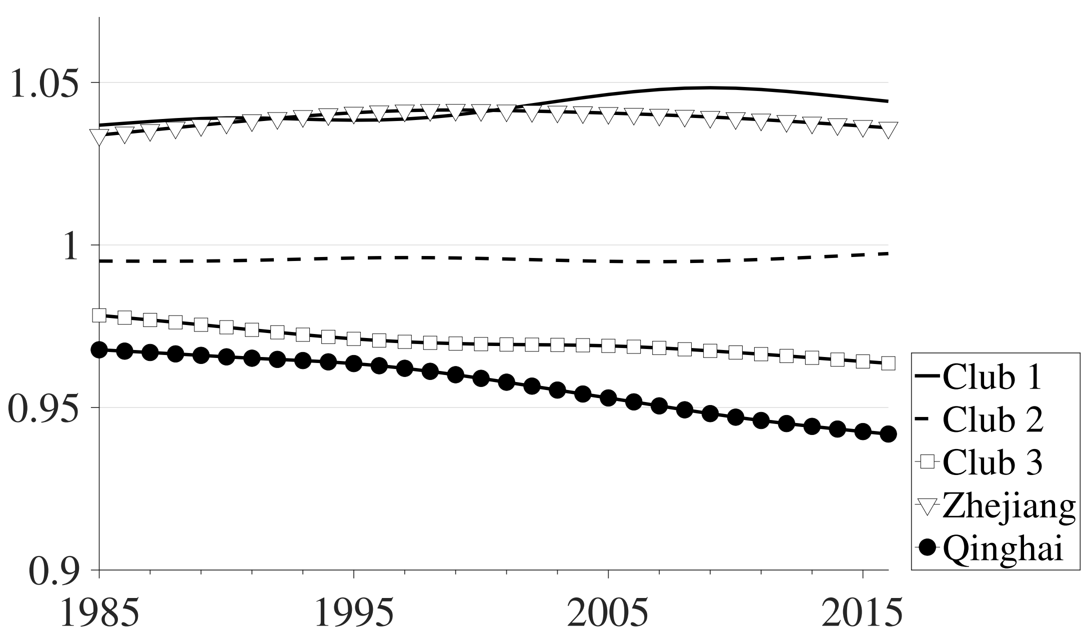
Figure 1: Relative transition paths of all provinces in China: PCHC. Authors' calculations using CHLR (2018). Relative transition paths of per capita human capital (PCHC) deflated by (a) consumer price index (CPI) and (b) living cost index (LCI). Sample: 31 Chinese provinces, 1985-2016.

of the four municipalities under direct administration of the central government of China – manifest the highest PCHC throughout the entire sample period considered (Figure 1), 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 province 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 Figure 1. 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 (Figure 2/(a)). Part of these results might be driven by the flow of migrants from these provinces to more prosperous 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. Furthermore, Zhejiang does not converge with the second club in the LCI sample, but diverges on a path between Clubs 1 and 2 (Figure 2/(b)).




(a) PCHC deflated by CPI




(b) PCHC deflated by LCI

Figure 2: 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.

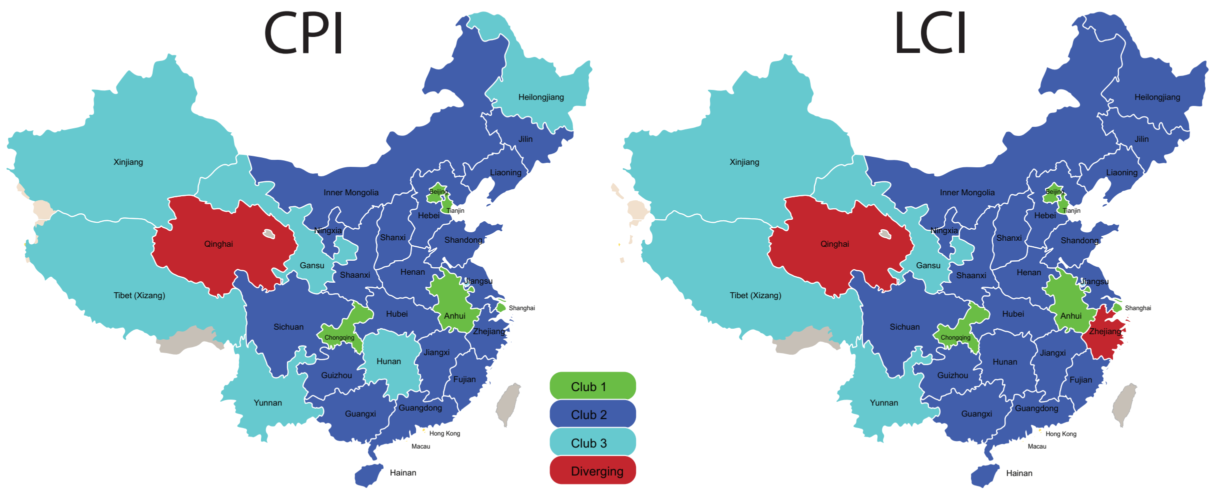



Figure 3: Convergence club classification: PCHC. Authors' creation using Wikimedia Commons. Convergence club classification results for per capita human capital (PCHC) deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985-2016.

To complement the analysis, Figure 3 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.[11] The east-west dimension is also evident in the diverging provinces detected in the samples. In the case of Zhejiang, a coastal province, it's 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. Zhejiang's divergent path may be 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 and 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 further 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

[11]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.

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.

## 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 (Figure 4/(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

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 | | | |

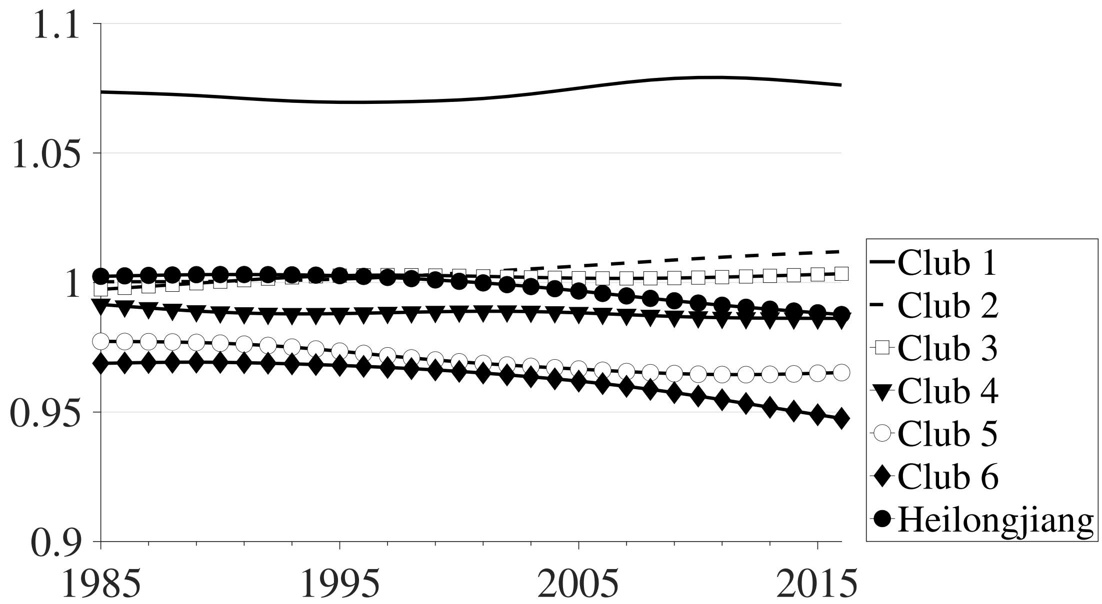
**Note:** Authors' calculations using CHLR (2018). Log($t$) test results for convergence in per capita labor force human capital (PCLFHC) for 31 Chinese provinces between 1985 and 2016, deflated by consumer price index (CPI) and living cost index (LCI). The table contains the speed of convergence ($\hat{\alpha}$), 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 $\hat{\alpha} = 0.171$.

future, as reflected in the PCHC classification outcomes. Going further, the clustering results in Table 3 shed light on a number of smaller subgroups within the second, largest club identified in both PCHC samples.[12] 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 (Figure 4/(a)).

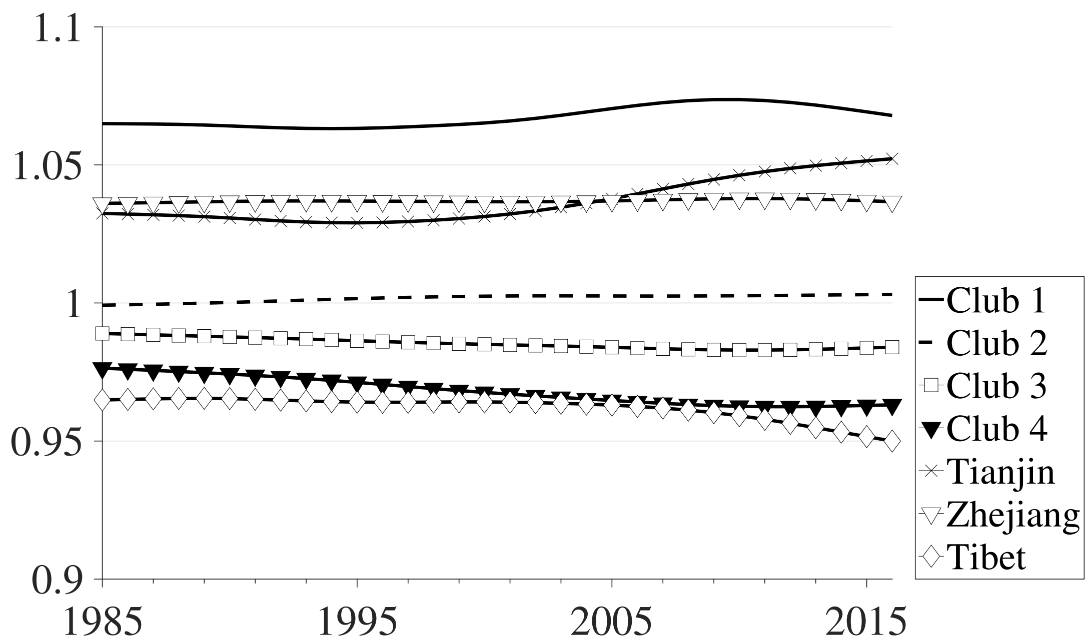
The regional patterns illustrated in Figure 5 reveal within-region heterogeneity to a significant degree. Most strikingly, while the recent literature provides evidence that coastal provinces, on average, tend to converge to the highest income levels in China (see, e.g., Tian et al., 2016), not all of 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

[12] 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).




(a) PCLFHC deflated by CPI




(b) PCLFHC deflated by LCI

Figure 4: 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.

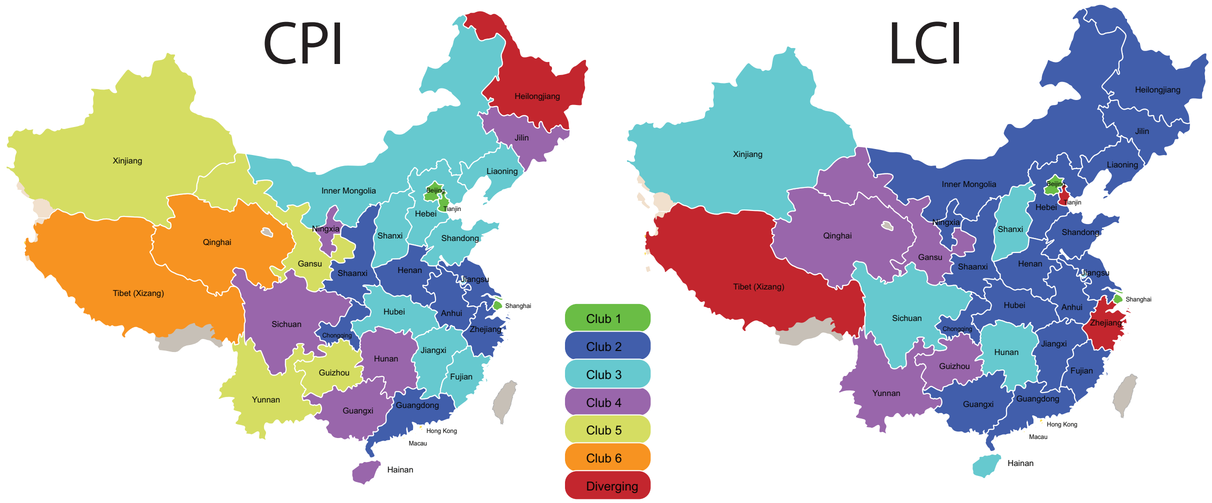



Figure 5: Convergence club classification: PCLFHC. Authors' creation using Wikimedia Commons. Convergence club classification results for per capita labor force human capital (PCLFHC) deflated by consumer price index (CPI) and living cost index (LCI). Sample: 31 Chinese provinces, 1985-2016.

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 (Figure 4/(b)). This finding suggests that when controlling for disparities in purchasing power, Tianjin does not yet reach the levels of PCLFHC exhibited by Beijing and Shanghai. Even so, Tianjin is evidently catching up with the provinces of Club 1. Similarly, Zhejiang displays a higher rate of human capital accumulation, once adjusted for the cost of living, diverging above Club 2. The second club, also the largest, includes most of the coastal and central provinces. Club 3 in the LCI sample consists of Shanxi, Hunan, Hainan, Sichuan, Xinjiang, whereas the lowest convergence club, Club 4, is formed by Guizhou, Yunnan, Gansu, Qinghai. Interestingly, Tibet separates from Club 4, clearly diverging away from the rest of the provinces. The corresponding visual evidence in Figure 5 lends further support to the similarities and differences between the CPI and LCI sample results.

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 the Appendix.

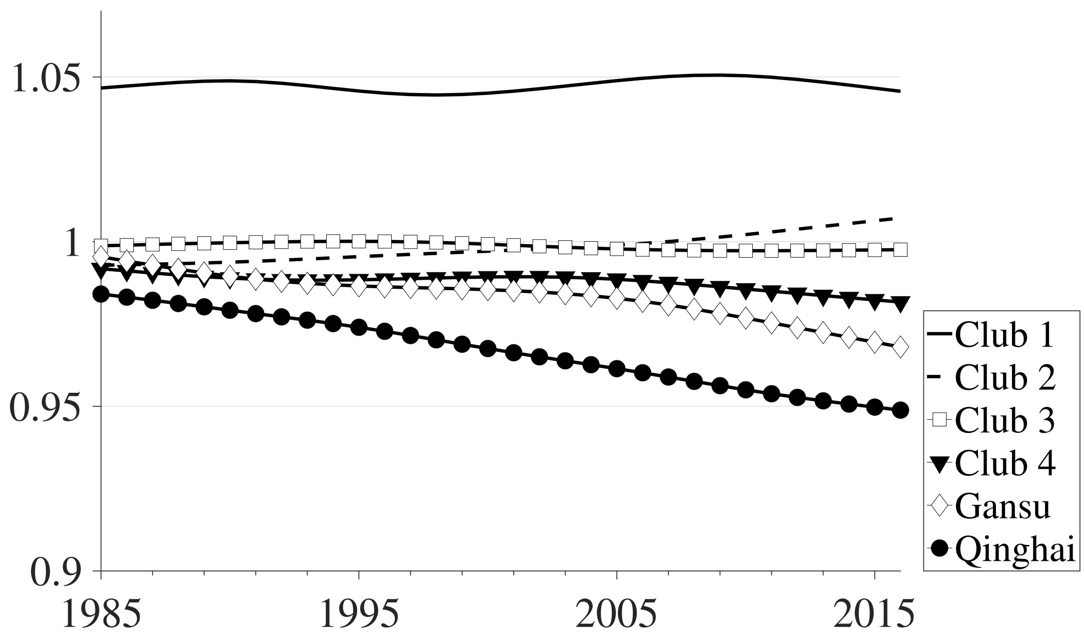
Convergence classifications for PCHC by urban and rural regions of 30 provinces are reported in Table 4 and illustrated in Figure 6.[13] While the null hypothesis of overall convergence is rejected at the 5% confidence level for both subsamples considered, the results display substantial differences. Consistent with the clustering patterns presented in Section 5.1, the highest of the four clubs detected in the urban sample includes Bei-

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

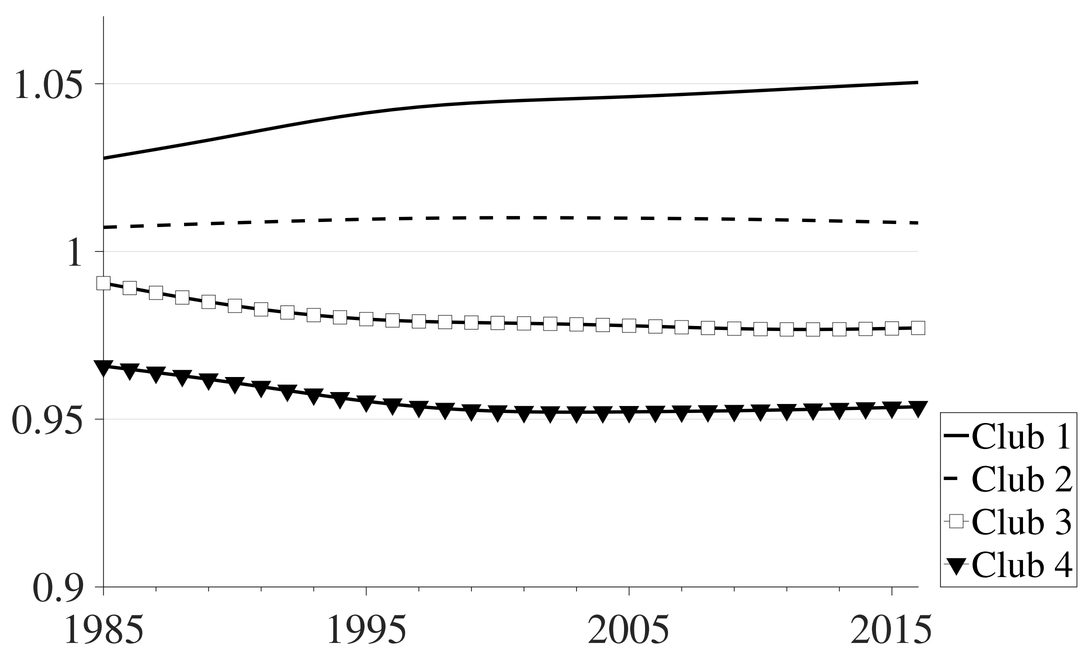
Table 4: Convergence club classification: Urban vs. Rural PCHC (LCI)

| 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 $\hat{\alpha} = 0.147$.




(a) Urban PCHC deflated by LCI




(b) Rural PCHC deflated by LCI

Figure 6: 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.

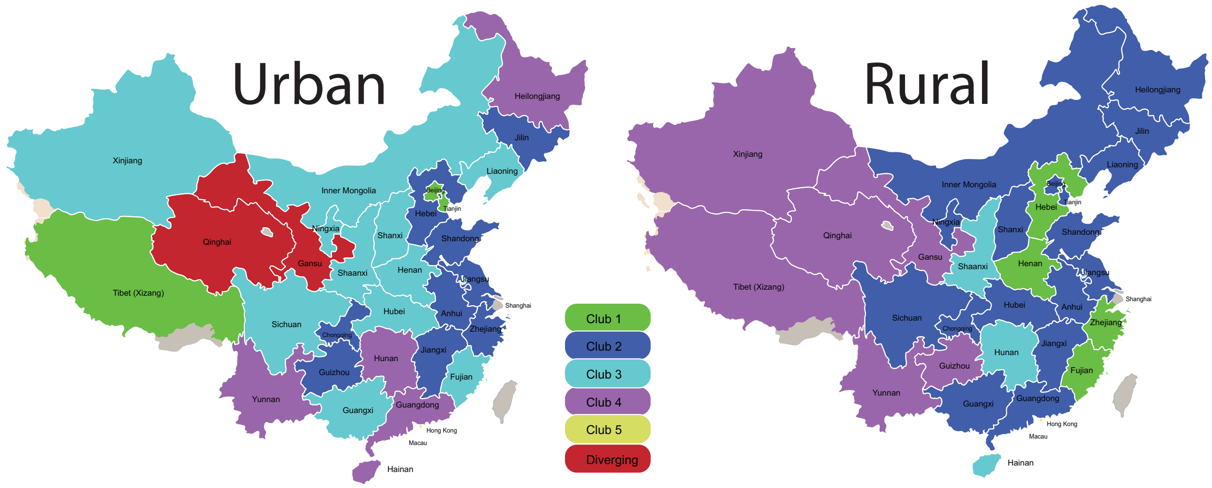



Figure 7: Convergence club classification: Urban vs. Rural PCHC (LCI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita human capital (PCHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985-2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

jing 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 converging into Club 2, while 11 mostly interior provinces converge into Club 3 (see Figure 7). Turning to Figure 6, 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 Figure 7). 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.

# 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. Most importantly, the J-F human capital estimates 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.

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).

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 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.

The results of the convergence tests for all three human capital proxies are reported in Table 7 with their corresponding transitional paths displayed in Figure 8. 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 Figure 8 are labelled "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.

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.

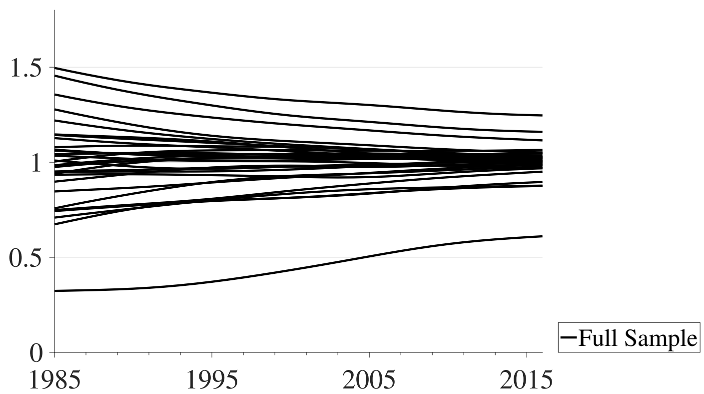
Table 7: Convergence club classification: Education-based human capital measures

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

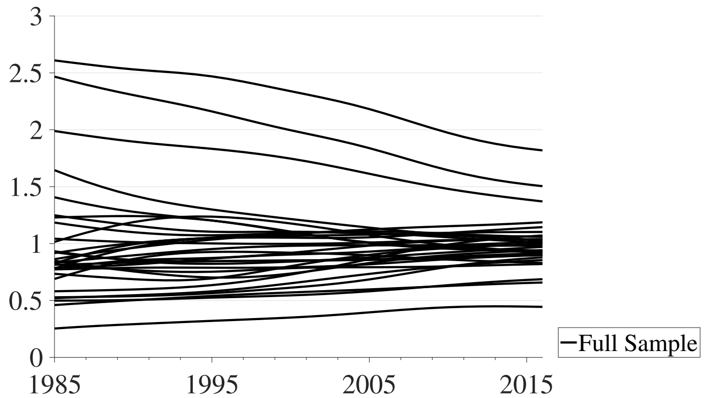
**Note:** Authors' calculations using the China Statistics Year Books 1995-2017. Log($t$) test results for convergence in average years of schooling of the labor force (AYS), proportion of the labor force with secondary education and above (PLFS), and proportion of the labor force with tertiary education 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 $t_{\hat{b}} < -1.65$.

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.

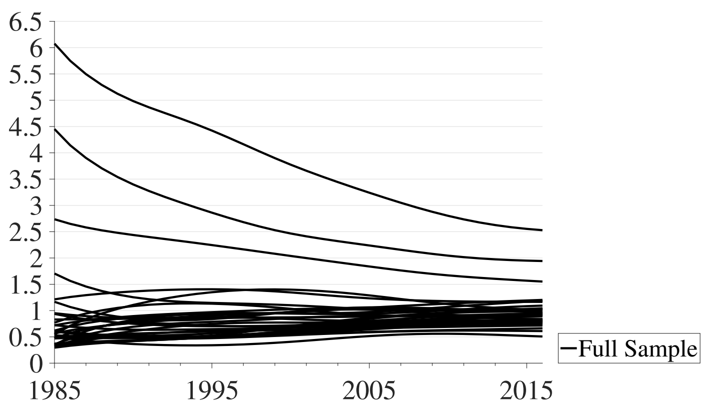
In sum, convergence in terms of average years of schooling or levels of educational attainment does not imply convergence in other forms of human capital accumulation, represented by the J-F approach, therefore, it would be misleading to extrapolate education convergence to human capital convergence.




(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

Figure 8: 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.

# 7 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.

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. Lastly, the results from the urban and rural samples indicate that the club classification may be driven by low human capital accumulation in rural areas for some provinces. In sum, 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.

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 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 C). 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 and 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. 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.

## Acknowledgements

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# A

Table A1: 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 A2: 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 $\hat{\alpha} = 0.065$.

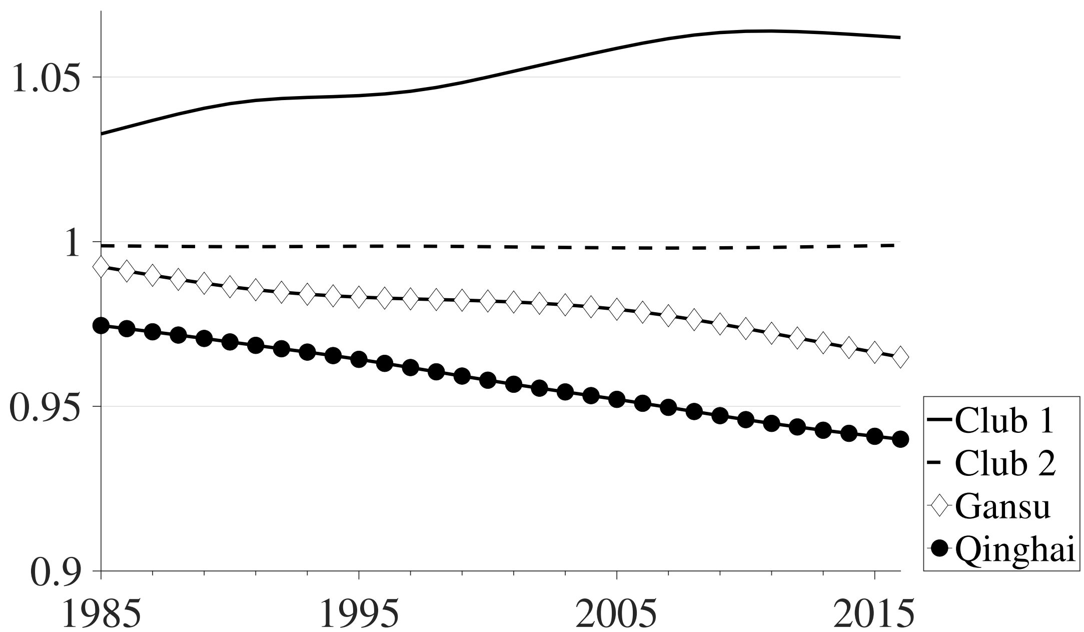
Table A3: Convergence club classification: Urban vs. Rural PCLFHC (LCI)

| Urban sample<br>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 | | | |

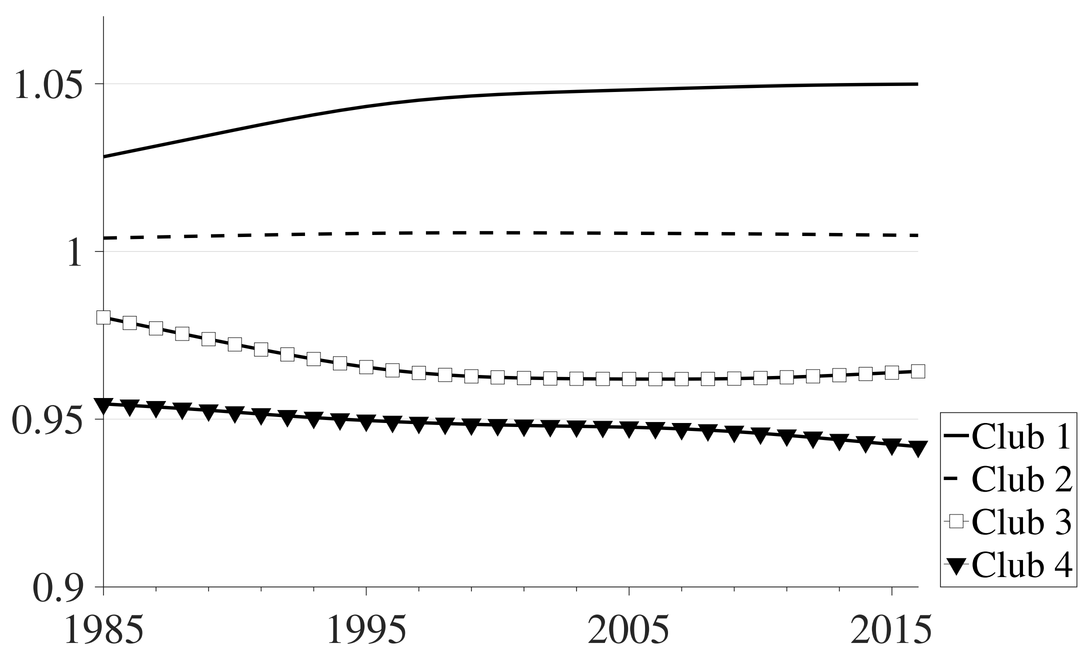
| Rural sample<br>Clubs | Provinces | $t_{\hat{b}}$ | $\hat{b}$ (*s.e.*) | $\hat{\alpha}$ |
|---|---|---|---|---|
| Full Sample | No overall convergence | -10.601 | -0.551 (0.052) | -0.275 |
| Club 1 | Beijing, Zhejiang, Henan | 0.955 | 0.186 (0.195) | 0.093 |
| Club 2 | Tianjin, Hebei, Shanxi, I. Mongolia, 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.

# B




(a) Urban PCHC deflated by CPI




(b) Rural PCHC deflated by CPI

Figure B1: 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.

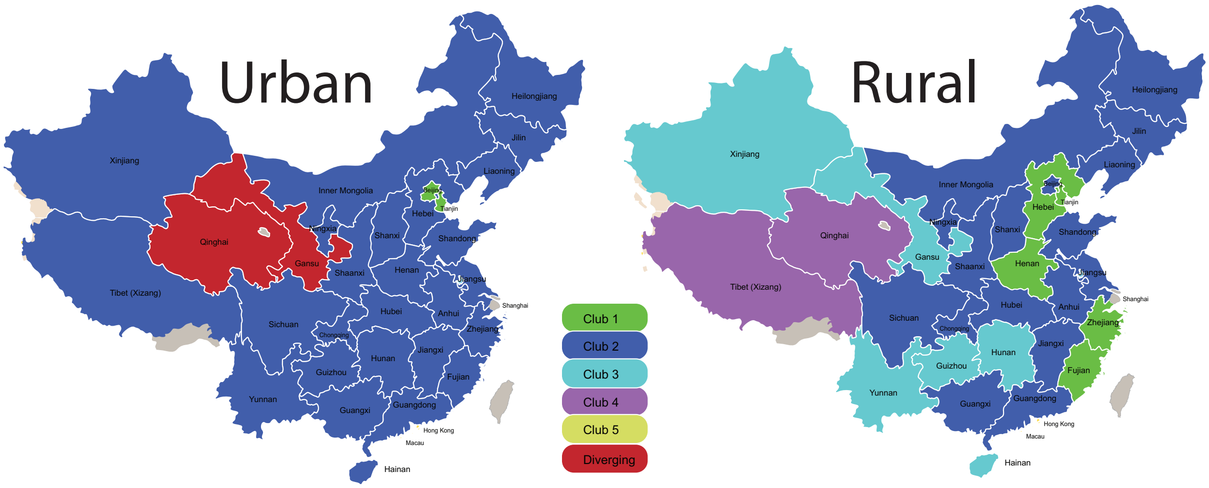
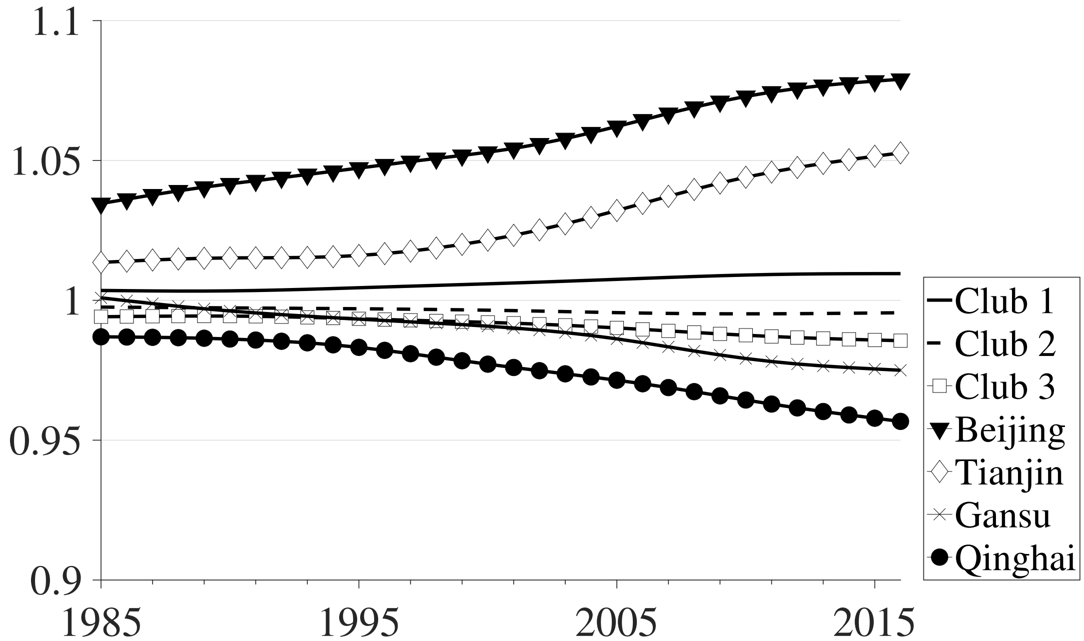
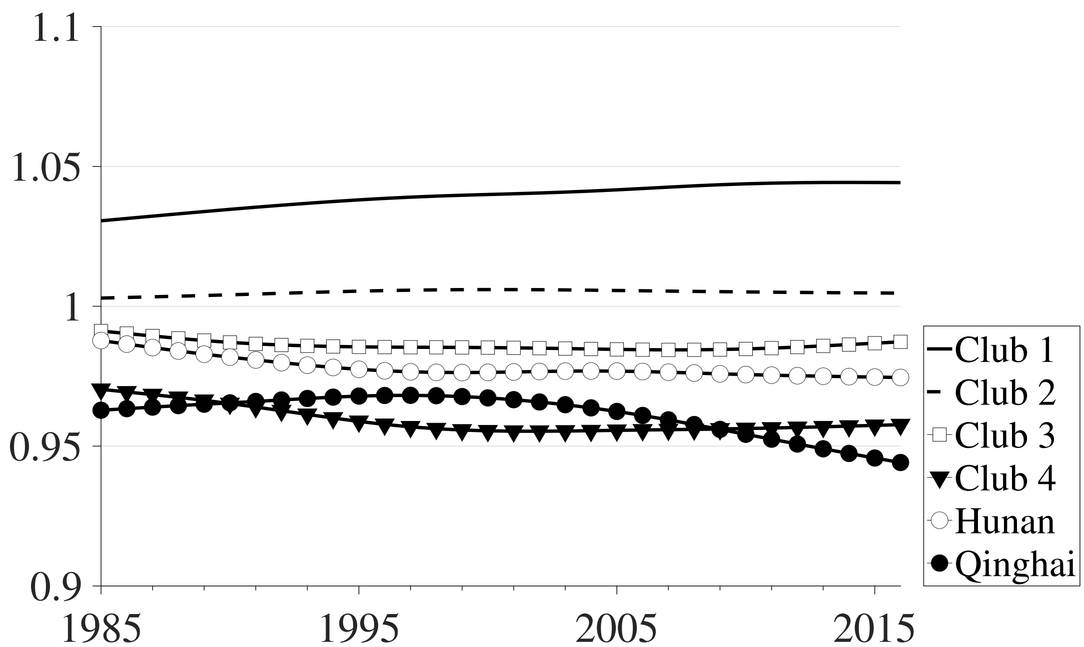



Figure B2: Convergence club classification: Urban vs. Rural PCHC (CPI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita human capital (PCHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985-2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.




(a) Urban PCLFHC deflated by CPI




(b) Rural PCLFHC deflated by CPI

Figure B3: 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.

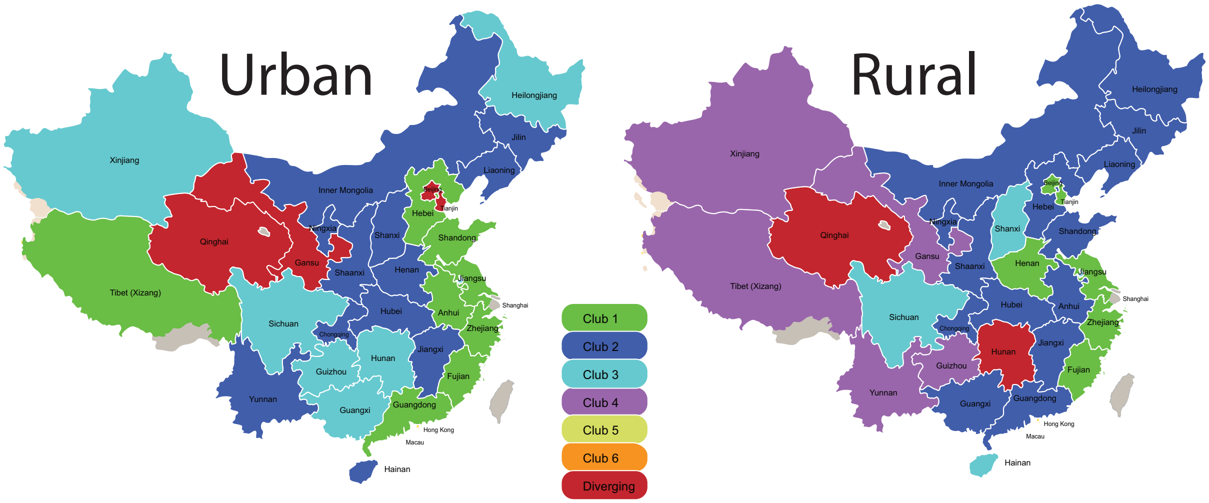
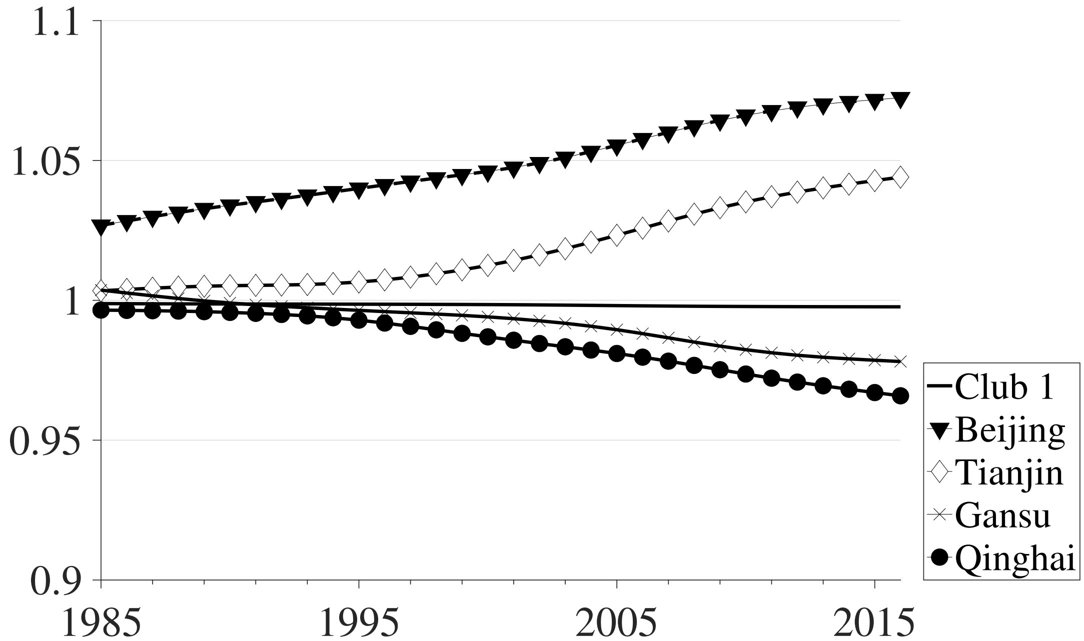
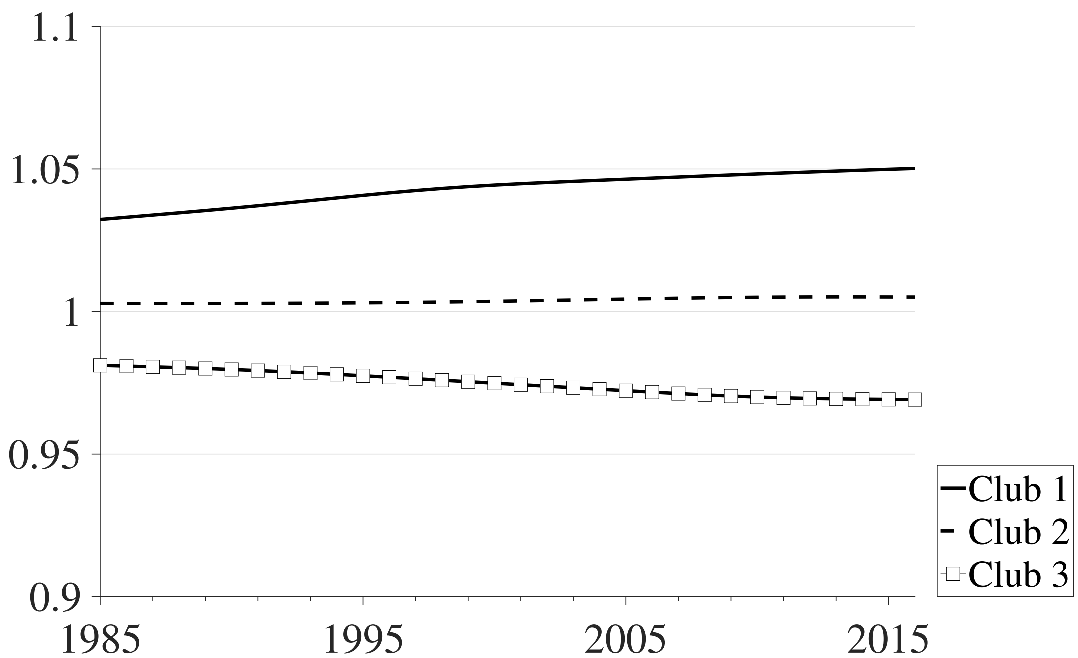



Figure B4: Convergence club classification: Urban vs. Rural PCLFHC (CPI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita labor force human capital (PCLFHC) deflated by consumer price index (CPI). Sample: 30 Chinese provinces, 1985-2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.




(a) Urban PCLFHC deflated by LCI




(b) Rural PCLFHC deflated by LCI

Figure B5: 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.

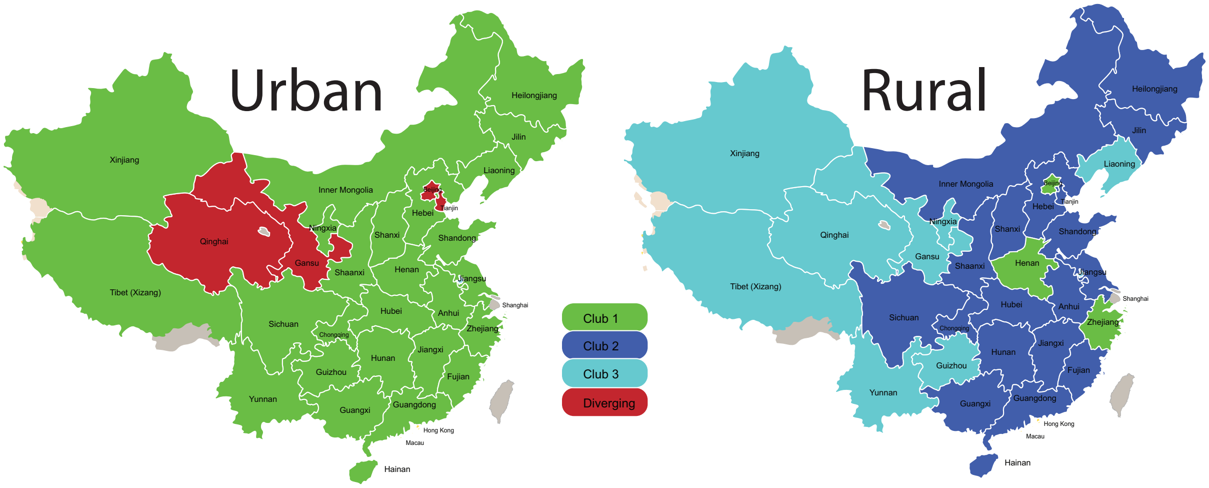



Figure B6: Convergence club classification: Urban vs. Rural PCLFHC (LCI). Authors' creation using Wikimedia Commons. Convergence club classification results for urban and rural per capita labor force human capital (PCLFHC) deflated by living cost index (LCI). Sample: 30 Chinese provinces, 1985-2016. Shanghai is not included since there is no urban and rural disaggregation of human capital stock for this province.

# C

Table C1: 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 |

*Continued*

Table C1: Continued

| | 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. Sample: 31 Chinese provinces, 1985-2016. Authors' calculations using CHLR (2018).