



Human capital quality and the regional economic growth: Evidence from China

Yi Zhang ^a, Sanjay Kumar ^b, Xianhai Huang ^c, Yiming Yuan ^{c,*}

^a School of Economics, Zhejiang University of Finance & Economics, Hangzhou, China

^b College of Business, Valparaiso University, Valparaiso, USA

^c School of Economics, Zhejiang University, Hangzhou, China

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ABSTRACT

China's economic development has advanced from a high-speed to a high-quality growth stage in recent years. The optimization and upgrading of the economic structure require high-quality human capital to support an innovation-driven economy. In this paper, a general equilibrium model of human capital (Xiang & Yeaple, 2018) is applied to estimate the cognitive and non-cognitive productivities based on Chinese provincial-level macro-data and individual labor's micro-data from 2008 to 2017. The weighted power mean of cognitive and non-cognitive productivities helps calculate the provincial-level human capital quality index (HCQI), which provides a realistic estimate of human capital quality. We find that the improvement of the HCQI leads to convergence in economic growth in China's provinces. HCQI can help explain the differences in economic growth levels in different regions of China. Our study provides a constructive step in understanding cognitive and non-cognitive abilities and HCQI in China, which could help guide education investment policy in China and its provinces.

1. Introduction

Globalization has accelerated the scale of the cross-border flow of production factors such as material capital, human capital, and technology. As a result, factor endowment, human capital structure, trade and investment structure, industrial reforms, and productivity growth have been affected worldwide. China's economic development has changed from a high-speed to a high-quality development mode in recent years. Such a change requires a shift from a factor and investment-scale-driven economy to an innovation-driven economy. Human talent drives an innovation-driven economy. For China, the new development mode requires strategic and innovative allocation of resources to attract and develop talent, promote and upgrade industrial structure, and create novel impetus for economic growth.

The 19th Communist Party Congress declared that socialism with Chinese characteristics had entered a 'new era.' President Xi Jinping stated, "We must take innovation as the first driving force to lead development and talent as the first resource to support development and innovation as the core position in the country's overall development." Talent plays a vital role in scientific and technological innovation, and nations create competitive advantages based on talent (Gu, 2019). Transforming and upgrading China's industrial structure for high-quality economic development requires high-quality human capital. For future growth and

* Corresponding author.

E-mail addresses: zhangyi34@zufe.edu.cn (Y. Zhang), sanjay.kumar@valpo.edu (S. Kumar), hxhz@126.com (X. Huang), yuanyiming@zju.edu.cn (Y. Yuan).

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competitiveness, China must enact policies to convert "demographic dividend" to "talent dividend".

Human capital should be multi-dimensional; the failure of the literature to address heterogeneity within human capital has occurred despite the growth of rich micro-econometric literature that has emphasized the distinction between cognitive skills and non-cognitive skills. An education system that is efficient in fostering one type of skill may be deficient in fostering the other. For example, the U.S. has low cognitive productivity (outside of the top 15) despite having a high human capital per worker (within the top 5) because of high output per worker and abundant resources. While some countries like Belgium, Finland, and the U.K., have low human capital per worker (outside of the top 10), these countries have high non-cognitive productivity (within the top 5). This is for provinces in China such as Guangdong, Jiangsu, and Zhejiang, which have a high average schooling index but a low non-cognitive human capital productivity ranking. Other provinces such as Hubei, Yunnan, and Sichuan rank within the top 10 in terms of non-cognitive human capital productivity, while their average years of schooling are relatively low.

The main contributions of this paper are as follows. First, despite the interest and importance, research progress in the domain of human capital has been hampered because of the difficulty of developing indicators that comprehensively measure human capital. Moreover, extant literature considers human capital as a single entity often measured using years of education. Ignoring non-cognitive abilities and only considering cognitive abilities developed through education fail to capture the connotations of human capital and may lead to biased and distorted estimations of the effect of human capital (Cubas et al., 2016; Erosa et al., 2010; Li & Zeng, 2012; Manuelli & Seshadri, 2014). In contrast to the extant literature, we adopt a general equilibrium model of human capital constructed by Xiang & Yeaple (2018), considering the production of cognitive and non-cognitive human capital individually in various provinces and regions of China, thereby enriching human capital's research paradigm and theoretical framework. Human capital can provide services as a factor content of trade, and production factors such as capital and labor have higher mobility within a country than across national borders. Therefore, we calculate the open-economy HCQI considering both the domestic and international trade flows. This process results in realistic human capital quality measurements for different provinces in China. Third, we empirically analyze the impact of China's human capital quality on regional economic growth. The results show that the difference in HCQI can help explain the differences in economic growth in different regions of China. We contrast results for different regions to make region-specific policy recommendations.

This study explores the influence of human capital quality on economic growth in different regions of China. Our results have government policy and managerial implications. Our model and results could help guide central and provincial government policies in creating a human capital structure suitable for high-quality economic development in China. Regional disparities in economic development could also be addressed by improving the quality of human capital. Our study highlights the need for education system reform in the country. It provides policy guidance for regional governments to establish a scientific talent classification and evaluation system, which could help create a talent and industrial structure suitable for high-quality growth.

The rest of the paper is organized as follows. In Section 2, we provide a review of the related literature. Section 3 discusses applying the general equilibrium model to measure provincial human capital quality in China. Section 4 outlines the data sources and parameter estimation procedure. Section 5 presents the empirical model and results. Section 6 concludes the paper with policy implications.

2. Literature review

Schultz (1960) proposed the concept of human capital, which is developed and acquired through investment in knowledge, skills, and health. The *quality* of human resources is difficult to measure precisely. Schultz suggested that human capital could be measured by examining *activities* that may help improve specific human *abilities*. His ideas kick-started research and helped build economic models for human capital, namely analyzing the relationship between labor investment activities and income. Barro & Lee (1993) proposed a simple and effective measure for human capital stock using education level. Due to the simplicity of the measure and easy availability of data, a large number of empirical studies use the average length of education as a proxy to measure human capital (Mankiw et al., 1992; Yao & Zhang, 2008; Huang et al., 2013; Jones, 2014; Malmberg, 2017; Liu et al., 2018).

With advancements in human capital theories, many scholars pointed out the pitfalls in measuring human capital by education level alone while ignoring other non-education-related human capital characteristics. Li et al. (2013) pointed out that education level alone cannot comprehensively measure human capital. A myriad of factors, including the economic structure and marketization levels, may affect the appropriate type and level of human capital in different regions and countries. Biased and distorted economic effects may be observed when education level is used for human capital measurement (Li & Zeng, 2012; Wang, 2015).

Compared with the traditional human capital theory, the new developments and approaches overturn the premise of homogeneity of workers. Bowles et al. (2001) challenged the hypotheses of labor market equilibrium and complete contract in traditional human capital models. They proposed the characteristics of "disequilibrium rent" and "incentive-enhancing preferences" possessed by laborers. These characteristics help explain the impact of non-cognitive abilities in obtaining economic returns. The reconstruction of the labor market model pointed out that the connotations of human capital should emphasize the production skills of cognitive abilities and the economic value of non-cognitive abilities. Non-cognitive abilities have been addressed by psychologists and economists, including Nobel laureate Heckman. Research shows that cognitive and non-cognitive abilities impact schooling, employment, work experience, occupation choice, and risky behaviors. A stream of literature further emphasizes the role of non-cognitive abilities in the labor market and considers that its effect is stronger than cognitive abilities for some behavioral outcomes (Heckman & Rubinstein, 2001; Heckman & Carneiro, 2003; Heckman et al., 2006). Recent human capital theories study the formation and cultivation mechanism of cognitive and non-cognitive abilities. They also discuss the influence of different abilities on economic and social behavior and output. Therefore, various 'abilities' are at the core of the new human capital theories, while education and health are often emphasized in the traditional human capital theories (Li & Zeng, 2012).

Psychologists divide cognitive abilities into two categories, i.e., fluid and crystallized intelligence. Fluid intelligence focuses on solving new problems and could be measured by IQ. Crystal intelligence mainly reflects the current knowledge level and increases with education and age (Huang & Xie, 2017). Cognitive abilities are well-understood, for which the academic community has developed relatively standardized and mature measuring tools (Heckman & Kautz, 2012). Non-cognitive abilities cover psychological factors such as personality characteristics, which are difficult to measure. The economic research community lacks consensus on its measures, while psychologists commonly use personality traits to assess non-cognitive abilities. However, as in our study, economists use non-cognitive skills or abilities as an umbrella term to express abilities not covered under cognitive abilities. Heckman et al. (2006) used the *Rotter Locus of Control Scale* and *Rosenberg Self-Esteem Scale* to measure non-cognitive abilities. Despite the lack of consensus in the research community, the "Big Five" personality structure model is widely used in empirical studies related to non-cognitive abilities (Cheng & Li, 2017; Wang & Zhang, 2019; Le & Hu, 2017). The model divides personality characteristics into five dimensions: conscientiousness, openness to experience, extraversion, agreeableness, and emotional stability. Each dimension contains six specific personality characteristics (Costa & McCrae, 1992). Relevant studies show that family and social circle may play a vital role in shaping an individual's non-cognitive abilities through genes, parental investment, and choice of children's growth environment (Cunha et al., 2010; Zhang & Zhu, 2018).

This paper focuses on the impact of cognitive and non-cognitive abilities on human capital accumulation and production. We do not parse various aspects of non-cognitive abilities such as leadership, communication, and social skills, which are not reflected in testing, nor will they improve with the years of education. We use occupation employment data to back out provinces' comparative advantages in fostering non-cognitive skills, quantify different provinces' efficiencies in producing non-cognitive and cognitive human capital, and summarize these differences into the HCQI. We take a macro perspective by quantifying the ways in which different provinces produce multiple types of human capital, and then clarifying the implications of such differences for aggregate output in a GE model.

Human capital undoubtedly plays a vital role in a country's economic growth and social development. However, due to the complex and multiple attributes affecting human capital and the difficulty of collecting relevant data, comprehensive human capital measures are challenging to obtain. Most studies use characteristics such as years of education and health levels to measure the level of human capital in different regions of China and elsewhere (Cai & Du, 2000; Chen et al., 2004; Wang et al., 2008; Huang et al., 2013; Zhou et al., 2019). Kendrick (1976) proposed a measure based on the total investment in human capital development. However, such data is scarce in China, with only a few studies using the investment approach (Qian & Liu, 2004; Zhang, 2000). Others have used the lifetime income method proposed by Jorgenson & Fraumeni (1989, 1992). Such studies include Li et al. (2010, 2013). Again, due to its complexity, such methods are seldom used in empirical research.

It is of practical significance to scientifically understand and measure human capital and study its role in China's economic development. This paper uses a general equilibrium model for cognitive and non-cognitive human capital using provincial macro-level and individual micro-level data in China based on new human capital theory developments. Using the model and data, we first calculate the cognitive and non-cognitive productivities and HCQI for 31 provinces and cities in China. Furthermore, we analyze the relationship between human capital quality and per capita output of different provinces and cities in China.

3. Measurement of provincial human capital quality in China

According to Walras' general equilibrium theory, when the labor market is in a state of equilibrium, the price of factors of production and the demand and supply of the labor force is also at equilibrium. Xiang & Yeaple (2018) applied the general equilibrium model to the labor market and constructed a production model of multiple human capital types. They derived expressions for cognitive and non-cognitive productivities, which can be aggregated into HCQI. The theoretical model first establishes the total supply of different kinds of human capital in various regions through the individual optimal choices of labor. Then the model obtains the total demand of different types of human capital in different regions according to the enterprise production behavior. Finally, equilibrium under the condition of clearing the international factor market is obtained. Xiang & Yeaple (2018) quantified cognitive and non-cognitive human capital productivities in high-income countries. We build on their model and focus on regions in China while considering the flow of goods and services and regional factor differences in China. Please refer to Xiang & Yeaple (2018) for more details.

3.1. Cognitive human capital productivity and non-cognitive human capital productivity

The focus of investment in education differs across the world. In China, school education primarily emphasizes examination results. Unlike most western countries, China's education system overemphasizes cognitive abilities at the cost of cultivating students' non-cognitive abilities. Following the literature, we assume that the average years of schooling can reflect cognitive human capital production in different regions of China. The higher the years of schooling, the higher the cognitive human capital. For a set of regions denoted by k , S^k is the average level of cognitive human capital, L_c^{ks} denotes the total supply of cognitive human capital, and L^k denotes the total labor supply. With a positive constant term b , S^k can be expressed as:

$$S^k = b \frac{L_c^{ks}}{L^k} \quad (1)$$

Note that subscript c is used to denote cognitive capital. Standard measures of a single type of human capital based on years of schooling and test scores can be applied to cognitive dimensions. Xiang & Yeaple (2018) used the Programme International Student

Assessment (PISA) scores to estimate the average level of cognitive human capital in different countries. However, the PISA test is taken only by students in Shanghai. In combination with the practical situation in China, we choose the average years of education as a proxy variable for the level of cognitive human capital. The data showed that provinces with higher average years of education had higher cognitive ability test scores.

Studies show that cognitive abilities improve with education, while non-cognitive abilities such as personality traits are relatively unaffected by the length of education (Cawley et al., 2001; Caspi et al., 2005; Heineck & Anger, 2010). Research shows that cognitive abilities are strongly correlated with education, and students in regions with higher average years of schooling score higher on cognitive ability tests. Therefore, we choose the average years of schooling to reflect the average cognitive human capital level in different provinces and cities in China. Our approach overcomes the shortage of micro-survey data. It helps analyze and compare the trends of human capital quality in various areas of China, which is conducive to studying the relationship between human capital quality and regional economic growth.

Cognitive human capital productivity can be calculated using average years of schooling, per capita GDP, and occupation employment share (Xiang & Yeaple, 2018). We also define a base region 0 against which any region can be compared.

$$\frac{S^k}{S^0} = \left(\frac{Y^k/L^k}{Y^0/L^0} \right)^\eta \left(\frac{p_c^k}{p_c^0} \right)^{1-\frac{1}{\theta}} \left(\frac{h_c^k}{h_c^0} \right) \tag{2}$$

Eq. (2) shows that the average years of schooling is related to the effects of resource input in a region. Y^k/L^k represents per capita income level, η is the elasticity coefficient of human capital production, p_c is the employment share of cognitive occupation, θ is the elasticity coefficient of labor supply, and h_c represents the productivity of cognitive human capital. Based on the availability of data on average years of schooling, per capita GDP, and occupation share employment of different provinces in China, h_c^k for various provinces and regions of China can be calculated using Eq. (2).

Employment distribution of the labor force is determined by the workers' endogenous choice and final goods producers' optimal hiring decisions. Workers choose occupations based on their cognitive and non-cognitive abilities. An individual's choice behavior will affect the total supply of cognitive and non-cognitive human capital. For example, a high share of employment in non-cognitive occupations may indicate comparative advantages in cultivating non-cognitive human capital leading to the high productivity of non-cognitive human capital. Xiang & Yeaple (2018) introduced a benchmark region for two types of human capital productivity, setting $h_c^0 = h_n^0 = 1$. In an open economy, the expression for the comparative advantage of cognitive and non-cognitive human capital productivities is as follows:

$$\frac{h_c^k/h_n^k}{h_c^0/h_n^0} = \left(\frac{p_c^k/p_n^k}{p_c^0/p_n^0} \right)^{\frac{\theta+\alpha-1}{\theta(\alpha-1)}} \left(\frac{1-x_c^k}{1-x_n^k} \right)^{\frac{1}{\alpha-1}} \tag{3}$$

x_i^k represents the net export rate of the type $i \in (c, n)$ labor force in region k . α and θ are labor demand and supply elasticity coefficients, respectively.

Under the open economy, a heterogeneous labor force can flow as an intermediate product of trade across the world and within a country such as China through internal migration. The labor supply and labor demand in different regions may not be equal. The factor market clearing in k regions must meet the following condition:

$$\frac{L_n^{kD}}{L_c^{kD}} = \frac{L_n^{kS}}{L_c^{kS}} \frac{1-x_n^k}{1-x_c^k} \tag{4}$$

In region k , L_c^{kD} and L_n^{kD} represent the total demand of cognitive and non-cognitive human capital, respectively. The total supply of cognitive and non-cognitive human capital in region k is represented by L_c^{kS} and L_n^{kS} , respectively. Economic interactions among regions within a country are stronger than those among countries. Therefore, both domestic and international trade flows should be considered. Domestic equilibrium requires that provinces' emigration of cognitive human capital must be equal to other provinces' migration of cognitive human capital. Let d^k be the migration costs for workers moving to another region. M_c is the set of provinces that import cognitive labor, and X_c is the set of provinces that export cognitive labor. Thus, domestic factor market clearing requires the following:

$$\sum_{k \in X_c} x_c^k L_c^{kS} + \sum_{k \in M_c} x_c^k L_c^{kS} d^k = 0 \tag{5}$$

We calculate the factor content of trade flows using steps similar to Davis & Weinstein (2001). We construct inter-provincial trade flows based on the inter-provincial input-output tables for 2007, 2012, and 2017. The interpolation method was used to supplement the missing years. We calculated the employment share of cognitive and non-cognitive occupations (p_c^k and p_n^k) for 31 provinces and cities in China. Our calculations provide the numbers of cognitive and non-cognitive workers relative to the numbers of these workers in region k 's labor force. Using these steps, we calculated the net export ratio of cognitive and non-cognitive human capital from 2008 to 2017. Finally, with known values of α and θ , the non-cognitive human capital productivity h_n^k of different provinces and cities in China can be calculated using Eq. 3.

3.2. Human Capital Quality Index (HCQI)

As per the general equilibrium model, the difference in per capita output can be divided into differences in human capital quality and output TFP. The HCQI is determined jointly by cognitive and non-cognitive human capital productivities.

$$\frac{Y^k/L^k}{Y^0/L^0} = \left(\frac{\theta^k}{\theta^0} H^k\right)^{\frac{1}{1-\eta}} \tag{6}$$

$$H^k = \left\{ p_c^0 \left\{ \left[\frac{p_c^0(1-x_c^0)}{p_c^k(1-x_c^k)} \right]^{\frac{1}{\alpha-1}} \frac{h_c^k}{h_c^0} \right\}^\theta + p_n^0 \left\{ \left[\frac{p_n^0(1-x_n^0)}{p_n^k(1-x_n^k)} \right]^{\frac{1}{\alpha-1}} \frac{h_n^k}{h_n^0} \right\}^\theta \right\}^{\frac{1}{\theta}} \tag{7}$$

In Eq. (5), θ^k denotes region k 's output TFP, which is equivalent to the residual error and represents the influence on the output from factors other than the human capital. H^k is HCQI for region k . Since our research deals with HCQI within the provinces of China, we embed migration costs into the model. Eq. (6) is the expression for HCQI with x_i^k denoting the net emigration of cognitive and non-cognitive labor in region k . Eq. (6) indicates that the HCQI is a weighted power mean function of cognitive and non-cognitive human capital productivities. The weights depend on the occupation employment shares and labor flows. In the context of this paper, we used Beijing as the benchmark region and calculated the HCQI of 31 provinces in China from 2008 to 2017.

4. Data sources and parameter estimation

Our study focuses on China and 31 of its provinces. This section reports on the data used and calculation methods for the parameters needed for the model.

4.1. Calculation of China's human capital production elasticity coefficient η

The production of human capital is related to input resources. The output elasticity coefficient η of human capital can be expressed as the proportion of education expenditure to the aggregate output.¹ The data on aggregate education spending comes from China's Fiscal Statistical Yearbook. National fiscal revenue mainly consists of tax and non-tax revenues. State fiscal expenditure includes central government expenditure and local fiscal expenditure. We add the central and local education expenditures to get the aggregate education expenditure. The result is then divided by national fiscal revenue to get η . China's human capital production elasticity coefficient η is estimated to be between 0.155 and 0.182. The total number of employed people is obtained from the China Statistical Yearbook.

4.2. Estimation of China's labor supply elasticity coefficient θ

The labor supply elasticity coefficient θ measures the degree of dispersion of workers with cognitive and non-cognitive abilities. The coefficient also governs the elasticity of aggregate supplies of human capital. The expression for θ is:

$$\ln \left[\frac{S^k}{(y^k)^\eta} \right] = \left(1 - \frac{1}{\theta} \right) \ln p_c^k + \ln h_c^k + C \tag{8}$$

y^k represents output per worker in region k . C is a constant. The elasticity coefficient of labor supply is obtained by regression estimation of Eq. (7) using relevant data of average years of schooling S^k , output per worker y^k , human capital output elasticity coefficient η , and cognitive occupation employment share p_c^k .

We estimate the labor supply elasticity coefficient in China using cognitive ability test scores and average years of schooling. The relevant data is derived from the China Family Panel Studies (CFPS) database, which reports results from a 2016 personal-level adult survey of 16 years and older participants. The database covers relevant information such as the provinces where the investigated individuals are located, education levels, cognitive test scores, and occupation codes. We cleaned the CFPS-2016 data by eliminating data points that had missing, unknown, and incapable memory test or sequence test scores. The final data contained 26,562 individual observations. Then we segregated data based on the provinces and cities and obtained the cognitive ability tests' average scores for every region.

The average years of schooling index can be obtained using an individual's education level in the CFPS database. The index could also be obtained by Barro & Lee's (2010) method, which involves a weighted average of the education level and population proportion of employees in different provinces. The index $S = 1.5$ (the population share of illiterate and semi-illiterate) + 7.5 (the population share of receiving primary education) + 10.5 (the population share of receiving junior high school education) + 13.5 (the population share of receiving senior high school education) + 17 (the population share of receiving tertiary education or above). Relevant data fields are derived from the China Demographic Yearbook, China Labor Statistics Yearbook, and China Demographic and Employment

¹ See Xiang & Yeaple (2018) for a detailed derivation.

Statistics Yearbook.

We now outline the method used to calculate the employment shares of cognitive and non-cognitive occupations. Xiang & Yeaple (2018) pointed out that leadership ability can be used to divide occupations into cognitive and non-cognitive. Other literature uses a more nuanced approach by considering dimensions such as leadership, communication, and social skills (Kuhn & Weinberger, 2005; Hummels et al., 2014; Deming, 2017). We also use multiple attributes to classify cognitive and non-cognitive occupations.

As government officials and managers demonstrate strong leadership skills, and service and sales employees have strong communication and social skills, we classify these two occupational categories as non-cognitive occupations. According to the ISCO-88 occupational classification, six occupation categories (professionals, technicians, clerks, craft workers, plant and machine operators and assemblers, and elementary occupations) are cognitive occupations. From the CFPS-2016 database, relevant information such as provinces where individual interviewees were located, current working status, occupation codes, and ISCO-88 occupation codes were extracted. Individuals whose working status shows unemployed, withdrawal from the labor market, inability to judge, and inapplicable are eliminated. Individuals whose occupation codes show no-answer, blank, no occupation classification, military personnel, and inconvenience classification are also eliminated. The final dataset contains a total of 22,805 valid observations. Hainan Province, Inner Mongolia Autonomous Region, Ningxia Hui Autonomous Region, Qinghai Province, Tibet Autonomous Region, and Xinjiang Uygur Autonomous Region yield a very small number of observations. Such regions are dropped as the sample size may limit statistical analysis.

Table 1 reports least square regression results for China’s labor supply elasticity coefficient. In the model of Eq. (7), a measure of cognitive capital is regressed with the average level of cognitive employment share. We use multiple measures of cognitive capital. Column (1) reports results using the log of cognitive ability test score normalized by the log of output per worker raised to the power of η . To represent the average level of cognitive human capital, Column (2) uses memory test scores. Values in Column (3) are obtained by regressing the cognitive occupation employment share of each province’s sequence test score after fine-tuning per capita GDP. Columns (4) and (5) use the average years of schooling index to reflect the level of cognitive human capital in different regions. The estimation results are obtained by regressing the cognitive occupation employment share of the logarithm of the average years of schooling after fine-tuning per capita GDP. The index of average years of schooling in Column (4) is derived from CFPS-2016 individual data, while for Column (5), we use Barro & Lee (2010) method.

The regression results of these five columns are all highly significant. The goodness of fit for Column (5) is highest with $R^2 = 0.641$, and the estimated labor supply elasticity coefficient is 0.5117. Using $(1 - 1/\theta) = 0.5117$, the elasticity coefficient of labor supply in China is $\theta = 2.0479$. Our estimation of θ is consistent with findings in the literature. Hsieh et al. (2019) believed that innate abilities are subject to the Fréchet distribution. They used a method different from ours and estimated $\theta = 2$, and concluded that the actual value falls between 1.5 and 2.5. Similarly, Burstein et al. (2019) and Lee (2020) estimated θ in the range from 1.78 to 2.62 and 1.48–2.5, respectively. Xiang & Yeaple (2018) used data from high-income developed countries and estimated $\theta = 1.973$, concluding that θ was between 1.746 and 3.014. Our estimates in Table 1 for θ fall between 1.4927 and 2.730. Therefore, we estimate that for provinces and cities in China, the elasticity coefficient of labor supply is equal to 2. Multiple estimation methods and validity from literature strengthen our estimate of θ .

4.3. Estimation of the elasticity of labor demand α in China

The labor demand elasticity coefficient α reflects the substitution elasticity between different workers, i.e., cognitive and non-cognitive abilities. The expression for estimating the labor demand elasticity coefficient differs based on economic conditions. Labor flow is important among provinces and cities in China. The expression for the labor demand elasticity coefficient includes the indices for the net export rate of cognitive human capital x_c^k and the net export rate of non-cognitive human capital x_n^k . The expression is as follows:

$$\ln\left(\frac{y^k}{S^k} \frac{1}{1-x_c^k}\right) = \frac{\alpha}{\alpha-1} \ln\left[1 + \frac{p_n^k(1-x_n^k)}{p_c^k(1-x_c^k)}\right] + \ln \Theta^k + D \tag{9}$$

In capitalist economies, labor demand primarily originates from enterprises. Therefore, the elasticity coefficient of labor demand should be calculated using enterprise-related data. To estimate α , we use employee structure data of listed companies from 2008 to 2017, which is derived from the iFinD database.² We extract the total number of employees and personnel in management, technical, production, financial, sales, and administrative jobs from the database. Other relevant indicators are also obtained from the iFinD database. Management and sales personnel are considered non-cognitive occupations using the occupation classification outlined above. Technical, production, financial, administrative, and other personnel are classified as cognitive occupations. The classification helps calculate the employment shares of cognitive and non-cognitive occupations in provinces and cities in China from 2008 to 2017. Consistent with the above estimation index of supply elasticity coefficient, S^k was expressed using the average years of schooling, which is obtained by the Barro-Lee calculation method. The data source and calculation method are the same as above. Per capita GDP for the relevant years is obtained from the Statistical Yearbook of different provinces and cities in China.

Table 2 reports the least square regression results for China’s labor demand elasticity coefficient under the closed-economy settings and trade or migration among region’s conditions. The regression model uses panel data of 31 provinces and cities in China from 2008

² iFinD database is compiled by Hithink RoyalFlush Information Network Company and is one of the major providers of databases in China.

Table 1
Estimation of labor supply elasticity coefficient θ in China.

	(1) Cognitive ability test score	(2) Memory test score	(3) Sequence test score	(4) Average years of schooling ^{CFPS2016}	(5) Average years of schooling ^{Barro & Lee}
$\ln p_c^k$	0.3301*** [4.97]	0.4042*** [4.50]	0.3294*** [4.96]	0.6338*** [5.77]	0.5117*** [6.41]
Constant	6.1123*** [92.33]	1.5186*** [16.99]	6.1022*** [92.30]	2.2365*** [20.45]	2.5199*** [31.72]
N	25	25	25	25	25
R ²	0.517	0.469	0.517	0.592	0.641
θ estimate	1.4927	1.6784	1.4912	2.7307	2.0479

Notes: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are *t*-statistics.

Table 2
Estimation of the elasticity of labor demand in China α .

	(6)	(7)
$\ln\left(1 + \frac{p_n^k}{p_c^k}\right)$	2.5503*** [6.41]	
$\ln\left[1 + \frac{p_n^k(1 - x_n^k)}{p_c^k(1 - x_c^k)}\right]$		2.7640*** [5.97]
Constant	7.8526*** [144.71]	7.8937*** [135.84]
N	310	310
R ²	0.118	0.104

Notes: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are *t*-statistics.

to 2017. Column (6) reports regression results using Eq. (8) under a closed economy with no trade or labor flow. With the free flow of labor and trade under an open economy, Column (7) reports results using Eq. (9). The results show a high level of significance. The results indicate that the elasticity of labor demand α to be 1.567 and 1.645 under closed and open economic conditions. Our estimation of elasticity agrees with the literature. Burstein et al. (2019) used CES total production function, using the relevant panel data of different occupations such as wages and employment in the United States, and calculated $\alpha = 1.78$. Xiang & Yeaple (2018) used cross-sectional data of 28 high-income countries and obtained $\alpha = 1.676$.

4.4. China's provincial human capital quality and per capita output

Education policy orientation differs among provinces in China. Some provinces advocate quality education. Students in these provinces may excel in exams; however, the worry is that too much emphasis on scores may lead to high scores but poor abilities. In contrast, some provinces follow the traditional exam-oriented education by using test scores as the only criterion for academic performance. Students are forced to memorize rather than think creatively. The orientation of education policy leads to differences in cognitive and non-cognitive human capital production. Our model framework highlights education policy trade-offs because provinces with imbalanced human-capital productivity tend to have relatively low HCQI. A high share of employment in non-cognitive occupations may indicate comparative advantages in cultivating non-cognitive human capital leading to the high productivity of non-cognitive human capital. Such a scenario is likely in provinces with relatively low average years of schooling. This is because many people in such provinces choose non-cognitive occupations despite their low education levels, improving their non-cognitive human capital productivity. On the contrary, in the areas with higher education levels, most people choose cognitive occupations, which strengthens the comparative advantage of cognitive human capital and makes the productivity of non-cognitive human capital lower.

We use Eqs. (5) and (6) to calculate HCQI. As per the expressions for HCQI, per capita output consists of human capital quality and output TFP. The human capital output elasticity coefficient η affects the contribution of HCQI and output TFP to per capita output. Using the data from 31 provinces and cities in China from 2008 to 2017, we calculate the impact of provincial human capital quality and output TFP on China's per capita output. The results are shown in Table 3. Besides the 31 provinces and cities, we also report the relevant parameters for China as a whole and the Eastern, Central, and Western regions. The first column in the table reports the average GDP per capita of different provinces and cities from 2008 to 2017. GDP for eleven eastern, eight central, and twelve western provinces and cities are CNY 44,575.35, CNY 41,886.53, and CNY 42,350.88, respectively. Per capita GDP for the eastern region is higher than that in the central and western regions. The second Column reports each region's output per capita relative to Beijing. Among the 31 provinces and cities, only Shanghai has a higher per capita GDP than Beijing. The relative per capita output index indicates a large income gap between different provinces and cities in China.

Does the quality of human capital and output TFP explain the income gap between different provinces in China? Columns (4) and

Table 3

The contribution rate of human capital quality and output TFP to output per capita from 2008 to 2017.

Province/Region	The average value of GDP per capita (1)	Output per capita relative to Beijing (2)	Average HCQI (3)	The contribution rate of HCQI (4)	Average of relative output TFP (5)	The contribution rate of output TFP (6)
Anhui	29,161.66	0.315	0.815	0.782	0.470	0.403
Beijing	92,480.21	1.000	1.000	1.000	1.000	1.000
Fujian	55,109.45	0.596	0.770	0.731	0.844	0.816
Gansu	21,594.48	0.234	0.831	0.800	0.359	0.292
Guangdong	57,314.60	0.620	0.829	0.798	0.810	0.776
Guangxi	27,965.80	0.302	0.882	0.860	0.419	0.351
Guizhou	21,901.23	0.237	0.804	0.769	0.375	0.308
Hainan	32,971.70	0.357	0.913	0.897	0.464	0.398
Hebei	35,463.80	0.383	0.839	0.810	0.537	0.473
Henan	32,445.06	0.351	0.819	0.786	0.511	0.446
Heilongjiang	33,851.26	0.366	0.859	0.833	0.505	0.439
Hubei	39,970.09	0.432	1.580	1.733	0.315	0.249
Hunan	34,193.59	0.370	1.057	1.070	0.413	0.346
Jilin	42,096.30	0.455	0.860	0.834	0.604	0.546
Jiangsu	71,710.30	0.775	0.830	0.799	0.975	0.970
Jiangxi	29,547.14	0.319	0.846	0.817	0.458	0.391
Liaoning	51,313.11	0.555	0.825	0.794	0.742	0.699
Inner Mongolia	58,751.35	0.635	0.821	0.789	0.835	0.805
Ningxia	35,917.70	0.388	0.962	0.955	0.473	0.407
Qinghai	32,903.70	0.356	0.783	0.745	0.541	0.478
Shandong	53,265.84	0.576	0.852	0.825	0.742	0.699
Shanxi	31,575.27	0.341	0.879	0.856	0.465	0.399
Shaanxi	38,504.83	0.416	0.856	0.829	0.564	0.502
Shanghai	93,147.47	1.007	1.106	1.129	0.910	0.892
Sichuan	29,881.43	0.323	0.860	0.834	0.454	0.387
Tianjin	91,671.97	0.991	1.444	1.556	0.687	0.637
Tibet	25,122.40	0.272	0.723	0.678	0.468	0.401
Xinjiang	33,249.40	0.360	0.889	0.868	0.480	0.414
Yunnan	23,004.40	0.249	0.866	0.841	0.363	0.296
Zhejiang	65,761.27	0.711	0.804	0.769	0.937	0.925
Chongqing	40,729.30	0.440	0.870	0.846	0.581	0.521
Eastern	44,575.35	0.482	0.910	0.897	0.595	0.543
Central	41,886.53	0.453	0.893	0.876	0.584	0.531
Western	42,350.88	0.458	0.910	0.897	0.571	0.516
National	43,954.07	0.475	0.906	0.891	0.590	0.538

The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, and Inner Mongolia.

Data source: Calculated and collated by the authors.

(6) report the contribution rate of human capital quality and the contribution rate of output TFP. To understand the values, as an example, we elaborate on the values of Anhui Province. The per capita output of Anhui Province is lower than that of Beijing. Two factors contribute to this disparity. First, the overall quality of human capital (Column 4) in Anhui Province is only 78.2 % of Beijing. Second, the output TFP of Anhui Province is 40.3 % of Beijing's per capita output. Together, the two effects result in Anhui's per capita output of $0.782 * 0.403 = 0.315$, which is at 31.5 % of Beijing's level.

The values in Column (2) are calculated using Statistical Yearbook data. Columns (4) and (6) are derived using model parameters discussed in Section 3. Specifically, the calculation formula for the contribution rate of human capital quality and the contribution rate of output TFP are $(H^k)^{\frac{1}{1-\eta}}$ and $\left(\frac{\theta^k}{\theta^l}\right)^{\frac{1}{1-\eta}}$, respectively. The findings reveal that for all provinces and cities except Fujian, Jiangsu, Inner Mongolia, and Zhejiang, the contribution rate of human capital quality is higher than that of output TFP. This indicates that the human capital quality has a meaningful impact on the per capita output. Human capital quality has a vital influence on the region's economic growth and income gap.

The contribution rate of TFP output is higher in the eastern region when compared to the central and western regions. This results in higher per capita output in the eastern region than the other two regions. Considering the whole country's perspective, China's contribution rate of human capital quality to per capita output is also higher than output TFP. This indicates that human capital quality improvements could be a driving force to increase per capita output in different provinces and cities in China. A comparable investment across the country in human capital development could help narrow the income gap in various provinces in China.

We now discuss the impact of changes in cognitive and non-cognitive human capital productivities and HCQI on per capita output growth. With an intent to make inferences that could help government policy-making, we explore how the changes in cognitive and non-cognitive human capital productivities affect the average years of schooling and total output in a region. Specifically, according to Dekle et al. (2008), the ratio of the subsequent equilibrium state to the initial equilibrium state can be used to express the change in

human capital productivity, i.e., $\hat{h}_i^k = h_i^{k'}/h_i^k$. k and k' represent prior and subsequent equilibrium states, respectively. We assume that the labor force quantity and output TFP in region k remain unchanged. The benchmark region can be used as the initial equilibrium state in region k . Under these conditions, Eq. (5) is transformed to:

$$\hat{Y}^k = \left[p_c^k (\hat{h}_c^k)^\theta + p_n^k (\hat{h}_n^k)^\theta \right]^{\frac{1}{\theta(1-\eta)}} \tag{10}$$

Eq. (10) shows that cognitive human capital productivity h_c^k and non-cognitive human capital productivity h_n^k affect the total output by influencing HCQI. Improvements in cognitive and non-cognitive human capital productivities can increase total output in a region.

The expression for change of average years of schooling can be derived and written as:

$$d \ln S^k = \left(\frac{1 + B p_c^k}{1 - \eta} \right) d \ln \tilde{h}_c^k - \left(\frac{B p_n^k}{1 - \eta} \right) d \ln \tilde{h}_n^k \tag{11}$$

where $B = \frac{(\theta-1)(\alpha-1)-\alpha\eta}{\theta+\alpha-1} > 0$. See Xiang & Yeaple (2018). Eq. (11) shows that an increase in the average years of schooling in a specific region could result from either an increase in cognitive human capital productivity or a decrease in non-cognitive human capital productivity. It is known that the decline in non-cognitive human capital productivity is mainly attributed to an increase in cognitive abilities of the personnel trained in the education system in a region. Better education and schools encourage workers to choose cognitive occupations, resulting in a relatively low share of non-cognitive occupations. In a region, workers' preference for cognitive occupations would encourage the population to accumulate cognitive human capital by increasing the average number of years of schooling. Such bias would also lead to a decrease in the level of non-cognitive human capital. This inference is supported by Eqs. (10) and (11).

A large part of economics literature uses years of education to measure human capital (Mankiw et al., 1992; Yao & Zhang, 2008; Huang et al., 2013; Jones, 2014; Malmberg, 2017; Liu et al., 2018). This biased and incomplete view of human capital overemphasizes the importance of school education in human capital development. Additionally, studies in the education domain exclusively focus on academic achievements, making cognitive abilities the only standard for evaluating education quality and education policies in a region or country (Zhou, 2015). The government, schools, and society may allocate resources using such a biased view - the education focus and government policies in China fall in this category. Chinese education is mainly "exam-focused," with a disproportionately large emphasis on tests that measure cognitive abilities alone. Such a focus may hinder the students' development, especially in non-cognitive abilities.

Due to a lack of research on cognitive and non-cognitive abilities, current human capital theories fail to provide meaningful and robust policy suggestions to drive education investment. The current state of research may even mislead the focus of education policies. Our study provides a constructive step in understanding cognitive and non-cognitive abilities and HCQI in China, which could help guide education investment policy in China and its provinces. We find that increase in the average years of schooling does not necessarily lead to a rise in total output in various regions. Despite some provinces in the central and western regions investing more in education (see Table 3), the resulting human capital does not lead to higher economic growth. A disproportionately high focus on cognitive abilities could be the reason. As a policy implication, we provide evidence to encourage regional and city governments to direct non-cognitive human capital development investments. A balanced focus on cognitive and non-cognitive capital development based on the need and demand of the industrial sector may be most helpful in driving the region's economic development.

5. Empirical strategy and results

5.1. Empirical model and estimation

Scholars have widely used the economic growth model of Barro & Sala-i-Martin (1992) to understand the relationship between China's human capital and regional economic growth (Cai & Du, 2000; Lin & Liu, 2003; Yao & Zhang, 2008; Wei et al., 2014; Liu et al., 2018). Based on the regression framework of the neoclassical growth model, this paper establishes the following empirical econometric model:

$$\ln(y_{it}) - \ln(y_{it-1}) = \alpha_1 \ln(y_{it-1}) + \alpha_2 \ln(HCQI_{it}) + \alpha_x X_{it} + \mu_i + \mu_t + \varepsilon_{it} \tag{12}$$

where y_{it} is the per capita output of province i in period t . $\ln(y_{it}) - \ln(y_{it-1})$ denotes per capita output change from period $t-1$ to t . HCQI is the core variable under investigation. X_{it} represent a set of control variables. μ_i and μ_t represent fixed effects controlling for provinces and years, respectively. ε_{it} is a random perturbation term.

Related studies have used cross-sectional data for empirical analysis (Barro et al., 1991; Mankiw et al., 1992). However, cross-sectional regression estimation sample size is often too small and may cause bias because of variable omissions. Research has effectively used panel data to estimate growth models to overcome such issues in recent years. Moreover, to address the endogeneity problem encountered in explanatory variables, a Generalized Method of Moments (GMM) is widely used (Bond et al., 2001; Wei et al., 2014; Liu et al., 2018). Proposed initially by Holtz-Eakin et al. (1988), the method has gained popularity (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Following the literature, we use a two-step system GMM to estimate Eq. (12).

5.2. Variable selection and data description

The primary response variable of interest in this paper is the growth rate of output per capita, which we use in a logarithmic form, $\ln(y_{it}) - \ln(y_{it-1})$. The core explanatory variable is the HCQI is calculated using relevant data for 31 provinces and cities in China. The estimated HCQI values are reported in [Table 3](#).

In the regression model, we control factors that may affect the economic growth in different regions of China. Relevant literature also helps in the identification of control variables. Our model's control variables are investment rate, economic openness, employment rate, and technical innovation level. Investment rate ($Invest_{it}$) is the proportion of gross fixed capital formation in GDP. The degree of economic openness ($Open_{it}$) is measured as the proportion of total imports and exports to the GDP. The unit of trade is \$10,000. USD figures are converted to RMB using the prevailing exchange rate before calculating the ratios. The employment rate ($Labor_{it}$) is expressed as the proportion of the employed population to the total population. Technical innovation level ($Tech_{it}$) is the number of patent applications per million people in the province. The panel data for 31 provinces and cities covers the period of 2008–2017. Relevant data is collected from the Annual "China Statistical Yearbook" and "Statistical Yearbook" of provinces and cities. The exchange rate is derived from the World Bank WDI database. [Table 4](#) reports the summary statistics of various variables.

5.3. Empirical results

Economic growth is a dynamic process with changes in growth affected by previous periods' growth levels. To account for this, [Eq. \(12\)](#) includes autoregressive terms. Moreover, we use a dynamic panel data model for estimation. We apply system GMM as it is less susceptible to weak instrument variables than difference GMM [Liu et al. \(2018\)](#). Both one- and two-step system GMM are used to estimate the panel data models. [Tables 5 and 6](#) report the estimated results from one-step and two-step system GMM, respectively. Arellano-Bond tests for both AR(1) and AR(2) models show no second-order serial autocorrelation for the disturbance term. Hansen's test shows that the instrument variables in each model are valid. Therefore, the system GMM estimation results are consistent and valid.

Various columns in [Table 5](#) report regression results with a different set of explanatory and control variables. Column (1) considers a model with only the core explanatory variable of HCQI. The coefficient of HCQI is positive and significant at 1 % confidence level. In Columns 2–5, additional control variables are added to the models. The HCQI coefficient is positive and significant in all the models indicating that human capital quality promotes growth in China's provinces. From the regression results in Column (5), it can be seen that the improvement in HCQI, employment rate, and economic openness contribute to economic growth. The coefficients for fixed capital investment and innovational level are positive but not significant. Despite a lack of statistical significance, qualitative results indicate that capital investment and innovation levels help economic growth. For every 1 % increase in HCQI, China's per capita output growth rate increases by 0.19–0.22 %. Similarly, a 1 % increase in economic openness aids in increasing the per capita output growth rate by 0.02 %. The rise in employment rate in provinces and cities in China also increases the per capita growth rate by 0.05–0.06 %, which is significant at the 10 % confidence level.

[Table 6](#) reports the estimation results using the two-step system GMM. The results are similar to that of the one-step system GMM. However, the estimated coefficients exhibit a higher degree of significance. Column (5) in [Table 6](#) indicates that the estimated coefficients of human capital quality, employment rate, and economic openness are significant at the 1 % confidence level. If the HCQI increases by 1 %, the per capita output will grow by 0.176 % points. An increase in the employment rate by 1 % drives economic growth by 0.047 % points. An increase in economic openness by one percentage point will increase per capita output by 0.019 % points. Of the significant explanatory variables, HCQI has the largest coefficient indicating the importance of HCQI in driving per capita economic growth in a province or city.

Both one-step and two-step system GMM yield negative and significant coefficients for initial per capita output. This indicates that different provinces in China have experienced a rapid conditional convergence in economic growth in the past decade. The regression results show that the estimated coefficients of prior per capita GDP are between 7.0 % and 9.7 %. The coefficient of HCQI is positive and highly significant in all models. This underlines the importance of HCQI in promoting economic growth.

Our human capital measure HCQI includes both cognitive and non-cognitive human capital. A section of the literature limits human capital to cognitive capital only, which is often measured by years in school. For each year of increase in the average years of schooling, [Yao & Zhang \(2008\)](#) showed that the average annual economic growth rate increases by 1.4–1.7 %, and the convergence rate of economic growth is between 6.9–7.5 %. Similarly, [Liu et al. \(2018\)](#) showed that when the level of human capital structure is upgraded by 1 %, the economic growth rate increases by 0.16–0.34 %. In contrast to these results, our empirical results show a much smaller increase in economic growth rate in response to a rise in human capital quality. In our estimation, when the quality level of human capital increases by 1 %, the economic growth rate increases by only 0.18–0.20 %. Our consideration of a comprehensive measure of human capital indicates that simple measures such as years of schooling may overestimate human capital's effect on economic growth.

Human capital is heterogeneous, and different types of human capital may have different effects on economic growth. We now report results when cognitive and non-cognitive human capital are considered individually in [Eq. \(12\)](#). [Table 7](#) reports the impact of individual human capital types on economic growth. There is no second-order autocorrelation in the model as the p -value for AR(2) is not significant. AR (1) p -value shows significance. Hansen's test also indicates that the selected instrument variables are valid. The tests indicate that the system GMM model is effective and consistent for estimation.

Columns (1) and (2) in [Table 7](#) are the estimation result of one-step system GMM, while Columns (3) and (4) report results for a two-step system GMM. It is clear from the table that non-cognitive human capital productivity coefficients are positive and significant at 1 % levels in all four columns. The cognitive human capital productivity coefficient is positive in all four columns but significant only

Table 4
Summary statistics.

Variable	Description	Observations	Mean	Std.	Min.	Max.
y_{it}	Per capita GDP	310	43,954.07	23,689.87	8824.00	128,994.10
HCQI	Human capital quality index	310	0.906	0.252	0.574	3.095
h_c	Cognitive human capital productivity	310	0.879	0.066	0.563	1.000
h_n	Non-cognitive human capital productivity	310	0.860	1.110	0.039	9.864
$Invest_{it}$	Investment rate	310	0.614	0.192	0.320	1.483
$Labor_{it}$	Employment rate	310	0.579	0.064	0.403	0.766
$Open_{it}$	Economic openness	310	0.288	0.344	0.017	1.800
$Tech_{it}$	Technical innovation level	310	3.497	5.514	0.009	33.265

Table 5
The impact of China's human capital quality on economic growth: one-step system GMM estimates.

Explanatory variables	Explained variable: $\ln(y_{it}) - \ln(y_{it-1})$				
	One-step system GMM				
	(1)	(2)	(3)	(4)	(5)
$\ln(y_{it-1})$	-0.0710*** [- 5.71]	-0.0761*** [- 5.85]	-0.0756*** [- 5.21]	-0.0966*** [- 7.43]	-0.0963*** [- 5.96]
$\ln(\text{HCQI})$	0.2157*** [3.71]	0.1990*** [3.51]	0.2247*** [3.63]	0.1907*** [3.48]	0.1908*** [3.51]
$\ln(\text{Invest}_{it})$		-0.0173 [- 0.94]	-0.0123 [- 0.64]	0.0136 [0.62]	0.0131 [0.38]
$\ln(\text{Labor}_{it})$			0.0625 [1.12]	0.0494 [1.12]	0.0499 [1.11]
$\ln(\text{Open}_{it})$				0.0206*** [2.65]	0.0205** [2.42]
$\ln(\text{Tech}_{it})$					-0.0002 [- 0.03]
Constant	0.8811*** [6.79]	0.9232*** [6.97]	0.9586*** [6.24]	1.2177*** [8.22]	1.2148*** [6.48]
AR(1) test value	-2.0585	-2.0507	-2.0277	-2.0317	-2.0709
p-value	0.040	0.040	0.043	0.042	0.038
AR(2) test value	0.9066	0.8141	0.7756	1.371	1.3605
p-value	0.365	0.416	0.438	0.170	0.174
Hansen test value	30.11	30.04	29.61	30.29	30.29
p-value	0.995	0.994	0.993	0.911	0.984
N	248	248	248	248	248

Notes: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are t-statistics.

in the two-step GMM. When the non-cognitive human capital productivity increases by 1 %, the per capita output growth rate increases by 0.04–0.05 %. The cognitive human capital productivity coefficient increases from 0.05 % to 0.09 % when control variables are included. See Columns (3) and (4). In general, our results indicate that both cognitive and non-cognitive human capital productivity promote economic growth. Considering the coefficients, cognitive human capital has a higher effect on economic growth in terms of magnitude.

The impact of human capital on economic growth depends on the productivity of cognitive and non-cognitive human capital. Various provinces and cities in China could grow based on their cognitive and non-cognitive productivity levels. Economic openness and technological innovation coefficients are positive and significant in Column (4). Like Table 6, a negative and significant coefficient of the AR(1) variable in Table 7 indicates economic growth convergence.

Industrial focus, government intervention, and economic development levels differ between regions within China. The impact of explanatory and control variables may vary between the provinces. Moreover, any government policy recommendation must be based on the regional analysis. Therefore, the national sample is subdivided into three major regions to examine the impact of human capital quality on regional economic growth. In 1986 the Seventh Five-Year Plan, adopted at the Fourth Session of the Sixth National People's Congress, divided China into three regions, i.e., 11 provinces and cities in the eastern region, ten provinces and regions in the central region, and nine provinces and regions in the western region. In 1997, the Fifth session of the Eighth National People's Congress established that Chongqing is set as a municipality directly under the central government and classified it under the western region. In 2000, the central government formulated the strategy for developing the western region and added Inner Mongolia and Guangxi to the western region. Our classification of cities and provinces into regions follows the classification used by the National People's Congress.

Table 8 reports the impact of human capital quality on economic growth in China's eastern, central, and western regions. The estimation results listed in Columns (1), (3), and (5) show the degree of impact of human capital quality on the per capita output growth rate in different regions. Columns (2), (4), and (6) report the impact of the combination of human capital, labor force, and technological innovation on economic growth in the three regions. Improving human capital quality in the eastern and central regions promotes economic growth significantly. The effect of human capital in the central region is stronger than that in the eastern and

Table 6

The impact of China's human capital quality on economic growth: two-steps system GMM estimates.

Explanatory variables	Explained variable: $\ln(y_{it}) - \ln(y_{it-1})$				
	Two-step system GMM				
	(1)	(2)	(3)	(4)	(5)
$\ln(y_{it-1})$	-0.0697*** [- 12.04]	-0.0780*** [- 13.82]	-0.0764*** [- 11.22]	-0.0966*** [- 12.50]	-0.0970*** [- 11.33]
$\ln(\text{HCQI})$	0.1995*** [11.11]	0.1812*** [9.38]	0.1973*** [7.94]	0.1774*** [6.47]	0.1761*** [6.17]
$\ln(\text{Invest}_{it})$		-0.0189*** [- 5.15]	-0.0148*** [- 3.90]	0.0089 [1.05]	0.0089 [0.99]
$\ln(\text{Labor}_{it})$			0.0496*** [2.67]	0.0464** [2.38]	0.0466** [2.39]
$\ln(\text{Open}_{it})$				0.0190*** [5.49]	0.0192*** [5.20]
$\ln(\text{Tech}_{it})$					0.0002 [0.11]
Constant	0.8649*** [14.16]	0.9403*** [16.58]	0.9534*** [12.89]	1.2091*** [14.64]	1.2138*** [13.19]
AR(1) test value	-2.0678	-2.0945	-2.077	-2.0481	-2.046
p-value	0.001	0.001	0.001	0.002	0.002
AR(2) test value	1.0566	0.9316	0.9428	1.4029	1.408
p-value	0.091	0.127	0.095	0.049	0.049
Hansen test value	30.1083	30.0429	29.61	30.3218	30.2883
p-value	0.994	0.994	0.993	0.988	0.985

Notes: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are t-statistics.

Table 7

The impact of different types of human capital on economic growth in China: system GMM estimates.

Explanatory variables	Explained variable: $\ln(y_{it}) - \ln(y_{it-1})$			
	One-step system GMM		Two-step system GMM	
	(1)	(2)	(3)	(4)
$\ln(y_{it-1})$	-0.0722*** [- 7.11]	-0.0993*** [- 5.99]	-0.0742*** [- 14.68]	-0.0992*** [- 12.93]
$\ln h_c$	0.0569 [0.78]	0.1007 [0.65]	0.0507** [2.20]	0.0917* [1.66]
$\ln h_n$	0.0455*** [7.36]	0.0400*** [6.29]	0.0444*** [20.17]	0.0395*** [15.12]
$\ln(\text{Invest}_{it})$		0.0112 [0.36]		0.0083 [0.70]
$\ln(\text{Labor}_{it})$		-0.0178 [- 0.30]		-0.0252 [- 1.06]
$\ln(\text{Open}_{it})$		0.0151** [1.96]		0.0150*** [5.37]
$\ln(\text{Tech}_{it})$		0.0046 [0.66]		0.0043** [1.97]
Constant	0.8923*** [8.31]	1.1878*** [6.93]	0.9130*** [17.92]	1.1790*** [15.15]
AR(1) test value	-2.1359	-2.1884	-2.2466	-2.2904
p-value	0.031	0.036	0.029	0.035
AR(2) test value	1.3627	1.7875	1.4922	1.8388
p-value	0.275	0.249	0.237	0.184
Hansen test value	30.3694	30.4474	30.3694	30.4474
p-value	0.993	0.978	0.993	0.978
N	248	248	248	248

Notes: *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are t-statistics.

western regions. For every 1 % increase in human capital quality, the central region's per capita output growth rate is 0.048 %. Our results indicate the significance of HCQI in the different regions, and the results support the positive influence of HCQI on the per capita output.

Analysis of control variables indicates that, in general, improvement in the investment rate, employment rate, and technical innovation level can significantly promote economic development in all three regions. In contrast, the degree of economic openness significantly contributes to the per capita growth in eastern and central regions only. The coefficient for economic openness is not significant for the western region. This indicates that the eastern region with a relatively high economic development level, a higher degree of openness to the outside world, and better material accumulation infrastructure creates a favorable external environment for

Table 8

The impact of human capital quality on economic growth in the eastern, central, and western regions: a comprehensive FGLS estimate.

Explanatory variables	Explained variable: $\ln(y_{it}) - \ln(y_{it-1})$					
	Eastern region			Central region		Western region
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(y_{it-1})$	-0.0650*** [- 6.73]	-0.0650*** [- 6.73]	-0.0767*** [- 4.59]	-0.0767*** [- 4.59]	-0.0930*** [- 8.71]	-0.0930*** [- 8.71]
$\ln(\text{HCQI})$	0.0173** [2.56]	-0.0447*** [- 4.11]	0.0484*** [9.81]	0.0167 [1.27]	0.0387*** [3.32]	0.0462** [2.35]
$\ln(\text{HCQI} * \text{Labor})$		0.0553*** [4.51]		0.0335** [1.98]		-0.0891*** [- 4.11]
$\ln(\text{HCQI} * \text{Tech})$		0.0066*** [8.02]		-0.0018 [- 0.87]		0.0042*** [2.80]
$\ln(\text{Invest}_{it})$	0.0966*** [7.00]	0.0966*** [7.00]	-0.0405*** [- 6.38]	-0.0405*** [- 6.38]	0.0188** [2.50]	0.0188** [2.50]
$\ln(\text{Open}_{it})$	0.0375*** [7.61]	0.0375*** [7.61]	0.0363*** [12.07]	0.0363*** [12.07]	0.0048 [1.10]	0.0048 [1.10]
Constant	0.9177*** [8.11]	0.9177*** [8.11]	0.9859*** [5.86]	0.9859*** [5.86]	1.0307*** [9.61]	1.0307*** [9.61]
Wald χ^2	149.74	149.74	2996.15	2996.15	72.19	81.78
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	99	99	72	72	108	108

Notes: (1) *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively; the values in parentheses are t-statistics. (2) The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, and Inner Mongolia.

the exertion of human capital effect. Of all the control variables, the investment rate plays the strongest role in driving the eastern region's per capita output. Moreover, both the employment rate and the degree of economic openness have a stronger impact than HCQI on economic growth. In the central region, the effect of human capital is stronger than that of all other influencing factors. Factors such as increasing investment rate and technological improvement can significantly promote economic growth in the western region.

Cognitive human capital significantly impacts the eastern and western regions' per capita output growth rate. In the western region, where the coefficient of cognitive human capital is highest when the productivity of cognitive human capital increases by 1 %, the economic growth rate increases by 0.1266 %. In contrast, the cognitive human capital coefficient is not significant in the central region. The non-cognitive human capital coefficient is significant only in the central region. As non-cognitive human capital productivity increases by 1 %, the central region's per capita output growth rate increases by 0.0153 %.

The coefficients in the order of most to least impactful on per capita output in the eastern region are coefficient of investment, cognitive human capital, employment rate, degree of economic openness, and technical innovation level. For the central region, an increase in the employment rate affect economic growth the greatest, followed by expanding openness and cognitive and non-cognitive human capital. Cognitive human capital is the most critical factor affecting economic growth for the western region, followed by an increased investment rate. Identification of factors that impact per capita growth could be helpful for government policymakers.

Despite controlling for various economic variables, our general results on the impact of cognitive and non-cognitive human capital hold for all three regions in China. The difference in the magnitude and significance levels of variables in Table 8 could be attributed to the regions' widely different industrial, economic, and social constructs. After over a decade of rapid economic growth, China has an uneven spatial distribution of industries with imbalanced regional development. There are significant differences in the economic development levels in the eastern, central, and western regions. The eastern region is the most economically developed. The region accounts for over 65 % of the national GDP. Besides a strong modern manufacturing base, a disproportionate number of multinational companies are headquartered in the region. In general, the region is an economic powerhouse and drives most of its research and development activities. These factors could explain the high impact and significance of coefficients of investment rate and cognitive human capital.

The central region connects east to west and north to south. The main industrial activities include transportation (about a quarter of the country's railways, highways, and rivers are in this area) and farming. These activities are labor-intensive. These factors help understand the importance of the employment rate on the per capita growth rate. Note that the employment rate coefficient has the most impact on the per capita growth in the region. The region also covers a large amount of rural population. Lack of access to natural resources and rural poverty issues have hampered the region's economic development. This provides a rationale for the lack of significance of the central region's cognitive human capital coefficient. See Table 8.

The western region lacks the industrial and economic advantages of eastern or central regions. Besides relatively smaller industrial infrastructure, tourism and farming are prominent industries. China's "tilt to the West region" policy has helped develop infrastructure. The policy has improved the regional economy and living standards. Of the three regions, students in the western region spend the least number of years in school. Every year, many college graduates volunteer for employment in the western region, explaining the importance of the significance of cognitive human capital in driving per capita growth. Note that, in Table 8, the coefficient of cognitive human capital has the largest impact on per capita growth in the western region. Similarly, the lack of technologically

advanced industries and general trade in the region could contribute to the insignificant coefficients for technical innovation and trade openness in Table 8.

5.4. Robustness tests³

5.4.1. Additional control variables

Results presented in earlier sections considered investment rate, employment rate, economic openness, and technical innovations as the control variables. To test the robustness of the results, we conducted regression with additional relevant control variables. Additional control variables considered are urbanization level, population growth rate, infrastructure, and government expenditure scale. In the updated model estimation results, the coefficient of $\ln(y_{it-1})$ remains negative and significant, which proves the conditional convergence of economic growth in different provinces in China. Moreover, the coefficient of HCQI remains positive and significant. The sign and significance of the coefficient of the core HCQI remain unchanged regardless of the estimation results from the one-step system GMM or two-step system GMM. This ascertains the robustness of our empirical findings.

5.4.2. Endogenous and exogenous variables

In the empirical regression model, we consider $\ln(y_{it-1})$ and $\ln(HCQI)$ as endogenous variables, while investment rate, employment rate, economic openness, and technical innovation level are exogenous variables. The first-order lag $\ln(y_{it-1})$ and second-order control variables in GMM are considered instrument variables. In contrast to our approach, Liu et al. (2018) considered the investment rate and other control variables as endogenous. To test the robustness of our results, we performed regression estimation using investment rate, employment rate, and economic openness as endogenous variables, which in turn reduced the number of instrument variables. With these changes, the two-step system GMM estimation results remain the same. The coefficient of the HCQI remains positive and significant. No significant difference in results is observed using the Liu et al. (2018) approach. Therefore, our results remain robust with different choices of endogenous and exogenous variables.

5.4.3. Different estimation methods

The benchmark model uses a one-step and two-step system GMM for estimation methods. To test the robustness of the methods, we use comprehensive FGLS to estimate the national samples. The regression results remain consistent with the conclusions of the benchmark model. The improvement of human capital quality significantly promotes an increase in per capita output growth rate, and the economic growth rate in different provinces in China tends to converge. The coefficient of HCQI estimated by comprehensive FGLS is smaller in magnitude than that of the benchmark regression model but remains significant at the 1 % confidence level. The significance of the control variables varies slightly. In summary, our main results are valid regardless of the regression methodology used.

5.4.4. Endogeneity and Instrument

Our model predicts that cross-regional migration may affect the total quantities of cognitive and non-cognitive labor in different provinces and cities in China. Meanwhile, the difference in economic development levels in different regions may cause the inter-regional mobility of the labor force. This correlation would tend to generate bias in the GMM estimation. To avoid such endogeneity, we constructed additional exogenous Instrumental Variables. Specifically, for each province k , $HCQI_k^*$ is the inverse distance weighted average of human capital quality index other than k . The instrumental variable method is implemented by the Two-Stage Least Square (2SLS) method. The estimation result of the two-stage least square method is consistent with our main result.

6. Conclusions and policy implications

China's economic development has progressed to a high-quality development mode. In this development mode, innovations supported by human talent drive the economy. The new development mode requires strategic and innovative allocation of resources to attract and develop talent, promote and upgrade industrial structure, and create novel impetus for economic growth. Using data from 31 provinces and cities in China, we study the relationship between human capital and economic growth.

Researchers have used years of schooling to measure the human capital in a region or country. However, human capital covers both cognitive and non-cognitive components. Years of schooling only measures the cognitive human capital. We provide a more realistic measure of human capital (HCQI) that uses weighted power mean of cognitive and non-cognitive productivities. We show that years of schooling do not necessarily lead to an increase in the total output. Moreover, disproportionately high investment and emphasis on cognitive abilities development (as is the case in China, where the education system overemphasizes test scores) lead to reduce the per capita output. We also find that using cognitive human capital (measures by years of schooling) exclusively may lead to biased results with overestimating human capital's effect on economic growth.

There are significant regional differences in the quality of human capital in 31 provinces and cities in China. Enhancing the cognitive and non-cognitive human capital would the per capita output of all provinces. In China and its regions, cognitive human capital productivity is more influential in affecting the output per capita than non-cognitive human capital productivity. It is the coordinated development of both cognitive and non-cognitive human capital that promotes the future pace of economic development.

³ For brevity detailed results are not provided in the paper. Please contact the authors for details on robustness tests.

The difference in human capital productivity in 31 provinces and cities in China cannot be attributed to the average years of schooling alone. Provinces with higher average years of schooling may not necessarily have higher cognitive human capital productivity because cognitive human capital productivity is the separation of resource inputs and incentives based on cognitive human capital production. The level of HCQI in provinces such as Yunnan, Sichuan, and Hubei is much higher than that measured by average years of schooling. This is because the average years of schooling only reflect the level of cognitive human capital, while the HCQI comprehensively captures the quality of human capital from both cognitive and non-cognitive dimensions. This also shows that the cultivation of non-cognitive human capital is crucial for improving human capital quality in different provinces and cities in China. Moreover, improving non-cognitive human capital could significantly contribute to the increase of per capita output in different regions in China.

Based on the findings in this paper, several policy recommendations could be made. Reforming the education system focused on developing non-cognitive abilities could improve the efficiency and returns from education investment. China's education system is primarily focused on developing and investigating cognitive abilities. While academic achievements reflect students' cognitive abilities, many important non-cognitive abilities are ignored. There is a need to re-examine the country's education system and talent selection methods, establish a more comprehensive education evaluation system, and promote non-cognitive human capital accumulation. Local governments should pay attention to developing personality traits and focus on cultivating cognitive and non-cognitive abilities. At the same time, investment in non-cognitive skills should be rewarded with better non-cognitive occupations. The education reforms should encourage students with leadership, communication, and teamwork skills to choose non-cognitive professions.

CFPS and iFind datasets are only available at the provincial level. This limits the scope of analysis in this study to a provincial-level analysis only. Availability of city-level data could allow for extensions and enrichment of the model and empirical analysis. Such an analysis would be further helpful to policymakers.

The educational policies should not only aim at improving examination results, graduation rates, and average years of schooling but also pay attention to whether the supply of the type of human capital matches the demand of the industrial structure. Such an initiative could help different kinds of human capital meet local, social, and economic development needs, reducing the mismatch and improving human capital allocation efficiency. Specifically, a synergy between education, training, and employment should be emphasized. With the development of science and technology, the economic growth model in the eastern and central regions has changed from labor-intensive to capital- and knowledge-intensive growth. The upgrading of the industrial structure has changed from traditional to modern industries, with priority to developing high value-added technology-intensive sectors. Economic development requires cognitive human capital and non-cognitive human capital, and balanced development can promote total output growth in different provinces in China.

Declaration of Interest Statement

All authors declare that No conflict of interest exists.

Data Availability

Data will be made available on request.

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References

- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277–297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29–51.
- Barro, R. J., & Sala-i-Martin, X. (1992). Public finance in models of economic growth. *The Review of Economic Studies*, 59(4), 645–661.
- Barro, R. J., & Lee, J. W. (1993). International comparisons of educational attainment. *Journal of Monetary Economics*, 32(3), 363–394.
- Barro, R. J., Sala-i-Martin, X., Blanchard, O. J., & Hall, R. E. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, 107–182.
- Barro, R. J. & Lee, J. W. (2010). A new data set of educational attainment in the world, 1950–2010. *NBER Working Paper 15902*.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143.
- Bond, S., Bowsher, C., & Windmeijer, F. (2001). Criterion-based inference for GMM in autoregressive panel data models. *Economics Letters*, 73(3), 379–388.
- Bowles, Samuel, Gintis, H., & Osborne, M. (2001). The determinants of earnings: A behavioral approach. *Journal of Economic Literature*, 39(4), 1137–1176.
- Burstein, A., Morales, E., & Vogel, J. (2019). Changes in between-group inequality: computers, occupations, and international trade. *American Economic Journal: Macroeconomics*, 11(2), 348–400.
- Cai, F., & Du, Y. (2000). Convergence and divergence of regional economic growth in China. *Economic Research Journal*, 10, 30–37+80.
- Caspi, A., Roberts, B. W., & Shiner, R. L. (2005). Personality development: Stability and change. *Annual Review of Psychology*, 56, 453–484.
- Cawley, J., Heckman, J., & Vytlačil, E. (2001). Three observations on wages and measured cognitive ability. *Labour economics*, 8(4), 419–442.
- Chen, Z., Lu, M., & Jin, Y. (2004). Regional differences in China's human capital and education development: Estimation of panel data. *World Economy*, 27(12), 7.
- Cheng, H., & Li, T. (2017). The Effects of Personality Traits on Wages: Empirical Analyses Based on the China Employer-Employee Survey (CEES). *Economic Research Journal*, 52(2), 171–186.
- Costa, P. T., Jr, & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and individual differences*, 13(6), 653–665.

- Cubas, G., Ravikumar, B., & Ventura, G. (2016). Talent, labor quality, and economic development. *Review of Economic Dynamics*, 21, 160–181.
- Cunha, F., Heckman, J. J., & Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3), 883–931.
- Davis, D. R., & Weinstein, D. E. (2001). An account of global factor trade. *American Economic Review*, 91(5), 1423–1453.
- Dekle, R., Eaton, J., & Kortum, S. (2008). Global rebalancing with gravity: Measuring the burden of adjustment. *IMF Staff Papers*, 55(3), 511–540.
- Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4), 1593–1640.
- Erosa, A., Koreshkova, T., & Restuccia, D. (2010). How important is human capital? A quantitative theory assessment of world income inequality. *The Review of Economic Studies*, 77(4), 1421–1449.
- Gu, S. Z. (2019). High-quality development requires the vitality of innovation to burst out. *Economic Research Journal*, 54(10), 4–23.
- Heckman, J. J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review*, 91(2), 145–149.
- Heckman, J. J., & Kautz, T. (2012). Hard evidence on soft skills. *Labor Economics*, 19(4), 451–464.
- Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3), 411–482.
- Heckman, J., & Carneiro, P. (2003). Human capital policy. *NBER Working Paper* 9495.
- Heineck, G., & Anger, S. (2010). The returns to cognitive abilities and personality traits in Germany. *Labour economics*, 17(3), 535–546.
- Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371–1395.
- Hsieh, C. T., Hurst, E., Jones, C. I., & Klenow, P. J. (2019). The allocation of talent and us economic growth. *Econometrica*, 87(5), 1439–1474.
- Huang, G. Y., & Xie, Y. (2017). Effects of cognitive ability and non-cognitive ability on the return of youth labor income. *China Youth Research*, 252(2), 56–64+97.
- Huang, Y. P., Liu, Y., Wu, Y. Q., & Li, W. P. (2013). Differential economic growth in China: Effects based on graded education. *Economic Research Journal*, 48(4), 94–105.
- Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, 104(6), 1597–1629.
- Jones, B. F. (2014). The human capital stock: a generalized approach. *American Economic Review*, 104(11), 3752–3777.
- Jorgenson, D. W., & Fraumeni, B. M. (1989). The Accumulation of Human and Nonhuman Capital, 1948-1984/RE Lipsey. In *The Measurement of Savings, Investment and Wealth*. HS Tice.
- Jorgenson, D. W., & Fraumeni, B. M. (1992). Investment in education and U.S. economic growth. *Scandinavian Journal of Economics*, 94, 51–70.
- Kendrick, John W. (1976). *The formation and stocks of total capital*. New York: Columbia University Press.
- Kuhn, P., & Weinberger, C. (2005). Leadership skills and wages. *Journal of Labor Economics*, 23(3), 395–436.
- Le, J. J., & Hu, B. W. (2017). The effect of non-cognitive ability on workers' wages and income. *China Population Science*, 181(4), 66–76+127.
- Lee, E. (2020). Trade, inequality, and the endogenous sorting of heterogeneous workers. *Journal of International Economics*, 125, Article 103310.
- Li, H. Z., Jia, N., Zhang, X. B., & Barbara, F. (2013). Regional distribution and development trends of human capital in China. *Economic Research Journal*, 48(7), 49–62.
- Li, H. Z., Liang, Y. L., Barbara, F., Liu, Z. Q., & Wang, X. J. (2010). Measurement and Index construction of human capital in China. *Economic Research Journal*, 45(8), 42–54.
- Li, X. M., & Zeng, X. Q. (2012). New human capital theory-research development of human capital theory based on capability. *Economic Perspectives*, (11), 120–126.
- Lin, Y. F., & Liu, M. X. (2003). China's economic growth convergence and income distribution. *The Journal of World Economy*, (8), 3–14+80.
- Liu, Z. Y., Li, H. Z., Hu, Y. J., & Li, C. H. (2018). Advanced human capital structure and economic growth-concurrently discussing the formation and reduction of the gap in the eastern, central and western regions. *Economic Research Journal*, 53(3), 50–63.
- Malmberg, Hannes. (2017). *Human capital and development accounting revisited*. mimeo. Institute for International Economic Studies.
- Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2), 407–437.
- Manuelli, R. E., & Seshadri, A. (2014). Human capital and the wealth of nations. *American Economic Review*, 104(9), 2736–2762.
- Qian, X. Y., & Liu, J. (2004). An empirical study on human capital level in China. *Statistical Research*, 3, 39–45.
- Schultz, T. W. (1960). Capital formation by education. *Journal of Political Economy*, 68(6), 571–583.
- Wang, C. C., & Zhang, C. S. (2019). Non-cognitive ability and wage income. *The Journal of World Economy*, 42(3), 143–167.
- Wang, D. H., Gong, L. T., & Li, H. Y. (2008). Health human capital, health investment and economic growth: A case study of cross-provincial data in China. *Management World*, 174(3), 27–39.
- Wang, Q. L. (2015). Skill formation, human capital and economic growth. *Labor Economic Review*, 8(1), 54–71.
- Wei, Q., Wang, A., & Wang, J. (2014). The rise of China's coastal areas: The power of the market. *Economic Research Journal*, 49(8), 170–183.
- Xiang, C., & Yeaple, S. (2018). The production of cognitive and non-cognitive human capital in the global economy. *NBER Working Paper* 24524.
- Yao, X. G., & Zhang, H. F. (2008). Education, human capital and regional economic differences. *Economic Research Journal*, 481(5), 47–57.
- Zhang, F. (2000). Estimation of China's physical capital and human capital. *Economic Research Journal*, (8), 65–71.
- Zhang, S., & Zhu, Y. (2018). New progress in research on optimal intergenerational human capital investment. *Economic Perspectives*, 687(5), 117–128.
- Zhou, J. K., Wang, G. D., & Huang, Z. X. (2019). Does productivity improvement affect rural human capital accumulation?—Research based on micro data. *Economic Research Journal*, 54(1), 100–115.
- Zhou, J. Y. (2015). Expansion of the connotation of human capital: Economic value and investment of non-cognitive ability. *Peking University Education Review*, 13(1), 78–95–189–190.