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Xiaobei Zhang
Zhejiang University of Finance and Economics

Haizheng Li
Georgia Institute of Technology and IZA

Xiaojun Wang
University of Hawaii

Belton M. Fleisher
Ohio State University and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Human Capital and the Economic Convergence Mechanism: Evidence from China*

We examine the mechanism by which human capital affects economic growth and convergence, using provincial level panel data from China. We specify alternative measures of human capital and apply them to an enhanced growth model which we estimate parametrically, nonparametrically, and with a threshold model. Our results show that economic convergence is pronouncedly conditional on human capital across all our measures of human capital. The positive "benefit of being backward" due to lower initial income is almost trumped by the negative impact of low levels of human capital among the poorest areas.

JEL Classification: R11, O47, C33

Keywords: human capital, economic convergence, regional economic development

Corresponding author:
Belton M. Fleisher
Department of Economics
The Ohio State University
1945 North High Street
Columbus, OH 43210
USA

E-mail: fleisher.1@osu.edu

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I. Introduction

We show that by recognizing the separate impacts of human capital on both convergence from low initial levels of GDP and on the GDP growth rate as well as how the measured effects of human capital varies over alternative measures we can reconcile unresolved inconsistencies in the growth literature. The effects of human capital on growth and convergence are more complex than originally recognized, for example, in the pioneering paper of Mankiw *et al.* (1992).

China's rapid economic progress over the past four decades provides a rare opportunity to explore these insights into the growth mechanism, and we believe that the results of our investigation have important policy implications for other developing countries as well as for China. China's extraordinary rate of progress has been accompanied by equally dramatic increases in income inequality, and regional income gaps in China are greater than in most countries of the world.[1] In 2014, the richest provinces/municipalities, such as Jiangsu and Tianjin, reached levels of GDP per worker that were about three times of those in the poorest provinces such as Gansu and Yunnan. This divergence is also apparent at the regional level, with the coastal region enjoying both a higher level and a stronger rate of growth of GDP per worker, and the west region falling farther behind (Meng *et al.*, 2005; Fleisher *et al.*, 2011).[2]

To achieve our goals, we construct education-based human capital measures and in addition apply an income-based comprehensive human capital measure to the Chinese growth patterns. We then use these measures to explain how human capital has affected regional economic growth and inequality in China. To accomplish our goal, we follow the theoretical work of Nelson and Phelps (1966) and complement and extend the empirical results reported by Benhabib and Spiegel (1994).

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[1] See, for example studies reported in Fleisher, Li, and Zhao (2010).

[2] Following the China Statistical Yearbook, we divide China into four regions: coastal (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan), northeast (Liaoning, Jilin, Heilongjiang), interior (Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan), and west (Inner Mongolia, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Sichuan and Chongqing). We combine Guangdong and Hainan, Sichuan and Chongqing to be consistent for all sample years, and we drop Tibet due to lack of data. The total sample thus consists of 28 provinces.

An advantage of our provincial-regional approach is that estimation results are less likely than cross-country data to be confounded by unobserved differences in unmeasured human capital quality and by unobserved heterogeneity in institutions across observations (e.g. Benhabib and Spiegel, 1994; Gennaioli *et al.,* 2013). We test robustness of empirical results by applying three human capital measures: (i) proportion of workers graduated from high school or above, (ii) average years of education for the workforce; and (iii) human capital stock per worker constructed using the Jorgenson-Fraumeni (J-F) framework. The J-F approach not only accommodates heterogeneous labor but incorporates many aspects of human capital accumulation that are not reflected in formal education alone.

Our estimation results reveal regional convergence only after we control for the impact of initial levels of human capital. The net human-capital impact depends on the relative magnitudes of its direct effect on growth and its indirect effect on the speed of convergence from initially low income levels. We find a strong positive effect of initial human capital on subsequent growth, which is consistent with human capital theory and the empirical evidence reported in former literature, for example, Nelson and Phelps (1966), Benhabib and Spiegel (1994), and Gennaioli *et al.* (2013). But only when measured by average years of education does the effect of human capital take the simple functional form specified in the canonical neoclassical convergence model. Both the operating channels and mechanism of human capital's effect on growth are much more complicated when the measure of human capital goes beyond mean schooling years. Recognizing this complexity is the key to resolving important puzzles that hinder our understanding of the growth process. We find that average education has the strongest effect on convergence in the early stage of development, while high-skilled human capital has the largest effect in more advanced stages. One example of the complicated impacts of human capital on growth is revealed in that the ability of low-income regions to catch up with their high-income counterparts is highly dependent on variation in their human capital as measured under the J-F framework but varies only slightly with differences in their high-skilled human capital endowments. We also find strong evidence that the mechanism of human capital's impact on growth changes across different human-capital threshold levels. .

The rest of the paper is organized as follows. Section II briefly reviews relevant literature. Section III introduces the human capital measures and describes our data. Section IV lays out the traditional convergence model and shows how its implications vary across our measures of human capital. Section V discusses the human capital threshold effect on convergence speed; Section VI presents semiparametric results showing the impact of various human capital measures on growth and convergence. The final section summarizes our results and offers policy recommendations.

II. The Role of Human Capital and The Impact of Human Capital Measurement

In its simplest form, neoclassical economic growth theory assumes diminishing marginal returns to capital (Solow, 1956), implying that poor countries will grow faster than rich ones, that capital will flow from rich countries to poor countries, and per-capita incomes will converge to the same level (Barro, 1991). However, income inequality among nations persists; and there is little evidence of absolute convergence. Richer implications follow from development of endogenous growth theory grounded in the work of Arrow (1962) and augmented with the introduction of the critical role of human capital by second generation growth theory pioneers, of which a partial list includes Lucas (1988), Prescott (1998), and Mankiw, Romer and Weil (1992).

The importance of human capital to economic growth is understated in earlier literature (Lucas, 2015). Although the theoretical and empirical importance of human capital for economic growth is now widely accepted (Barro, 1991; Barro and Sala-i-Martin, 1992; Mankiw, Romer and Weil, 1992), others have not (Bils and Klenow, 2000; Pritchett, 2001), its role in determining the relative speed at which poor nations converge to the level of their richer counterparts is not entirely understood (Krueger and Lindahl, 2001). Adding to the mix, Azariadis and Drazen (1990) find that human capital is a necessary but not a sufficient condition for economic growth, because countries that grow fast tend to have high human capital, while some countries with high human capital don't grow as fast as might be expected. Benhabib and Spiegel

(1994) show that changes in the stock of human capital have no impact on GDP per capita growth rate, while the average level of human capital does. They attribute human capital's impact on technology (i.e. TFP) to an endogenous growth component along with a catch-up component.

Complicating our understanding of the role of human capital in growth is that earlier literature reveals little consensus on the appropriate measure of human capital. Obviously, controversy over the appropriate modeling of the role of human capital in the growth process cannot be resolved without agreement on its measure. Alternative human capital measures have led to different or even conflicting results (Krueger and Lindahl, 2001; Pritchett, 2001). Hanushek and Woessmann (2012) argue that simple measures of school attainment overstate human capital (i.e. skill acquired) in Latin American countries and that this error explains why these countries have suffered poor growth despite high initial levels of schooling. Hanushek (2013) further emphasizes the importance of the measurement issue. While many earlier studies settle on school-enrollment rates by schooling level or literacy rates as acceptable proxies for human capital, other researchers proxy human capital with average years of education, and some use more complexly constructed indicators (Barro and Lee, 1993; Klenow and Rodriguez-Clare, 1997).

The human-capital indicators listed above measure only the formal schooling components of human-capital formation and thus reflect the quality of investments in human capital poorly. Moreover, informal investments in human capital such as early-life investments are particularly critical as demonstrated by Heckman (2006) and numerous references cited therein. Additionally, post-schooling human capital accumulation via on-the-job learning and other aspects of human capital, including health and abilities (both cognitive and non-cognitive), are likely to affect the impact of human capital on economic growth. In addition, Gennaioli *et al*. (2013) emphasize the importance of entrepreneurial human capital, and point out that focusing on worker education alone substantially underestimates both private and social returns to human capital.

As recent studies have explored alternative solutions to measuring human capital, the performance of human capital in empirical models has improved significantly. Jones (2014) implements a generalized human capital accounting method and points out that assuming perfect substitution among different skill levels of human capital understates differences in human capital across countries and is an important contributor to underestimation of impact of human capital on growth. Manuelli and Seshadri (2014) model human capital acquisition as a standard income maximization problem, allowing the quality of human capital to vary across countries. They find that human capital plays a central role in determining nations' real GDP per worker.

The earlier literature specifying the human capital mechanism embodied in model specification typically assumes a simple (log-) linear relationship between output growth and human capital over time and across regions, whereas recent studies point to a more complex process. Durlauf and Johnson (1995) adopt a regression tree methodology and find that a linear human-capital growth relationship is rejected. Kalaitzidakis *et al.* (2001) find evidence supporting nonlinearity between human capital and economic growth, and Ketteni and Mamuneas (2007) provide further evidence supporting a semiparametric model with more flexible specifications on human capital.[3]

An important contributor to the diversity of research outcomes on the effect of human capital is that for developed countries the major source of growth is technological progress, which depends on highly-educated labor; while developing countries rely on technology spillover from developed countries instead of original innovation. Thus, highly-educated labor contributes less to the economic growth of developing countries than to those at the technology frontier. Another factor confounding research outcomes is diversity in the ways human capital externalities' influence economic growth are accounted for (Gennaioli *et al.*, 2013; Glaeser and Lu, 2018)

III. Human Capital Measures and Data

[3] In Ketteni and Mamuneas (2007), information and communication technology, initial income, and human capital also enter the specification nonlinearly.

The diverse specifications of human capital's role in economic growth as well as of its measurement are critical complications to identifying its role in the economic growth process. We construct three measures of human capital, two of which are education-based, and the other one is a new-to-the-growth literature, i.e., comprehensive measurement based on the Jorgenson-Fraumeni (J-F) lifetime income approach.

We use various data sources to calculate two provincial level of human capital based on schooling alone that are commonly used in the literature. They are (i) average years of schooling (AEDU) and (ii) the proportion of the workforce that has completed high-school education or above (HSCH) for 1985-2014.[4]

Our third measure is based on the Jorgenson Fraumeni (J-F) lifetime income-based approach (Jorgenson and Fraumeni, 1992a, 1992b), which is also calculated at the provincial level. The J-F method is based on the market value of an asset, and in our case this asset is labor. For human capital, this means calculating the present value of expected lifetime income to capture the payoff to all types of human capital investments such as pre-school education, formal education, and on-the-job learning. The J-F framework maintains the neoclassical assumption that wages equal marginal products of labor and uses wage returns to capture the productivity gains from human capital investments (Hall and Jones, 1999; Jones, 2014).

The J-F method has been applied to a number of countries to construct human capital accounts and has been adopted by the OECD. Li *et al.* (2013) and Li *et al.* (2014) apply the J-F method to estimate human capital in China at the national level and for selected provinces. To estimate population human capital, the J-F approach begins with estimating each individual's expected lifetime income and then aggregates over all individuals to obtain total human capital stock H_t, i.e.,

$$H_t = \sum_s \sum_a \sum_e \sum_r mi_{s,a,e,r,t} \cdot l_{s,a,e,r,t} \qquad (1),$$

where the subscript *t* denotes the year and the subscripts *s*, *a*, *e* and *r* denote individual

[4] Our data are collected from various years of the *China Statistical Yearbook*, *China Population and Employment Statistical Yearbook* and other statistical yearbooks.

characteristics of gender, age, educational attainment, and location (urban vs. rural area), respectively. The variable $mi_{s,a,e,r,t}$ is average expected lifetime labor income for an individual with the above characteristics, and $l_{s,a,e,r,t}$ is the population in the specific category.

In the J-F approach, the life cycle is divided into five stages. The fifth (and final) stage is retirement. The preceding four stages, in reverse chronological order, are (i) work-only, (ii) work-school (i.e., an individual may study in school or work), (iii) school-only, and (iv) pre-school. For example, an average individual at the age of 16-26 is in the work-school stage of the lifetime work cycle, so he/she could choose either to be employed or to attend school, and the expected lifetime income for an individual (gender *s*, age *a*, education *e*, at year *t*) $mi_{s,a,e,t}$ would be

$$mi_{s,a,e,t} = ymi_{s,a,e,t} + [senr_{a+1,e+1,t+1} \times sr_{s,a+1,e+1,t+1} \times mi_{s,a+1,e+1,t} + (1 - senr_{a+1,e+1,t+1}) \times sr_{s,a+1,e,t+1} \times mi_{s,a+1,e,t}] \times \frac{1+G}{1+R} \quad (2),$$

where, *ymi* denotes the individual's expected current annual income if working, *sr* stands for the individual's probability of surviving to the next year, and *senr* is the probability that an individual with educational attainment *e* will enroll in education level *e+1*. *G* is a constant, representing the exogenous real income growth rate, and *R* is the discount rate.[5] The real income growth rate *G* reflects overall productivity growth (Jorgenson and Fraumeni 1989, 1992a, 1992b).[6]

Equation (2) specifies the present value of an average individual's lifetime income at age *a* as equal to the discounted expected lifetime income of an average individual at age *a+1* plus his/her income in the current year, where the expectation is based on the projected survival rate and the estimated probabilities of being in the labor market or being enrolled in a higher level of schooling. We use the well-known Mincer model to estimate current year income *ymi* with household survey data from

[5] Because we calculate urban and rural areas separately, the location subscript *r* is suppressed in Equation (2).

[6] G equals the rate of Harrod-neutral technical change.

China.[7] Future income is estimated with a projected exogenous labor income growth rate *G* and then discounted to the present value before summation.[8] Expected income streams for individuals at other stages of the lifetime work cycle are constructed similarly.

Following equation (1), we implement the J-F method and calculate individual lifetime income in a backward recursive fashion. The calculation starts at the retirement age when the lifetime income from the market is zero and moves through the preceding four stages incorporating the probabilities of working and schooling. Individual lifetime income is then multiplied by the population for each subgroup in each gender, age, educational, and location division using decennial census data and quinquennial population sample surveys.[9] We define the result of these calculations as human capital per worker (LFHC), total **l**abor **f**orce **h**uman **c**apital calculated with the J-F approach, divided by the size of labor force.[10]

Our calculations of the J-F based human capital, LFHC, and the two education-based measures AEDU and HSCH are reported for the years 1985-2014 in Table 1 and Figure 1. Unsurprisingly, all three measures of human capital increased significantly over the sample period. The proportion of the labor force with at least a high-school degree (HSCH), which was only 13.04% in 1985, rose to 32.56% by 2014.[11] Average years of schooling (AEDU) increased by 3.61 years, from 6.21 years (barely more than primary school) to 9.82 years (graduated from middle school). Human capital per worker (LFHC) has grown more rapidly than the education-only based measures—over four-fold from 37.6 thousand yuan to 163.4 thousand yuan in constant prices

[7] We used multiple survey data, including UHS (Urban Household Survey), CHIP (Chinese Household Income Project), CHNS (China Health and Nutrition Survey), CHFS (Chinese Household Finance Survey), and CFPS (Chinese Family Panel Studies) for various years to estimate earnings.

[8] R is constant across all provinces and years and is set at 4.58% as used by Jorgenson and Fraumeni (1992a) and the OECD consortium (OECD, 2010). G is constant over years for each province and is set in the range of 4%-8% based on provincial historical growth. The choice of within-province constant values for R and G leaves the cross-province annual difference in human capital growth unaffected.

[9] Additional details specific to China are laid out in Li *et al.* (2013), Li *et al.* (2014) and Li *et al.* (2016).

[10] The labor force in China is defined as those aged 16 or above to the legal retirement age.

[11] China has taken several measures to educate its large population, such as the nine-year compulsory education implemented in 1986, massive college expansions since 1999, etc.

during 1985-2014[12].

The regional disparity of human capital is at least as striking as that of regional income in China (see Figure 1 and 2), even though the regional gap in AEDU decreased over the sample period. In 1985, the coastal region's HSCH was 17.71%, but the interior and west's HSCH were only 10.01% and 9.44%, respectively. By 2014, the coast region's advantage in HSCH over the interior and west regions had grown from 7.7 and 8.27 to 8.86 and 11.60 percentage points respectively. The regional LFHC gap also increased rapidly, with the coast region's LFHC in 2014 reaching 1.77 and 2.39 times that of the interior and west regions, respectively.

IV. Human Capital Measures and Neoclassical Convergence

Following Mankiw, Romer and Weil (1992) (henceforth MRW), we derive our benchmark growth equation

$$Dy_{i,t} = \beta_0 + \beta_1 \ln(s_{i,t}) + \beta_2 \ln(n_{i,t} + g + \delta) + \beta_3 \ln(y_{i,t-\tau}) + \beta_4 h_{i,t-\tau} + \alpha_i + \varepsilon_{i,t} \qquad (3),$$

where (i) Dy is the annual growth rate of GDP per worker, s is the fraction of output invested in physical capital, n is the labor force growth rate, g is the technology growth rate, δ is the rate of depreciation; (ii) subscripts i and t refer to the province and year, respectively, subscript τ denotes the time span of sub-periods (which is four years in our case); (iii) α_i is the provincial fixed effect. The variables $y_{i,t-\tau}$ and $h_{i,t-\tau}$ are initial year GDP per worker and initial human capital per worker in each sub-period, respectively.[13,14]

We divide our sample of 28 provinces into nine sub-periods of four years each following Islam (1995).[15] The dependent variable Dy is defined as the average annual

[12] In order to compare human capital estimates across provinces, we construct a provincial living cost index to adjust earnings. The living cost index construction follows Li *et al.* (2014), which uses the methodology in Brandt and Holz (2006), which we update to 2014.

[13] The MRW model is widely used in the literature (for example, Islam, 1995; Kalaitzidakis *et al.,* 2001). In empirical estimation, human capital enters in log form in some studies, while others use a non-log form (Barro, 1991, 2001).

[14] Essentially, β_4 captures the endogenous growth component while β_3 (as modified in the next section) captures the catch-up component of human capital's impact on growth; See Benhabib and Spiegel 1994.

[15] In theory, the longer the time period, the average growth rate is closer to the steady state growth rate;

growth rate of real GDP per worker in a sub-period. Following MRW, we define the rate of saving s as the average share of physical capital investment in GDP, and n is the average annual growth rate of the labor force. We set the growth rate of total factor productivity g and the depreciation rate δ as constants over time and across provinces, with δ and g equal to 0.05 and 0.04 following Fleisher *et al.* (2010).

Table 1 reports summary statistics for selected years 1985, 1995, 2005, and 2014.[16] Real GDP per worker grew steadily, more than doubling at a steady rate between 1985 and 1995. At the regional level, we see in Figure 2 for 1985 that the west's GDP per worker was 57% of the coast's, falling to around 40% in 1995 and 2005 and rising to 51% in 2014. The ratios between interior/northeast and the coast followed a similar trend, none of the regional gaps showing steady convergence over the sample period.

Table 1 shows that the saving rate s was relatively stable before jumping to over 50% in the last period 2009-14. The rate of labor force growth reflects the impact of the one-child policy, declining steadily, from 2.9% in the first sub-period of 1985-1988 to only 0.2% in the last sub-period. However, sluggish growth in labor-force was swamped by its growing quality as reflected in the increase of all three human capital measures.

We follow Islam (1995) in applying provincial fixed-effects (FE) estimation to control for bias arising from omitted time-invariant variables. Although FE estimation does not mitigate potential bias arising from interprovincial labor migration in response to regional income differentials, we note that Barro *et al*. (1991) reports (page 136), "We find little contemporaneous interplay between net migration and economic growth across U.S. states." Specifically, Barro notes, "… we observe little

however, the number of observations will become smaller. We divide the sample period into nine sub-periods: 1985-1988, 1988-1991, 1991-1994, 1994-1997, 1997-2000, 2000-2003, 2003-2006, 2006-2009, and 2009-2014 to construct panel data. All the sub-periods cover four years except for the last period, which cover 6 years. We also estimated the models with three-year and five-year sub-period, and the results are generally consistent.

[16] GDP deflators are constructed following Fleisher *et al.* (2010) to adjust for price changes across time and purchasing power differences across provinces.

change in the estimated β coefficients when we hold net migration rates constant."

Since we believe that internal migration within the United States is much freer than that in China, we are comfortable in assuming that omitting a measure of internal migration does not lead to major estimation bias. Additionally, in the estimation, initial GDP per worker y_0 is specific to each sub-period in our panel (i.e., each sub-period is treated one time period in the panel data). Thus equation (3) is not a dynamic panel data model and we need not apply dynamic panel estimation techniques such as that developed by Arellano and Bond (1991).

Estimation results based on the MRW model are reported in Table 2. Column (1) reports results for a benchmark model that does not include a measure of human capital, while columns (2)-(5) report estimation results using alternative measures of human capital. The coefficient of the initial income level is insignificant in Column (1), indicating that when no human capital measure is included, there is no evidence of convergence, suggesting bias from omission of human capital. When human capital is included, initial income becomes significantly negative, indicating evidence of conditional convergence, i.e., poor provinces will catch up to rich provinces, holding their saving rate, labor force growth and human capital constant.[17] We see in column (5) that the rate of convergence is highest when all measures of human capital are included.[18]

As hypothesized, the initial level of all human capital measures has positive and statistically significant direct effects on the subsequent growth. This finding is significantly different from studies using cross-country data, which often find an insignificant or even negative impact of human capital on growth (for example, Islam,

[17] Our results represent conditional convergence, i.e., the convergence depends on controlling other variables in the model. Absolute convergence implies that provinces converge to the same steady-state level of per-capita income regardless of their initial conditions.

[18] Barro and Sala-i-martin (1992) report a speed of around 2%, often refer as "iron law of convergence". For convergence within a country, the estimated speed of convergence sometimes is much higher than 2%, for example, in Badinger *et al.* (2004). Based on the results in Table 2, the speed of convergence is the second highest when only AEDU is included (4.03%) and the lowest with LFHC (1.64%), with HSCH (2.92%) in between."

1995).[19] We believe that a likely reason for the dissimilarity of results across studies is the heterogeneity of human capital quality and measurement across countries. This heterogeneity is substantially mitigated when within-country data are used. As can be seen in Table 2 column (5), when all human capital measures are included in our specification, the effect of AEDU and LFHC remain significant, but the estimated coefficient of HSCH becomes insignificant. We conjecture that the reason is that the mechanisms through which human capital affects convergence are largely captured by the combination of AEDU and LFHC.

An attempt to capture the diverse mechanisms of different human capital measures is reported in Table 3, where we compare the impacts of each human capital measure on the growth disparity between the west and coast regions over the period 1985-2014. For example, in Table 2 column (2) we see that a one percentage point increase in initial-year HSCH is associated with a 0.30 percentage point higher subsequent annual growth rate. To establish a perspective on the magnitude of the HSCH impact on growth, we multiply the 1985 gap in HSCH between the coast and west regions (8.27 percentage points as shown in Table 3 column (2)) by 0.30, obtaining a 2.48 percentage point lower growth rate of the west relative to the coast as reported in Table 3 column (4). As shown in the bottom panel of Table 3, this this growth-rate disadvantage of the west had increased to 3.48 percentage points by 2014.

Table 3 column (4) shows the direct effect (β_4 in equation (3)) of the different human capital measures on economic growth. In 1985, the initial year of our sample period, AEDU has the largest impact on the coast-west gap, inducing a 4.45 percentage points lower growth rate for the west, followed by HSCH and then LFHC. The same pattern continued through 2005,[20] but in 2014 HSCH has the largest impact, -3.48 percentage points. We conjecture that the changing relative impacts of the alternative human-capital measures arise from the relative importance of general

[19] Our results are not comparable to Gennaioli *et al.* (2013) because their cross-sectional analysis focuses on *levels* instead of *growth rates*.

[20] The human capital measure used in Benhabib and Spiegel 1994 is similar to AEDU, but they use the logarithm format.

education as reflected in AEDU in the early stages of economic development, when imitation and adoption of new technologies is more important than innovating technology at the frontier. At more advanced stages of development, the relative importance of high skilled human capital measured by HSCH becomes critical (e.g. Gennaioli *et al.,* 2013).

We turn now to the impact of the alternative human-capital measures on the convergence coefficient (β_3 in equation (3)).[21] We see in the first row of Table 2, column (2) that for human capital specification HSCH, a one percent lower level of initial GDP corresponds to 0.028 percentage point higher subsequent rate of growth. This effect of human capital on growth operates in conjunction with the direct discussed above. Returning to our illustration based on the west-coast gap, the 1985 income gap of 55.55% implies that the West had a growth advantage through convergence of 1.56 (55.55*0.028) percentage points. This is shown in Table 3 column (3). By the year 2014, the West-Coast income gap had grown by nearly 12 percentage points, and thus the convergence advantage of the west through lower initial income rose to 1.88 percentage points.

The effects of human capital on convergence specified above correspond respectively to the endogenous growth and catch-up components in Benhabib and Spiegel (1994). Returning to Table 3, we find that for the HSCH measure, the net growth disadvantage of the west is -0.92 percentage points (1.56-2.48) in 1985, expanding to -1.60 percentage points by 2014. For AEDU, the west's total growth disadvantage is -2.34 percentage points in 1985 and -0.54 percentage points in 2014.

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[21] Based on Mankiw et al. (1992) and Islam (1995), the speed of convergence λ is given by $\frac{d\ \ln(y_t)}{dt} = \lambda[\ln(y^*) - \ln(y_t)]$, where $\lambda=(n+g+\delta)(1-\alpha)$, y^* is the steady state level of income per worker, y_t is the actual value at time *t*, α is the elasticity of output with respect to capital. It implies that $\ln(y_t) = (1-e^{-\lambda\tau})\ln(y^*) + e^{-\lambda\tau}\ln(y_{t-\tau})$, which we can transform it to $\ln(y_t) - \ln(y_{t-\tau}) = (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s) - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta) - (1-e^{-\lambda\tau})\ln(y_{t-\tau})$. Since the dependent variable in our model (3) is annual average growth rate, the convergence coefficient $\beta_3 = -(1-e^{-\lambda\tau})/\tau$, then we can get the speed of convergence $\lambda = (-\frac{1}{\tau}\ln(1+\tau\beta_3)*100)\%$, which is very close to β_3. For example, a convergence coefficient of -0.028 corresponds to a speed of convergence, of 2.92%.

In contrast to HSCH, the AEDU measure of human capital measure implies a substantially smaller growth disadvantage for the west after 2005. This contrast is consistent with the preceding discussion that high skilled human capital measured by HSCH becomes increasingly important as the economy reaches a more advanced stage, when technology advance and innovation are the critical engine for growth. Finally we note that for all measures of human capital, the divergence effect between west-coast declined from 1985 to 1995 but increased significantly from 2005 to 2014.

V. The Human Capital Impact on the Convergence Speed

The MRW specification restricts the convergence coefficient to a constant value, i.e., β_3 in equation (3). Our results discussed above and other studies suggest that the impact of human capital on economic growth is more complex than represented in the original MRW model. Since Azariadis and Drazen (1990), there is a growing body of evidence that countries with different initial conditions follow different law of motions to convergence (Bloom *et al.*, 2003; Owen *et al.*, 2009; Cohen-Cole *et al.*, 2012). For example, Durlauf and Johnson (1995) apply regression tree analysis and find that convergence paths were different among countries that had different level of human capital.

We relax the assumption of a constant impact of human capital on the rate of convergence, we modify equation (3) as,

$$Dy_{i,t} = \eta_0 + \eta_1 \ln(s_{i,t}) + \eta_2 \ln(n_{i,t} + g + \delta) + \phi(h_{i,t-\tau}) \ln(y_{i,t-\tau}) + \eta_3 h_{i,t-\tau} + \alpha_i + u_{i,t} \quad (4),$$

where initial human capital influences the speed of convergence via $\phi(h_{i,t-\tau})$.[22] The convergence function $\phi(h_{i,t-\tau})$ follows Hansen (1996, 1999), defining a series of human-capital thresholds at which the speed of convergence changes. The threshold specification assumes that human capital's impact on productivity changes discontinuously when the accumulation of human capital surpasses certain levels

[22] The convergence, or catch-up effect, can also be specified as a function of the gap to the frontier. See Benhabib and Spiegel 1994.

(Durlauf and Johnson, 1995). For example, in the Mincer (1974) model, productivity changes reflected in observed wages can be discontinuous in years of schooling as workers achieve higher academic degrees. Similar thresholds are likely to be present when individuals' human capital accumulation is aggregated into regional human-capital stocks.[23]

We specify our threshold model with thresholds endogenously determined and estimated within the model (Hansen, 1999) as

$$\phi(h_{i,t-\tau})=\phi_1 I(h_{i,t-\tau}\le\gamma_1)+\phi_2 I(\gamma_1<h_{i,t-\tau}\le\gamma_2)+...+\phi_j I(\gamma_{j-1}<h_{i,t-\tau}\le\gamma_j)+\phi_{j+1} I(h_{i,t-\tau}>\gamma_j) \quad (5),$$

where $I(\cdot)$ is an indicator function equal to one when the condition in the parentheses is true, and zero, otherwise. Human capital $h_{i,t-\tau}$ is the threshold variable, with thresholds $\gamma_1,\gamma_2,...,\gamma_j$ ($\gamma_1<\gamma_2<...<\gamma_j$, $j\ge 1$). When $\phi_1 = \phi_2 = \ldots = \phi_j$, there is no threshold effect, corresponding to MRW model (3).

The number of thresholds j can be determined using a likelihood ratio test proposed by Hansen (1996). It is a sequential test and the asymptotic distribution of the test statistics is bootstrap simulated. We first determine whether the threshold effect is statistically significant. If the null hypothesis of no threshold against the alternative of single threshold is rejected, we go on to test the null hypothesis of single threshold against the alternative of double threshold effect, and so on. The number of thresholds is determined when the null hypothesis cannot be rejected.

Test results on the number of thresholds are reported in Table 4 for alternative human capital measures. The null of no threshold against the alternative of single threshold cannot be rejected for the HSCH and AEDU human-capital measures; but for LFHC, we can reject the null in favor of the alternative of a single threshold. We continue the test with two thresholds for LFHC, but the null of single threshold cannot be rejected. To summarize, there is no evidence of threshold effect for HSCH and

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[23] Recent research such as Gennaioli *et al.* (2013) and Glaeser and Lu (2018) not only find overwhelming evidence of positive impact of human capital on regional development, they also highlight the key contribution of high-skilled labor (or entrepreneurs) and the importance of the human capital externality. Inasmuch that high-skilled labor are more likely to be concentrated in more developed regions, our empirical specifications can partially control for the spillover effect too.

AEDU, and we proceed to estimate the model with LFHC using the single threshold estimation to investigate its mechanism.

Following Hansen (1999), we estimate the threshold parameters by minimizing the sum of squared errors of the threshold regression model. This is done by searching over the value of γ equal to the distinct values of threshold variable $h_{i,t-\tau}$. Once the threshold $\hat{\gamma}_j$ is identified, the slope coefficients ϕ_j and other parameters are estimated by OLS.

The single threshold model estimation results for LFHC are reported in Column (1) of Table 5. The speed of convergence is very low and statistically (and also economically) insignificant when the human capital level is below the threshold, and it becomes much larger and statistically significant at human capital levels above the threshold, implying that insufficient human capital hampers the growth of low-income regions. Thus we infer that the convergence specified in the simpler neoclassic model only occurs when human capital is sufficiently high. As can be seen in Table 5, when the LFHC level is above the threshold, the convergence parameter is somewhat higher than the MRW estimate reported in Table 2 (-0.020 vs. -0.016); the direct effect of LFHC is almost identical to the MRW estimate.

The estimated threshold of 3.62 for LFHC in logarithmic form is equivalent to RMB 37.44 thousand per worker in 1985 Beijing prices based on the J-F human capital measure. This threshold is approximately equal to average and median LFHC in 1985, with 17 of provinces below and 11 above. By 2002, all the sampled provinces had attained human capital above the threshold level, enabling learning from advanced regions.

We conjecture that the existence of a threshold for the J-F measure arises from LFHC's capturing more than formal schooling, including higher school quality, increased degree of urbanization, and improvement in the health care system, all of which play positive roles in the accumulation of labor force human capital.

It is reasonable that LFHC exhibits threshold effects even when they are not evident for the HSCH and AEDU measures. We note also that the HSCH measure more accurately reflects accumulation of high levels of human capital than does AEDU. AEDU's apparently constant effect on the speed of convergence is consistent with Hansen (2000) where no threshold exists when human capital is measured by the literacy rate. China's implementation of nine-year compulsory education in 1986 probably gave AEDU a short-term boost, but from 1985 to 2014 AEDU grew only 1.52% annually, compared to annual growth of 5.16% for HSCH. While compulsory education contributed to AEDU growth, HSCH accelerated under the rapid expansion of higher education in China beginning in 1999. Acceleration of LFHC was even greater than that of HSCH, rising 6.85% annually from 1985-2005, then 9.27% annually from 2005-2014.

VI. A More General Mechanism of Human Capital on Convergence

We now address the puzzle that several widely cited studies, employing a variety of models on human capital's effect yield conflicting results. For example, Kalaitzidakis *et al.* (2001) report that the growth impact of human capital, measured as years of schooling, is negative for countries with low levels of human capital but positive for countries with middle levels. Mamuneas *et al.* (2006) investigate the relationship between human capital and multifactor productivity (TFP) growth and show that the estimated elasticity varies substantially across countries. Soukiazis *et al*. (2008) find that while human capital can account for the convergence of the advanced countries, its impact in developing countries is mixed.

Our resolution of these mixed and sometimes conflicting results is based on an analysis of the two mechanisms through which human capital affects economic growth: (i) indirectly through convergence toward an equilibrium growth path (i.e. the catch-up channel) and (ii) directly on the growth path itself (i.e. the endogenous growth channel).

To begin, we relax the linear specification of equation (4), allowing for a flexible functional representation of the direct effect of human capital on growth:

$$Dy_{i,t} = \eta_0 + \eta_1 \ln(s_{i,t}) + \eta_2 \ln(n_{i,t} + g + \delta) + \phi(h_{i,t-\tau}) \ln(y_{i,t-\tau}) + g(h_{i,t-\tau}) + \alpha_i + u_{i,t} \qquad (6),$$

where initial human capital affects the rate of growth directly via a flexible functional form $g(h_{i,t-\tau})$, and indirectly via the speed of convergence $\phi(h_{i,t-\tau})$.[24] Maintaining the threshold specification for $\phi(h_{i,t-\tau})$, we estimate the direct effect of human capital $g(h_{i,t-\tau})$ using a nonparametric procedure.[25]

To implement the estimation of $g(h_{i,t-\tau})$, we follow the procedure proposed by Robinson (1988) which employs a double residual method to partial out $g(h_{i,t-\tau})$ by removing the conditional expectations. Then nonparametric techniques can be applied to estimate $g(h_{i,t-\tau})$.[26] We apply the Gaussian kernel-weighted local polynomial regression and select bandwidth following Silverman's rule of thumb (Silverman, 1985).

Nonparametric estimation results based on the HSCH and AEDU human-capital measures are reported in Table 5, Columns (2) and (3), and results based on LFHC incorporating the threshold estimates are reported in Column (4).[27] The nonparametric results for $g(h_{i,t-\tau})$ are illustrated in Figure 3, where the horizontal axis shows the initial-year human capital level and the vertical axis shows the nonparametric fitted effect of human capital on economic growth.

As shown in Figure 3, the direct effect of human capital as measured by HSCH and LFHC on growth varies with its level. The impact of AEDU on growth, illustrated in the middle panel, is generally linear; and a one-year increase in AEDU is estimated to increase subsequent economic growth rate by 3.1 percentage points, greater than

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[24] In order to avoid the problem of dimensionality, we assume that nonlinearity is separable for convenience and we keep the parametric form for other variables.

[25] Ideally, we would estimate the model using the threshold method and the non-parametric approach simultaneously. Unfortunately, as far as we know, there is no applicable method that combines the threshold effect and nonparametric effect in one model. Based on our communications with Bruce Hansen, developing an estimation method for a semiparametric model with unknown threshold is still ongoing work.

[26] Another approach by Yatchew (2003) is to partial out the nonparametric component by differencing. It yields similar results in our data to those obtained using Robinson's approach.

[27] Specifically, we allow the threshold dummy variable D_H to interact with initial income, where $D_H = I(\ln(LFHC_{i,t-\tau}) > 3.62)$, the estimate 3.62 is based on regression results of Equation (4).

the 2.6 percentage points reported in the linear MRW model (Table 2).

Table 6 complements Figure 3 by dividing the direct marginal effect of human capital into segments. When HSCH is below 28.96%, a one percentage point increase raises growth by approximately 0.24 percentage point, similar to that of the MRW estimate reported in Table 2; but in the range of 28.96% - 39.94%, its impact on growth is three-fold higher, reaching 0.75 percentage points.[28] Similarly, in the lower range, the marginal impact of LFHC on growth is 0.033 percentage points; it is 0.044 percentage points in the higher range, with both estimates greater than the estimated value of 0.026 based on the MRW model (Table 2).

Our results show that the classical MRW model fits best when human capital is measured by AEDU. When measured by HSCH, human capital's direct effect on growth varies over its level, and when measured most comprehensively by LFHC, the human capital affects growth indirectly via a threshold mechanism as well as through a direct channel that varies with its level.

To further illustrate the mechanism and overall impact of alternative measures of human capital, we compare regional growth disparity between the west and coastal regions as in Table 3. We now allow human capital's effect on convergence to vary with its level, in contrast to the constrained specification embodied in the MRW model, and report the varying impacts of HSCH on the west-vs-coast disparity in Table 7 and those based on LFHC in Table 8 using the results reported in Table 5.

In 1985 and 1995, HSCH in both the west and coast regions was below the cutoff value of 28.96% reported in Table 6 and thus operated under the same working mechanism, with the slope coefficient of $g(h_0)$ equal to 0.0024. Summing up the indirect catchup effect (positive because of west's lower initial per-capita GDP) and the direct human capital effect (negative because of west's lower human capital), our model predicts that the west had a growth disadvantage of 0.76 percentage points in

[28] The graph also shows that the marginal effect becomes much smaller when HSCH rises above 39.94%, suggesting an upper bound or even declining role of HSCH when it reaches certain level. However, because only three provinces (municipal cities) reached the level of HSCH above 39.94%, the estimation for this portion may not be very accurate, and thus we did not report it in the table.

1985 and 0.09 percentage points in 1995.

However, after 2005, when HSCH in the coastal region has surpassed the cutoff value of 28.96% while the west remained below it, the coast's larger coefficient for $g(h_{i,t-\tau})$, i.e., 0.75 (as shown in Table 6) increased its direct growth advantage over the west, leading to an increase in the west's growth disadvantage relative to the coast. We see in Table 7 column (5) that the overall impact of the HSCH on the west's growth is -0.40, a net disadvantage of falling behind the coast. However, the net effect of above-threshold HSCH on the coast's growth is 5.48, greatly enlarging the coast-west gap. Much strong divergence is found for 2014, with west's below-threshold disadvantage being -1.30 percent points and the coast's advantage being 7.22 percentage points.

Allowing for threshold effects that reflect the west and coast regions' being under different human capital mechanisms reveals how the traditional MRW growth model does not capture the full impact of human-capital on regional divergence thus underestimating its impact on regional divergence.

Somewhat stronger magnification of the impact of human capital on regional divergence emerge under the LFHC specification, because as shown in Tables 4 and 6, there is a threshold effect for LFHC's indirect impact on growth as well as the direct effect's $g(h_0)$ marginal impact rising with the level of human capital. Following the same procedures as applied in Table 7, we see in Table 8 that the overall effect of human capital is to reduce the west's growth by 1.77 and 1.63 percentage points relative to the coast in 1985 and 1995, respectively. From the coast's perspective, the overall divergence effect is 0.33 advantage in 1985 and 0.77 disadvantage in 1995, when the coast and west are under different human capital mechanisms. By 2014, with both regions above the same thresholds and thus governed by the same human capital mechanism the west was diverging from the coast under a growth disadvantage of 2.10 percentage points per year. Again we see that the MRW model is incapable of revealing the complex impact of human capital on growth whereas our more flexible mechanism reveals it. Moreover, consistent with the results in Table 3, both Table 7 and 8 show that the effects of human capital on west-coast divergence decrease from 1985 to 1995, but increase significantly from 2005 to 2014, predicting growing regional disparity in subsequent years.

VII. Conclusions

We investigate the mechanism of the effect of human capital on economic growth and convergence using provincial level panel data of China. We use three related but distinct human capital measures and employ both linear and nonlinear procedures, including threshold function and nonparametric estimation. We specify a general framework that allows human capital to affect not only the rate of growth directly, but also indirectly through convergence toward an equilibrium growth path.

We find substantially larger and varying impacts of human capital on growth and convergence than can be revealed under the linear specification pioneered by Mankiw, Romer, and Weil (MRW, 1992). Our results from parametric estimation, threshold model estimation and semi-parametric estimation all confirm that economic convergence is pronouncedly conditional on human capital across all measures. We find that the positive "benefit of being backward" due to lower initial income is almost trumped by the negative direct growth impact of insufficient human capital.

Our human capital measures include average years of education (AEDU), the proportion of labor force with high school education or above (HSCH), and the comprehensive measure of human capital intensity based on Jorgenson-Fraumeni (J-F) framework (LFHC) which has not previously been used in estimating models of growth and convergence. Our results show that the role of human capital differs across these measures, and the introduction of the new measure, LFHC, deepens our understanding of the mechanism by which human capital affects economic growth.

While our results confirm that human capital generally exhibits significantly positive effects on economic growth, we find strong evidence that the speed of convergence depends on the level of human capital; moreover the marginal effect of human capital on economic growth varies with the human capital levels and across human capital measures.

Although the canonical neoclassical endogenous growth model with human capital as pioneered by MRW works well when human capital is measured by average years of education, its relative simplicity cannot fully capture the multiple channels through which human capital affects growth. Overall, estimation based on the more flexible specifications as we have employed in this paper reveals a greater impact of human capital on enlarging regional gaps and their divergence than can be revealed under the simpler MRW model, across all three measures of human capital. Our results show that the complicated mechanisms are best revealed when the comprehensive human capital measure based on the J-F framework is used with nonparametric and threshold estimation.

We find that high skilled human capital as measured by the proportion of high-school graduates (HSCH) has the largest effect on promoting the growth of developed regions, while insufficient LFHC shows the largest effect in hindering the growth of less developed regions. The general education-based measure AEDU shows the largest effect on convergence at an early stage of economic development, but its impact diminishes as the country moves to a more advanced development stage.

Rather disturbingly, we find that while the impact of regional discrepancies in human capital on divergent growth rates diminished from 1985 to 1995, it increased substantially from 2005 to 2014. Our results reinforce the findings of Glauben *et al.* (2012) that a low level of high school education attainment is one of the major causes of the middle-income trap and emphasize that, for China in particular, regional disparity in human capital may prolong and even magnify regional income inequality over time.

Our results suggest that to elevate poor regions out of poverty, government policy should first focus on improving the human capital of basic labor, followed by promoting senior high-school and college graduation to enhance complementarity with high-technology industries. China has introduced several physical-capital-oriented policies in an attempt to reduce regional economic inequality. Our results show that human capital is a critical complement to such policies.

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Table 1
Variable Definition and Descriptive Statistics

Var.	Definition	1985		1995		2005		2014	
		Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
y	Real GDP per worker	0.27	0.13	0.58	0.32	1.40	0.69	3.51	1.37
Dy	Average growth rate of y	0.06	0.02	0.09	0.02	0.12	0.02	0.10	0.02
HSCH	High-school or above, %	13.04	7.02	18.07	8.82	23.56	9.32	32.55	9.09
AEDU	Average education	6.21	1.28	7.71	1.10	8.71	0.95	9.82	0.80
LFHC	Human capital per worker	37.60	11.33	40.16	11.96	89.09	38.77	163.42	90.89
n	Average growth rate of labor	0.03	0.01	0.01	0.01	0.01	0.01	0.002	0.014
s	Rate of saving	0.30	0.07	0.29	0.09	0.36	0.10	0.51	0.12

Notes:

1. The average growth rate is calculated as $Dy = [\ln(y_t) - \ln(y_{t-\tau})] / \tau$, where t is the final year, and $t-\tau$ refers to the initial year for each sub-period defined as 1985-1988, 1994-1997, 2003-2006 and 2009-2014.
2. HSCH is the proportion of labor force graduated from high school or above. AEDU is the average years of education of the labor force
3. The unit of y and LFHC is RMB thousand yuan.

Table 2

Human Capital Measures and Economic Convergence Based on the MRW Model

	(1) No human capital	(2) HSCH	(3) AEDU	(4) LFHC	(5) All human capital measures
$\ln(y_o)$	-0.004	-0.028***	-0.038***	-0.016***	-0.052***
	(0.005)	(0.007)	(0.011)	(0.005)	(0.010)
$HSCH_0$		0.003***			0.001
		(0.001)			(0.001)
$AEDU_0$			0.026***		0.024***
			(0.006)		(0.008)
$\ln(LFHC_0)$				0.026***	0.023**
				(0.007)	(0.009)
$\ln(s)$	0.031***	0.037***	0.039***	0.028***	0.037***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)
$\ln(n+g+\delta)$	-0.154***	-0.154***	-0.123***	-0.155***	-0.125***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)
Constant	-0.229***	-0.300***	-0.365***	-0.344***	-0.473***
	(0.033)	(0.033)	(0.051)	(0.049)	(0.069)
Provincial Fixed Effects	YES	YES	YES	YES	YES
# of Obs.	252	252	252	252	252
Adj. R-squared	0.515	0.542	0.555	0.526	0.567

Notes:

1. The dependent variable is the average annual growth rate of GDP per worker in the subsequent sub-period as defined in the note of Table 1. Subscript *0* denotes the initial year.
2. Robust standard errors are in parentheses.
3. The asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 3
The Effect of Human Capital on the West-Coast Convergence
Based on the MRW Model

Base year	Human capital measure	(1) Initial income(y_0) gap, %	(2) Initial human capital(h_0) gap	(3) Catching-up effect due to lower y_0	(4) Growth effect due to human capital h_0	(5) Net effect
1985	HSCH	-55.55	-8.27	1.56	-2.48	-0.92
	AEDU	-55.55	-1.71	2.11	-4.45	-2.34
	LFHC	-55.55	-53.63	0.89	-1.39	-0.50
1995	HSCH	-92.27	-8.82	2.58	-2.65	-0.07
	AEDU	-92.27	-1.58	3.51	-4.11	-0.60
	LFHC	-92.27	-49.47	1.48	-1.29	0.19
2005	HSCH	-90.61	-9.96	2.54	-2.99	-0.45
	AEDU	-90.61	-1.32	3.44	-3.43	0.01
	LFHC	-90.61	-68.21	1.45	-1.77	-0.32
2014	HSCH	-67.06	-11.60	1.88	-3.48	-1.60
	AEDU	-67.06	-1.19	2.55	-3.09	-0.54
	LFHC	-67.06	-87.31	1.07	-2.27	-1.20

Notes:

1. The calculation is based on the results reported in Table 2. All gaps are calculated as the difference between west and coast region. Column (5) is the sum of columns (3) and (4).
2. The initial income gap is calculated as $[\ln(y_{0w}) - \ln(y_{0c})] \cdot 100$, the difference between west and coast region.
3. In column (3), initial HSCH human capital gap is measured as difference in percentage points; initial AEDU gap is the difference in years of education; initial LFHC gap is measured as $[\ln(LFHC_w) - \ln(LFHC_c)] \cdot 100$, all of them calculated as west minus coast region.
4. The unit for columns (3)-(5) is percentage points.

Table 4
Hansen Test for the Number of Thresholds

	F-value	P-value	F-critical value of 90%, 95%, 99%
A: Single threshold vs. no threshold (null)			
HSCH	10.900	0.517	(20.031, 23.792, 29.189)
AEDU	10.900	0.300	(16.015, 19.463, 25.309)
$\ln(LFHC)$	18.190	0.073	(16.603, 21.237, 27.984)
B: Double threshold vs. single threshold (null)			
$\ln(LFHC)$	4.370	0.747	(12.273, 13.724, 17.563)

Table 5
Nonlinear effects of Human Capital on Convergence

	(1) Threshold LFHC	(2) Nonparametric HSCH	(3) Nonparametric AEDU	(4) Threshold & Nonparametric LFHC
$\ln(y_0)I(\ln(LFHC_0)\le 3.62)$	-0.003			
	(0.007)			
$\ln(y_0)I(\ln(LFHC_0)>3.62)$	-0.020***			-0.026***
	(0.006)			(0.008)
$\ln(LFHC_0)$	0.025**			
	(0.010)			
$\ln(y_o)$		-0.022**	-0.047***	0.001
		(0.007)	(0.010)	(0.009)
$\ln(s)$	0.026***	0.035***	0.042***	0.019**
	(0.008)	(0.008)	(0.008)	(0.009)
$\ln(n+g+\delta)$	-0.138***	-0.158***	-0.133***	-0.138***
	(0.013)	(0.015)	(0.015)	(0.013)
Constant	-0.300***			
	(0.056)			
Provincial Fixed Effects	YES	YES	YES	YES
# of Obs.	252	252	252	252

Notes:

1. Robust standard errors are in parentheses;
2. The asterisks *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively.

Table 6
The Estimated Coefficient of Human Capital Based on Nonparametric Model

	Human Capital Level	Slope Coefficient of $g(h_0)$
HSCH(%)	<28.96	0.0024
	(28.96, 39.94)	0.0075
AEDU	Full Range	0.031
$\ln(LFHC_0)$	(3.32, 4.61)	0.033
	(4.61, 5.63)	0.044

Notes:

1. When HSCH is less than 28.96%, a one percentage point increases raises growth by approximately 0.24 percent points; in the range 28.96-29.94%, its impact on growth is 0.75 percentage points.
2. When ln(LFHC) is less than 4.61, its marginal impact on growth is 0.033 percentage points; when in the range of 4.61-5.63, its marginal impact on growth is 0.044 percentage points.

Table 7
The Non-linear Effect of HSCH on the West-Coast Convergence

Base year	Base Region	HSCH (%)	(1) Income gaps	(2) HSCH gaps	(3) Growth effects due to y_0	(4) Growth effects due to HSCH	(5) Net effects
1985	West	9.44	-55.55	-8.27	1.22	-1.98	-0.76
	Coast	17.71					
1995	West	14.69	-92.27	-8.82	2.03	-2.12	-0.09
	Coast	23.51					
2005	West	19.78	-90.61	-9.96	1.99	-2.39	-0.40
	Coast	29.74	90.61	9.96	-1.99	7.47	5.48
2014	West	27.72	-67.06	-11.60	1.48	-2.78	-1.30
	Coast	39.32	67.06	11.60	-1.48	8.70	7.22

Notes:

1. The gaps for income and HSCH are calculated in the same way as in Table 3.
2. The growth effects of HSCH at different ranges are calculated based on the estimates reported in Table 6.

Table 8
The Non-linear Effect of LFHC on the West-Coast Convergence

Base year	Base Region	$\ln(LFHC_0)$ (threshold $\gamma_1 = 3.62$)	(1) Income gaps	(2) LFHC gaps	(3) Growth effects due to y_0	(4) Growth effects due to LFHC	(5) Net effects
1985	West	3.36	-55.55	-53.63	0.00	-1.77	-1.77
	Coast	3.89	55.55	53.63	-1.44	1.77	0.33
1995	West	3.46	-92.27	-49.47	0.00	-1.63	-1.63
	Coast	3.94	92.27	49.47	-2.40	1.63	-0.77
2005	West	4.16	-90.61	-68.21	2.36	-2.25	0.11
	Coast	4.80	90.61	68.21	-2.36	3.00	0.64
2014	West	4.62	-67.06	-87.31	1.74	-3.84	-2.10
	Coast	5.43					

Notes:

1. The gaps for initial income and LFHC are calculated in the same way as in Table 3.
2. Based on Column (4) Table 5, When LFHC is below the threshold, $\phi = 0$; and when LFHC is above the threshold, $\phi = 0.026$.
3. The growth effects of LFHC at different ranges are calculated based on the estimates reported in Table 6.

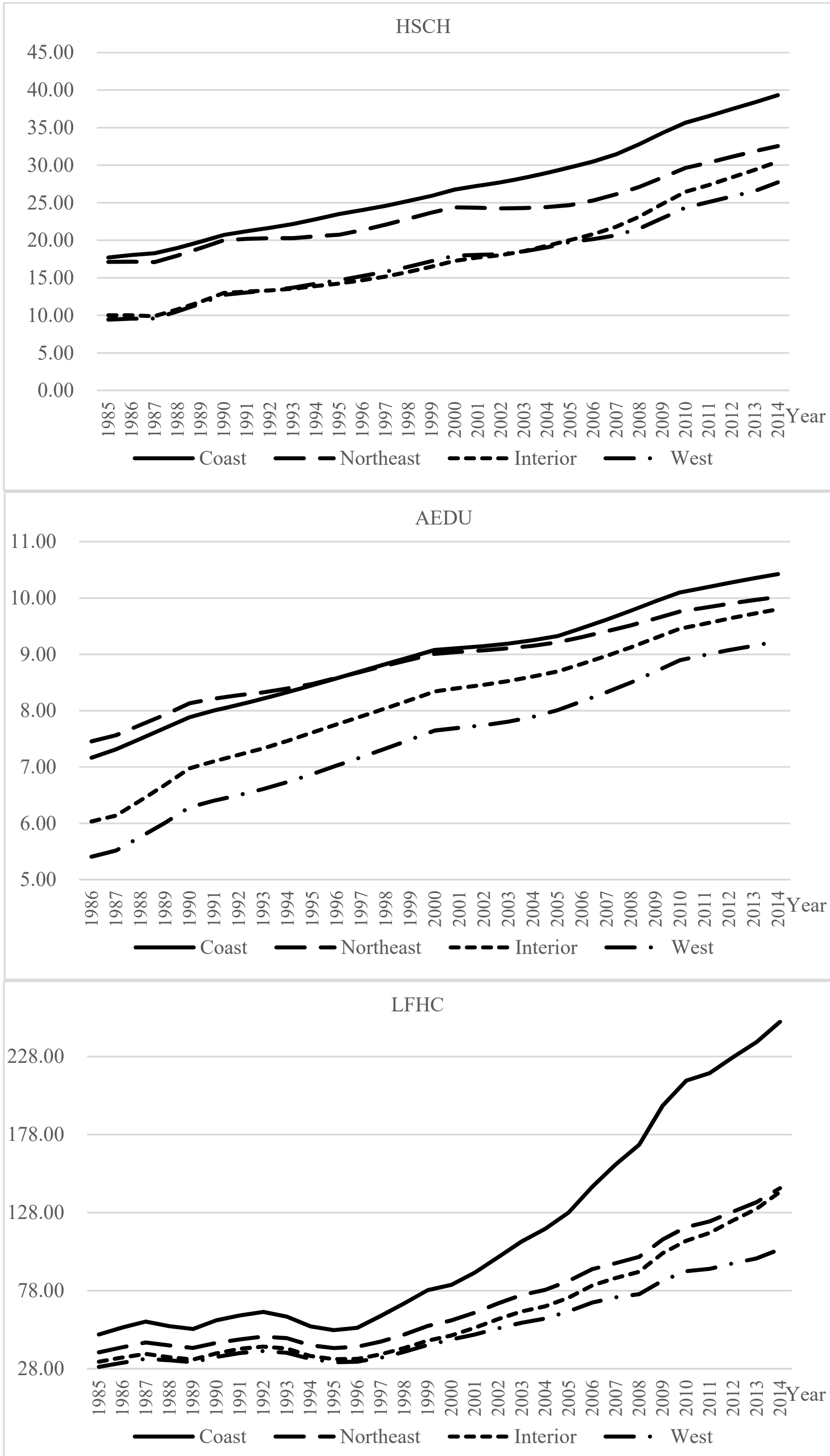

Figure 1 Human Capital by region

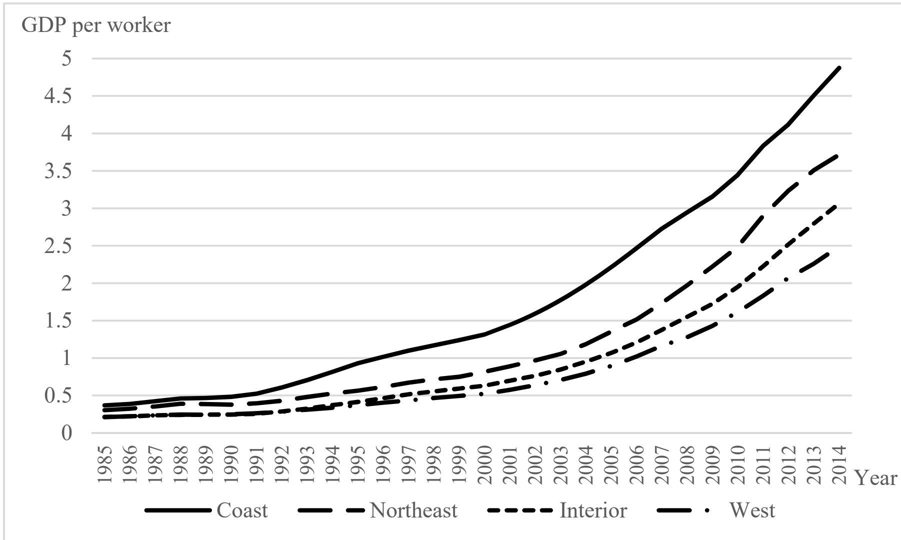

Figure 2 GDP per worker by region

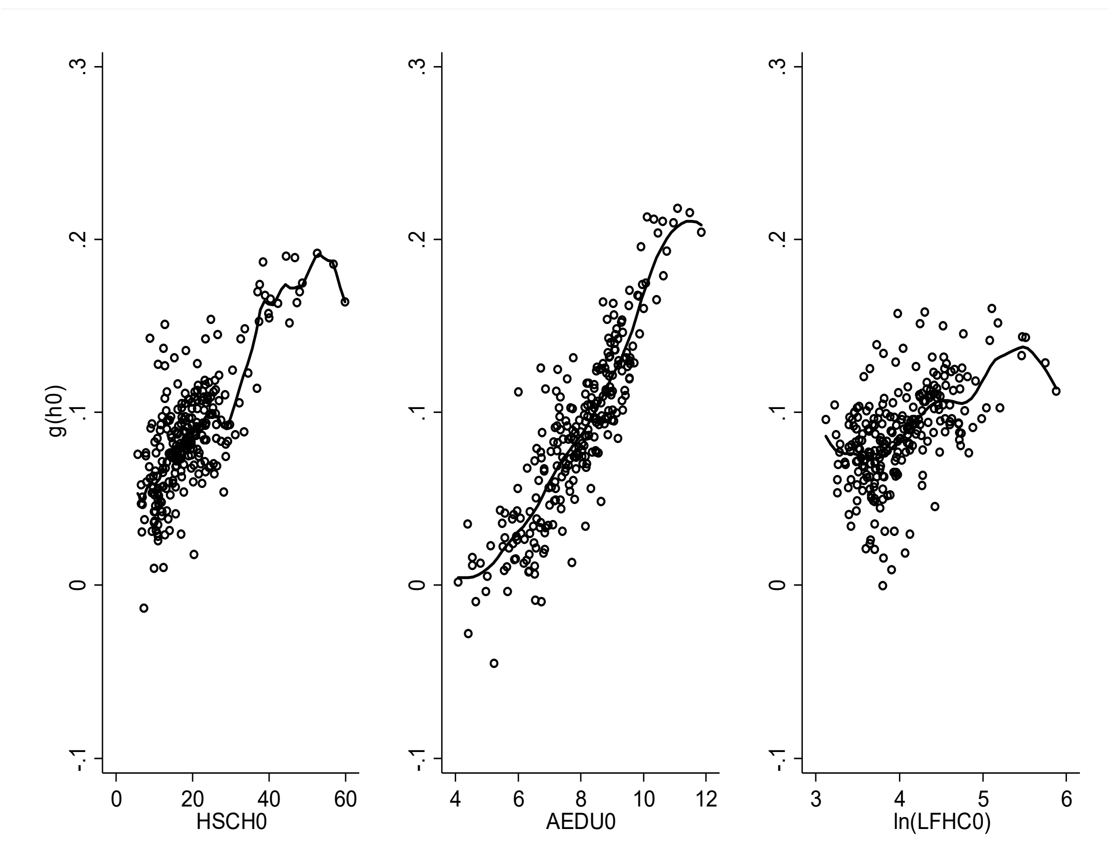

Figure 3 Non-parametric Estimation of Human Capital on Growth