CHAPTER 7

Human Capital Agglomeration Effect and Regional Disparity in China

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7.1 Introduction

This chapter shows why interregional income inequality in China during 1991–2004 was expanded by Barro regression using Chinese regional macro data and Chinese population census data.

Since the 1990s, China has fully adopted a market economy to revitalize its economy. In the process, restrictions on domestic labor migration were relaxed. China's fluid population in 1990 was 33.84 million, while in 2010, it was 221.43 million (Table 7.1); that is, the fluid population has increased 6.5 times in 20 years. However, despite the relaxation of labor migration restrictions, the interregional income gap

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between coastal and inland regions in China has widened since the 1990s. Could we think this income gap is caused by the human capital agglomeration effect based on China's internal migration policy, the household registration system (*hukou*)? China's *hukou* system requires that each person be guaranteed long-term employment in the area to obtain urban *hukou*. Workers with high human capital are more likely to get such jobs. Therefore, after the restrictions on labor migration were eased, workers with higher human capital accumulated in coastal areas with high wages, while such workers flowed out of the inland regions. While such labor migration has increased average per capita income in coastal regions, it has delayed economic development in inland regions. As a result, a gap in income levels has emerged between the coastal and inland regions. Thus, the disparity in human capital accumulation due to China's household registration system has caused the widening of income disparities between regions in China since 1990. In this chapter, using Barro regression, we examine the hypothesis that the human capital agglomeration effect causes the widening of income inequality.

The remainder of this chapter is organized as follows. Section 7.2 describes the characteristics and causes of income inequality among Chinese regions since 1990 and the "human capital agglomeration effect" hypothesis that explains these factors. Section 7.3 describes the Barro regression and method for testing when incorporated into the human capital agglomeration effect hypothesis. Section 7.4 presents the data for verification and summarizes the empirical results. Section 7.5 compares the factors contributing to population movement and income inequality during Japan's rapid economic growth with those in China. Finally, Sect. 7.6 summarizes the conclusions and discusses future issues.

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7.2 Income Inequality Between Regions in China Since the 1990s and Relevant Factors

Figure 7.1 shows the evolution of four statistical indicators (Gini coefficient, standard deviation of logarithm indicating σ convergence[1], coefficient of variation, and tile index) that indicate regional differences in the gross regional product (GRP) per capita in China over the period 1978–2020. The figure shows that China's interregional income inequality narrowed from 1978 but increased after 1991.[2] In other words, the evolution of China's interregional income inequality since 1978 has been V-shaped, with 1990 at the bottom. The "rich/middle class vs. poor" hypothesis (Chen, 2000a) and the "club convergence" hypothesis between the eastern and mid-western regions explain this fact.

The rich/middle class vs. poor hypothesis classifies the economy according to income levels. It explains the evolution of income inequality

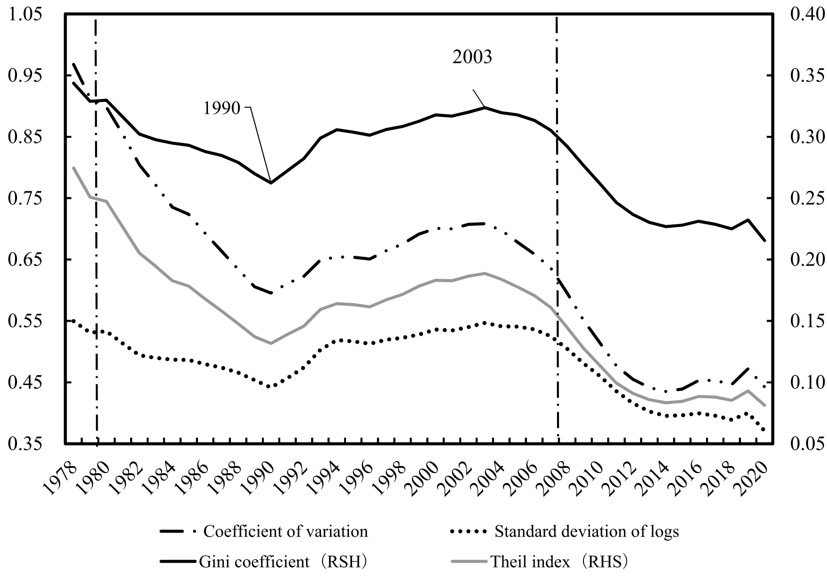

Fig. 7.1 Trends in income disparity between regions in China (1978–2020) (*Source* Authors' creation based on the data from *China Compendium of Statistics 1949–2008* (NBSC) until 2008 and *China Statistical Yearbook*, each year since 2009)

among regions in China based on convergence in income levels. First, the hypothesis points out that in the early stages of economic development, the economy was divided into a small number of rich and a majority of poor. It further pointed out that subsequent economic development would lead to the emergence of a middle class and narrowing the gap between the rich and the poor, creating a so-called "economic convergence."[3] However, further economic development has widened the gap between the rich/middle class and the poor, and convergence is no longer observed.

On the other hand, Cai and Du (2000), who argue for a club convergence hypothesis between the eastern and mid-western regions, show China's interregional income inequality during 1978–1998 by measuring the average tile contribution between each region. They pointed out that China already had two "clubs"—an eastern regional club and a mid-western regional club[4]—and that even if there was economic convergence within the clubs, there was no economic convergence between them. Similarly, Chen (2000b) measured China's economic convergence by decomposing it into convergence within the coastal regions (regions with developing economies) and convergence between coastal and inland regions (regions with lagging economic development). The results indicated that income inequality between coastal and inland regions has been growing almost consistently, although there has been some narrowing of income inequality within coastal regions.

The V-shaped transition in China's interregional income inequality is analyzed based on this fact. The economic convergence explains the reduction in China's interregional income inequality in the 1980s within the coastal regions. This expansion of income inequality is caused by the widening gap between the coastal and inland regions.

However, neither of the above two hypotheses does say a fact that is extremely important when considering China's interregional income disparities. Table 7.1 summarizes the fluid population using Chinese Population Census data for 1982–2020 and shows that labor migration in China has been rapid since 1990.

According to Yan (2004), the inter-provincial migration population in China, which was 10.81 million in the late 1980s, more than tripled to 34 million by the late 1990s. Among these, the outflow of the working population from less economically developed regions to more economically developed regions has been particularly significant, meaning that

Table 7.1 Trends in China's migration population (1982–2020)

Year	*Migration Population (mn people)*	*Increase (mn people)*	*Increase (times)*	*Average growth rate (%)*	*Source*
1982	657				The Third Nationwide Population Census
1990	3,384	2,727	5.2	22.7	The Fourth Nationwide Population Census
1995	6,017	2,633	1.8	12.2	Tabulation on the 1995 1% Population Sampling Survey of China
2000	12,107	6,090	2.0	15.0	The Fifth Nationwide Population Census
2005	14,735	2,628	1.2	4.0	Tabulation on the 1995 1% Population Sampling Survey of China
2010	22,143	7,408	1.5	8.5	The Sixth Nationwide Population Census
2020	37,582	15,439	1.7	5.4	The Seventh Nationwide Population Census

Source Authors' creation based on Cao (2004) for 1982, Yan (2005) for 1990 and 1995, and the Nationwide Population Census since 2000

migrant labor has been in full swing among China's regions since the 1990s.

According to the Harris–Todaro model, if such labor migration occurs, wages will fall in urban areas with advanced economic development due to the influx of labor. In contrast, labor becomes scarce in less developed areas with lower wages, causing wages to rise and income levels to level off among regions. However, as Fig. 7.1 shows, the income disparities between regions in China have widened since the 1990s. The reasons for this are as follows.

Historically, the Chinese government has implemented a social policy—a *hukou* system that prevents workers from easily migrating between regions. This policy clearly distinguishes between urban and rural households. It stipulates that people without *hukou* in a region cannot receive social security or education for their children. In order to obtain *hukou*, which is the registered residency status of a particular individual in another region, a person must be employed long term by a company or government agency in that region. Workers with higher levels of human capital (university graduates or those with a high school education or higher) are more likely to be employed in the long term in urban areas or more developed areas (coastal areas). They are more likely to become residents (obtaining household registration) in these areas.

Meanwhile, most workers who migrated from inland to coastal areas as simple laborers lack high educational qualifications and are unlikely to be employed long term and can only find temporary work. Many migrant workers return to their hometowns for these reasons (Wang, 2006).[5] In other words, owing to the household registration system, workers with higher levels of education (human capital level) are more likely to be employed long term in other areas and, therefore, more likely to take up household registration. Therefore, they are more likely to migrate to other regions. In this sense, workers with low human capital levels are restricted from migrating to other regions. Therefore, high human capital will be concentrated in coastal areas where the economy is developed and high wages are available. Thus, human capital accumulation may impact the economic development of the two regions (coastal and inland). In other words, while workers with high levels of human capital accumulated in the coastal region promote further economic development, the outflow of workers with high levels of human capital in the inland region causes economic development to stagnate (Fig. 7.2).

This can be considered one hypothesis to understand why China's interregional income inequality widened even after 1990 when labor mobility became freer. In this chapter, we test this hypothesis within the analytical framework of Barro et al. (1992, 2004). The results indicate that the economic convergence among the Chinese regions since the 1990s is not absolute but is more likely to be a conditional convergence, that is, economic convergence that considers the above possibilities.

7.3 Empirical Model

7.3.1 Basic Model

Barro et al. (1992, 2004) found that groups of economies in different economic states (e.g., GRP per capita) had a process to achieve the same long-run equilibrium. The groups with lower income (or output) levels grew faster than those with higher income. As a result, the lower-income group's income can approach the higher-income group's per capita income level. If so, we believe that there is a convergence between these

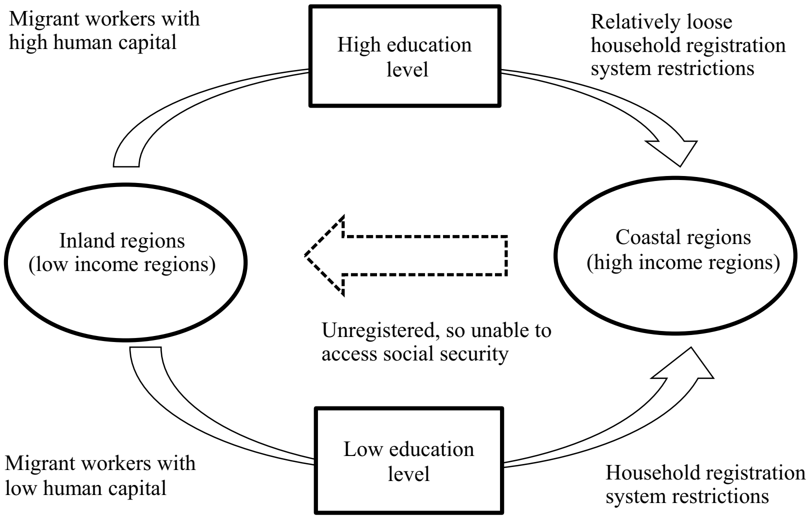

Fig. 7.2 Human capital agglomeration effect hypothesis (*Source* Authors' creation)

economic groups. Applying this concept to the issues of income inequality and regional disparities, if economic convergence (hereafter abbreviated as "convergence") is detected, income inequality and regional inequality decrease; otherwise, income inequality and regional disparities increase.

There are two methods for verifying convergence: β- and σ-convergence. This chapter uses β-convergence, which measures whether a process exists from a particular economic state (initial state) to long-run equilibrium.[6] The Barro regression method presented by Barro et al. (1992, 2004) was used to measure β-convergence. β convergence is determined by measuring β, which is called the convergence coefficient in the following equation:

$$\begin{aligned}\bar{G}(t_0, t_T)_i &= const. + b \times \ln y_{i,t_0} + B\left(\ln y_i^*(\Phi)\right) + u(t_o, t_T)_i \\ &= const. + b \times \ln y_{i,t_0} + \sum_{l}^{k} c_{i,l} z_{i,l} + u(t_o, t_T)_i \end{aligned} \tag{7.1}$$

where y_i is the per capita real GRP in the region i and $\overline{G}(t_0, t_T)_i \equiv \ln\left(y_{i,t_T}/y_{i,t_0}\right)/T$ is the average per capita real GRP growth rate from period t_0 tot_T. b is the coefficient for estimating convergence, where $b = -\left(1 - e^{-\beta_i T}\right)/T$. $B\left(\ln y_i^*(\Phi)\right) = x + \left(1 - e^{-\beta_i T}\right)/T \times \ln y_i^*$ summarize the per capita real GRP in the long-term equilibrium and various control or environmental variables that could affect its value.[7]

There are two additional ideas for beta convergence: absolute and conditional. If they converge to the same long-term equilibrium, it is called absolute convergence. However, if the long-term equilibria of each group are different and convergence appears after controlling for certain conditions, then the convergence is conditional.[8]

In the actual measurements, the two convergence properties were determined as follows. Even without considering the influence of $B(\ln y^*(\Phi))$ in Eq. (7.1), if $\beta > 0$, which indicates convergence, is significantly measured, the convergence is determined to be absolute convergence. In contrast, if $B(\ln y^*(\Phi))$ differs between groups, convergence between groups does not appear as it should ($\beta > 0$ is not significant).[9] However, if convergence appears certain conditions are met, i.e., by incorporating as new explanatory the control or environmental variables that are determinants of $B(\ln y^*(\Phi))$ and are thought to influence convergence, such convergence is considered conditional convergence (Barro et al. 1992, 2004). The $\sum_l^k c_{i,l} \times z_{i,l}$ in Eq. (7.1) represents a set of state, control, or environmental variables that may affect $B(\ln y^*(\Phi))$, and c displays weight parameters corresponding to each variable.

7.3.2 *Barro Regression with Human Capital Agglomeration Effect*

Next, let us consider measuring the human capital agglomeration effect in the Barro regression.

In Barro regression, if we take into account some variables that determine $B(\ln y^*(\Phi))$, we should use quantification methods such as the ordinary least squares (OLS), instrumental variable (IV), two-stage least squares (2SLS), and generalized method of moments (GMM). The IV method is used when problems arise, such as a simultaneous equation bias or endogeneity (simultaneity). When endogeneity occurs, the estimated values do not have the desirable properties of consistency and lack bias. However, using the instrumental variables method, finding the appropriate control variables will obtain estimated values that hold consistency.

To apply this approach to conditional convergence in Barro regression, we would add additional explanatory variables to the empirical model, such as control variables responsible for different long-run equilibria and control for the endogenous nature of these variables.

When using the IV method in Barro Regression with conditional convergence, we must add some choice variables as factors that give rise to differing long-term equilibria as additional explanatory variables. Moreover, we must control for the endogeneity of these variables. Suppose the estimated value of β is not significant when these are not controlled for but is significant when controlled. In that case, these control variables can be considered factors that generate conditional convergence.

The following steps were required to apply the above ideas and methods to the factor analysis of China's interregional income inequality since 1990. First, we find the control variables related to the human capital agglomeration effect, which has been a factor that prevents β convergence between Chinese regions since 1990. Second, we add the finding control variables and control for endogeneity using instrumental variables (IV). If convergence can be observed through such a process, then these control and manipulated variables may be among the factors that have increased regional disparities since 1990.

Let us consider the control variables related to the human capital agglomeration effect and the instrumental variables that control for them. We examine the statistical indicators related to the human capital agglomeration effect.[10] Tables 7.2a and 7.2b show for the central-western and coastal regions: (1) average growth rate for per capita GRP; (2) the graduate ratio or proportion of university graduates in the region to all nationwide university graduates; (3) the graduate employee ratio or the proportion of university graduates in the region to all employed people in the region; (4) net immigration rate [(labor inflow—labor outflow) (those residing in the region for five years or more + labor outflow)]; and (5) per capita GRP.[11] Table 7.2a lists the group corresponding five central-western regions (Sichuan, Hubei, Henan, Hunan, and Shanxi Provinces) in graduate ratio. Table 7.2b lists six coastal regions (Zhejiang Province, Jiangsu Province, Tianjin Municipality, Beijing Municipality, Guangdong Province, and Shanghai Municipality) in order of average growth rate.

When looking at the central-western region group, the "graduate ratio" in Sichuan, Hubei, and Henan is among the highest in the nation (in the top 10, with a deviation from the nationwide average for the three provinces of 2.06%).[12] Their graduate employee ratio is among the lowest (lower than 12, with a deviation from the nationwide average for the

Table 7.2a Statistical indicators related to "human capital agglomeration effect" (central-western regions)

	(1)		(2)		(3)		(4)		(5)	
	Average growth rate	*Nationwide ranking*	*Graduate ratio*	*Nationwide ranking*	*Graduate-employee ratio*	*Nationwide ranking*	*Net immigration rate*	*Nationwide ranking*	*Per-capita GRP(RMB)*	*Nationwide ranking*
Sichuan Province	8.51	18	6.17	3	2.33	22	−56.81	27	7,895	26
	−0.55		**2.73**		**−2.24**		**−49.84**		**−6,169**	
Hubei	8.23	22	5.57	4	3.84	12	−19.04	22	9,898	17
Province	**−0.83**		**2.13**		**−0.73**		**−12.07**		**−4,166**	
Henan	10.19	8	4.74	8	2.20	24	−44.30	25	9,201	19
Province	**1.13**		**1.30**		**−2.37**		**−37.33**		**−4,863**	
Hunan	9.22	13	4.54	11	2.63	19	−59.33	28	9,165	21
Province	**0.16**		**1.10**		**−1.94**		**−52.36**		**−4,899**	
Shaanxi	8.47	20	4.25	12	3.69	15	−7.57	18	8,587	23
Province	**−0.59**		**0.82**		**−0.87**		**−0.60**		**−5,477**	
Nationwide average	9.06		3.44		4.57		−6.97		14,064	

Note The bold font shows each indicator's deviation (from the average)

1. Average growth rate: 1991–2004, the data from *China Compendium of Statistics 1949–2008*
2. Proportion of region's graduates among all graduates nationwide (graduate ratio): 1995–2000, the data from *China Statistical Yearbook* (for each year)
3. Graduates as a proportion of all employees in the region (graduate employee ratio): 1996–1999, the data from *China Labor Statistical Yearbook* (for each year) and *China Statistical Yearbook* (for each year)
4. Net immigration rate: 1995–2000, the data from the Nationwide 1% Population Census and Fifth Nationwide Population Census
5. Per capita Gross Regional Product: 2004, the data from *China Compendium of Statistics 1949–2008*

Source Authors' creation

Table 7.2b Statistical indicators related to human capital agglomeration effect (Coastal regions)

	(1)		(2)		(3)		(4)		(5)	
	Average growth rate	*Nationwide ranking*	*Graduate ratio*	*Nationwide ranking*	*Graduate-employee ratio*	*Nationwide ranking*	*Net immigration rate*	*Nationwide ranking*	*Per-capita GRP(RMB)*	*Nationwide ranking*
Zhejiang Province	11.86 **2.80**	1	3.10 **−0.33**	16	2.93 **−1.63**	18	1.19 **8.16**	14	24,352 **10,288**	4
Jiangsu Province	11.08 **2.02**	2	7.67 **4.24**	1	3.74 **−0.83**	13	10.14 **17.11**	11	20,223 **6,159**	6
Tianjin Province	10.61 **1.56**	3	2.31 **−1.12**	20	8.91 **4.34**	3	27.60 **34.57**	5	30,575 **16,511**	3
Beijing Municipality	10.01 **0.95**	9	5.53 **2.10**	6	19.81 **15.25**	1	46.74 **53.71**	2	41,099 **27,035**	2
Guangdong Province	9.60 **0.54**	11	4.87 **1.43**	7	4.27 **−0.29**	11	49.50 **56.47**	1	20,870 **6,806**	5
Shanghai Municipality	9.52	12	4.61	9	13.15	2	37.40	4	46,755	1

(continued)

Table 7.2b (continued)

	(1)		*(2)*		*(3)*		*(4)*		*(5)*	
	Average growth rate	*Nationwide ranking*	*Graduate ratio*	*Nationwide ranking*	*Graduate-employee ratio*	*Nationwide ranking*	*Net immigration rate*	*Nationwide ranking*	*Per-capita GRP(RMB)*	*Nationwide ranking*
	0.46		**1.17**		**8.58**		**44.37**		**32,691**	
Nationwide average	9.06		3.44		4.57		−6.97		14,064	

Note The bold font shows each indicator's deviation (from the average)

1. Average growth rate: 1991–2004, the data from *China Compendium of Statistics 1949–2008.*
2. Proportion of region's graduates among all graduates nationwide (graduate ratio): 1995–2000, the data from *China Statistical Yearbook* (for each year)
3. Graduates as a proportion of all employees in the region (graduate employee ratio): 1996–1999, the data from *China Labor Statistical Yearbook* (for each year) and *China Statistical Yearbook* (for each year)
4. Net immigration rate: 1995–2000, the data from Nationwide 1% Population Census and Fifth Nationwide Population Census
5. Per capita Gross Regional Product: 2004, the data from *China Compendium of Statistics 1949–2008*

Source Authors' creation

three provinces [−2.18%]). Let us consider the graduate ratio as a surrogate variable for a region's education and the graduate employee ratio as a surrogate variable for workers' human capital level in a region. The level of workers' human capital in these regions is shallow despite the high level of education. Since regions with a high level of education, such as Japan and the U.S., also have a high level of workers' human capital, it seems paradoxical that there is a negative relationship between the level of education and workers' human capital in the central-western regions of China, as shown in Table 7.2a. However, if we take into account the labor migration between regions or the net immigration rate, the reason for these points could be explained.

For example, Sichuan and Hubei provinces rank third and fourth nationwide in graduate ratio. However, their net immigration rates, which show the situation of the migration of labor, are −56.81% (ranked 27th) and −19.04% (ranked 22nd), respectively. These facts show that, in these provinces, more people move out than move in.[13] It is natural to suppose that the laborers who move out from these regions involve many university graduates who received a high level of education in Sichuan and Hubei provinces (workers with a high level of human capital). If so, we should consider that the paradoxical relationship in Sichuan and Hubei provinces between a high level of education (a high graduate ratio) and a low level of human capital among workers (graduate employee ratio ranking 22nd and 12th) shown in Table 7.2a, is because many workers with high human capital move away. These factors give rise to the low average economic growth rate in Sichuan and Hubei provinces (ranked 18th and 22nd, respectively, among the 29 provinces, municipalities, and autonomous zones) and, as a result, they both rank low in the country in terms of per capita GRP (nationwide rankings of the 26th and 17th, respectively). We found similar results in other central-western regions.

On the other hand, the percentage of college graduates in Shanghai is lower than in Sichuan (3rd in the nation) and Hubei (4th). However, the percentage of college graduates among employees (2nd) is much higher than in those two provinces due to the high net migration rate (4th). Therefore, these factors also contributed to Shanghai's high average growth rate (12th place, with a deviation from the national average of 0.46%) and high GRP per capita (1st).

Beijing has a high graduate ratio (6th), as well as a very high net immigration rate (2nd), and graduate employee ratio (1st). The economic growth rate (9th) is also relatively high. Therefore, we presume that, in

Shanghai and Beijing, the agglomeration of high human capital promotes higher economic growth, and regions such as Sichuan Province and Hubei Province experience the outflow of high human capital workers, deteriorating the economic growth rate in inland regions (mid-western regions).

Thus, it can be considered that many workers with a high level of human capital gather in coastal regions (regions with relatively high economic growth rates), as shown by the cases of Shanghai and Beijing Municipalities. While many workers with high human capital move out of central-western regions (regions with relatively low economic growth), as shown by the cases of Sichuan and Hubei provinces. These data support our hypothesis about the human capital agglomeration effect.

To test our human capital agglomeration effect hypothesis, we take statistical indicators relating to human capital agglomeration and the associated statistical indicators shown in Tables 7.2a and 7.2b as surrogate variables. We consider two types of surrogate variables: type 1, which is an indicator of the level of human capital in the regions and does not consider labor migration, and type 2, which is an indicator of the human capital agglomeration effect that takes into account the effects of migration of labor.[14] In particular, we take the level of education (graduate ratio) in the region and the level of workers' human capital (graduate employee ratio) in the region as type 1 surrogate variables (for example, "ln Averedu, Percen unv empl year, and unv.s year"). The following equation defines type 2 surrogate variables:

$$hca_i = \frac{\sum_{j=1}^{I} M_{i,j} - \sum_{j=1}^{R} T_{i,j}}{\sum_{j=1}^{Q} S_{i,j}} \times \Lambda_i \equiv m_i \times \Lambda_i \tag{7.2}$$

where Λ_i represents the human capital level (e.g., average years of education or "percentage of college graduates") or the human capital level of workers (employees; e.g., "percentage of college graduates among employees") in region i; $\sum_{j=1}^{I} M_{i,j}$ represents the gross number of labor inflows into the region; $\sum_{j=1}^{R} T_{i,j}$ represents the gross number of the labor outflow of the region; and $\sum_{j=1}^{Q} S_{i,j}$ represents the permanent population of at least five years' duration. Thus, $\left(\sum_{j=1}^{I} M_{i,j} - \sum_{j=1}^{I} T_{i,j}\right) / \sum_{q=1}^{Q} S_{i,q} \equiv m_i$ represents expresses the level of net immigration. The stronger a region's human capital agglomeration effect the higher the value of hca_k, which will positively affect on the economic growth rate. Hence, considering the human capital agglomeration effect, we modify the Barro regression equation as follows:

$$\bar{G}(t_0, t_T)_i = const. + b \times \ln y_{i,t_0} + \sum_{\gamma=1}^{p} c_{i,\gamma} \times hca_{i,\gamma} + \sum_{l}^{k} c_{i,l} z_{i,l}(\Theta) + u(t_o, t_T)_i \tag{7.3}$$

Here, the term $\sum_{\gamma=1}^{p} c_{i,\gamma} \times hca_{i,\gamma}$ represents the human capital agglomeration effect. $\sum_{l}^{k} c_{i,l} z_{i,l}(\Theta)$ represents the new control variables that affect the real per capita GRP in long-term equilibrium, such as surrogate variables of the level of human capital (average number of years in education). Other variables include the rate of investment in physical capital, dependence on foreign trade (foreign trade effect), the proportion of foreign direct investment in the GRP (FDI effect), birth rate, and government spending.

In this chapter, we consider endogeneity between the average number of years in education, which is extremely important in generating the human capital agglomeration effect, and the average growth rate of per capita GRP for the following reasons. The average number of years in education (the level of human capital) at any given period is a stock variable.[15] If the accumulation of human capital does not depend on the quality of education in the region, but instead, as suggested in this chapter, is produced by the human capital agglomeration mechanism, high economic growth and high per capita GRP in a region could be an incentive for workers with a high level of human capital to gather in that region. We detect endogeneity between the average years in education and the average growth rate of per capita GRP, as shown in Tables 7.4, 7.5, 7.6, and 7.7.

7.4 Data and Estimation Results

7.4.1 Data

We use the following data: (1) regional macro data in "China Compendium of Statistics 1949–2008," published by the National Bureau of Statistics of China in 2010 (hereafter abbreviated as "New China 60"); (2) "Tabulation on the 1995 1% Population Sampling

Survey of China" and "The Fifth Nationwide Population Census" (2000) published by Population Census Office under the State Council, and other related data. As shown in Fig. 7.1, the 1991–2004 period is when regional disparities widened in China; to be consistent with the macro data used in this chapter, the period estimated in this chapter is set to 1979–2007. Moreover, taking reform from 1978 and actively beginning to flow into FDI from 1986 into account, we divide our estimated periods into (a) 1979–2007 (to verify post-reform convergence), (b) 1987–2007 (to verify convergence considering the FDI effect), (c) 1991–2004 (the period needed to verify the hypothesis in this chapter), and (d) 1991–2007 [extension of period (c)]. Below, we list the variables used for the tests and the data used for these variables.

1. $\overline{G}_i$(Dependentvariable): Average growth in real per capita GRP in the period = per capita GRP adjusted using the nationwide consumer price index. [16] [Data: "New China 60"]
2. $\ln y_{i,t_0} \equiv \ln GRP_t$: Real per capita GRP in the initial term of the calculation period (logarithmic value). [Data: "New China 60"]
3. $z_{i,1} \equiv$ G.cons._Y_t: Government spending as a proportion of expenditure-based GRP (average value for each calculation period. [Data: "New China 60"]
4. $z_{i,2} \equiv$ I_Y_t: Ratio of fixed capital formation to GRP in "expenditure method GRP" (average value for each estimation period). [Data: "New China 60"]
5. $z_{i,3} \equiv$ trade_Y_t: Total overseas trade value as a proportion of GRP (average value for each calculation period) [Data: "New China 60"]
6. $z_{i,4} \equiv$ fdi_Y_t: Foreign direct investment as a proportion of GRP (average value for each calculation period) [Data: "New China 60"]
7. $z_{i,5} \equiv$ ln_fer$_t$: Birth rate during the calculation period (initial term, logarithmic value) [Data: "New China 60"]
8. $Nmig_t$: Net immigration rate during the calculation period. [Data: National Population Census (1995, 2000)]
9. Human capital level (explanatory and control variables): (a) $\ln Averedu$: Logarithmic value of average education (average for each calculation period); (b) Percen.unv_empl_year: Ratio of university graduates to employees (average for each calculation

period); (c) unv. s_year: Proportion of the region's university graduates within all graduates nationwide (average for each calculation period). [Data: Fifth National Population Census (each province), China Statistical Yearbook (for each year)].

10. Human capital agglomeration effects (explanatory and instrumental variables): (a) hca_ ln_AvereduFL: Average education of the foreign labor (logarithmic value) × net immigration rate (which shows the $\mu_j \times m_i$ effect in the theoretical model presented in the appendix); (b) hac_Percen.unv_empl_year: Proportion of university graduates within all employees' times net immigration rate; (c) hca_unv. s_year: Proportion of all students' nationwide times net immigration rate.

Table 7.3 summarizes the basic statistics for the various variables listed..

7.4.2 Estimation Results

Table 7.4 presents estimates for 1979–2007 to show the convergence among regions after the reform. Table 7.5 presents estimates for 1987–2007 to examine the convergence among regions after FDI inflows. Tables 7.6 and 7.7 verify the human capital agglomeration effect.

First, we discuss the estimation results in Table 7.4. Columns (1)–(4) show the estimation results using OLS, whereas columns (5)–(7) present the estimation results using the IV, 2SLS, and GMM methods, respectively. The human capital agglomeration effect is not considered in columns (1)–(3). Column (1) does not consider regional characteristics or differences in human capital levels across regions. At the same time, columns (2) and (3) are the estimation results after considering these factors and adding the primary selection, state variables and regional dummies in this chapter. Column (4) shows the estimation results when including the human capital agglomeration effect without considering the endogeneity of average education. These estimation results show the following. The result in column (1) shows absolute convergence during this period but is fragile. These are consistent with Fig. 7.1, which shows that China's interregional income inequality narrowed once from 1978 but widened again after 1990. Columns (2), (3), and (4) present estimates that consider regional characteristics (regional dummies) and the level of human capital (average education level) across regions, and the estimated coefficient of ln_GRP_t, which indicates convergence, is

Table 7.3 Descriptive statistics of variables

	Obs	*Mean*	*Std. Dev*	*Min*	*Max*
G_9107	29	0.102	0.014	0.077	0.129
ln_GRP_91	29	6.347	0.469	5.622	7.628
G.cons._Y_9107	29	0.154	0.085	0.102	0.574
I_Y_9107	29	0.447	0.077	0.266	0.635
trade_Y_9107	29	0.034	0.050	0.000	0.175
fdi_Y_9107	29	0.002	0.005	0.000	0.024
ln_fer_91	29	−1.770	0.310	−2.551	−1.409
Dummy_Region	29	0.345	0.484	0.000	1.000
Nmig_9500	29	−0.072	0.353	−0.837	0.495
ln_Averedu_2000	29	2.039	0.103	1.816	2.301
unv.s_9506	29	0.034	0.019	0.003	0.077
Percen.unv_empl_9699	29	0.046	0.039	0.010	0.198

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Table 7.4 Measurement of convergence in 1979–2007 (Dependent variable: Average growth rate of per-capita GRP)

	(1) *OLS*	*(2)* *OLS*	*(3)* *OLS*	*(4)* *OLS*	*(5)* *IV*	*(6)* *2SLS*	*(7)* *GMM*
Const.	0.121***	0.163***	0.107***	0.125***	0.027	0.027	0.014
	0.000	**0.000**	**0.001**	**0.000**	**0.496**	**0.391**	**0.636**
In_GRP_79	−0.007*	−0.018***	−0.027***	−0.030***	−0.023***	−0.023***	−0.022***
	0.077	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
G.cons._Y_7907		0.040***	0.037***	0.031**	0.034***	0.034***	0.034***
		0.006	**0.005**	**0.012**	**0.004**	**0.000**	**0.000**
I_Y_7907		−0.019	−0.019	−0.033*	−0.006	−0.006	−0.008
		0.372	**0.303**	**0.087**	**0.757**	**0.698**	**0.556**
trade_Y_7907		0.039	0.031	0.035	0.062	0.062*	0.079**
		0.378	**0.417**	**0.337**	**0.155**	**0.067**	**0.013**
ln_fer_79		−0.007	0.008	−0.010	0.007	−0.007	−0.002
		0.391	**0.305**	**0.141**	**0.329**	**0.216**	**0.541**
Dummy_Region		0.018 ***	0.018***	0.014***	0.013***	0.013***	0.012***
		0.000	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**
ln_Averedu_8907			0.056**	0.056***	0.091***	0.091***	0.102***
			0.013	**0.008**	**0.000**	**0.000**	**0.000**
hca_ ln_AvereduFL_2000				0.004*			
				0.061			
Percen.unv_empl_99					−0.330	−0.330***	−0.408***
					0.009	**0.000**	**0.000**
hac_Percen.unv_empl_9699					0.402	0.402***	0.488***
					0.034	**0.005**	**0.001**

(continued)

Table 7.4 (continued)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) 2SLS	(7) GMM
VIF (Mean, Max)		1.94, 3.15	2.54, 5.58	2.75, 6.02			
Ramsey RESET test		F(3, 19) = 1.23 Prob > F = 0.32	F(3, 18) = 0.73 Prob > F = 0.55	F(3, 17) = 1.2 Prob > F = 0.33			
Wu-Hausman F test:					4.98 F(1,18) P-value = 0.04		
Durbin-Wu-Hausman chi-sq test					6.3 Chi-sq(1) P-value = 0.01		
Underidentification test(Anderson canon. corr. LM statistic)						Chi-sq(4) P-val = 0.00	Chi-sq(4) P-val = 0.01

	(1) OLS	*(2) OLS*	*(3) OLS*	*(4) OLS*	*(5) IV*	*(6) 2SLS*	*(7) GMM*
Weak identification test(Cragg-Donald Wald F statistic)						101.038	89.344
Sargan statistic						Chi-sq(3) P-val = 0.158	
Hansen J statistic							Chi-sq(3) P-val = 0.38
R^2 *(Adj.*R^2*; Centered* R^2*)*	0.111	0.610	0.698	0.735	0.760	0.837	0.822
Observations	29	29	29	29	29	29	29

Note

1. Instrumented: ln_Averedu$_{2000}$; Instruments: hca_ln_AvereduFL, unv.s$_{2005}$ and others
2. Bold type, where P (>|t|), ***, ** and * show significance levels of 1%, 5% and 10%, respectively

Table 7.5 Measurement of convergence in 1987–2007 (Dependent variable: Average growth rate of per-capita GRP)

	(1) OLS	*(2) OLS*	*(3) OLS*	*(4) OLS*	*(5) IV*	*(6) 2SLS*	*(7) GMM*
Const.	0.082***	0.154***	0.125***	0.129***	−0.020	−0.020	−0.019
	0.004	**0.000**	**0.000**	**0.002**	**0.654**	**0.562**	**0.682**
ln_GRP_87	0.001	−0.010*	−0.022***	−0.023**	−0.012*	−0.012**	−0.014**
	0.896	**0.080**	**0.008**	**0.013**	**0.089**	**0.023**	**0.012**
G.cons._Y_8707		0.053***	0.053***	0.053***	0.050***	0.050***	0.050***
		0.006	**0.003**	**0.005**	**0.001**	**0.000**	**0.000**
I_Y_8707		−0.024	−0.028	−0.031	−0.004	−0.004	-0.004
		0.268	**0.162**	**0.192**	**0.856**	**0.815**	**0.786**
trade_Y_8707		0.055	0.060	0.061	0.121**	0.121***	0.119***
		0.273	**0.199**	**0.203**	**0.011**	**0.000**	**0.000**
FDI_Y_8707		0.464	0.531	0.505	0.159	0.159	0.106
		0.226	**0.138**	**0.185**	**0.623**	**0.525**	**0.491**
ln_fer_87		0.007	0.007	0.007	0.007	0.007	0.007
		0.483	**0.460**	**0.476**	**0.363**	**0.236**	**0.413**
Dummy_Region		0.014***	0.015***	0.015***	0.008	0.008**	0.008*
		0.006	**0.002**	**0.005**	**0.091**	**0.023**	**0.080**
ln_Averedu_8907			0.052**	0.053**	0.103***	0.103***	0.109***
			0.040	**0.045**	**0.000**	**0.000**	**0.000**
hca_ ln_AvereduFL_2000				0.001			
				0.810			
Percen.unv_empl_99					−0.510***	−0.510***	−0.532***
					0.003	**0.000**	**0.000**
hac_Percen.unv_empl_9699					0.399*	0.399***	0.439***
					0.054	**0.009**	**0.006**
VIF (Mean, Max)		1.97, 3.32	2.66, 6.86	2.8, 6.1			

	(1) *OLS*	(2) *OLS*	(3) *OLS*	(4) *OLS*	(5) *IV*	(6) *2SLS*	(7) *GMM*
Ramsey RESET test		F(3, 18) = 1.5 Prob > F = 0.24	F(3, 17) =1.09 Prob > F = 0.38	F(3, 16) = 01.04 Prob > F = 0.40			
Wu-Hausman F test:					10.603 F(1,17) P-value = 0.005		
Durbin-Wu-Hausman chi-sq test:					11.14 Chi-sq(1) P-value = 0.0008		
Underidentification test(Anderson canon. corr. LM statistic)						Chi-sq(3) P-val = 0.000	Chi-sq(3) P-val = 0.0260
Weak identification test(Cragg-Donald Wald F statistic)						61.003	56.655
Sargan statistic						Chi-sq(2) P-val = 0.7907	
Hansen J statistic							Chi-sq(2) P-val = 0.7426
R^2Adj.R^2	0.001	0.455	0.539	0.735	0.689	0.789	0.791
Observations	29	29	29	29	29	29	29

Note
1. Instrumented: ln_Averedu$_{2000}$; Instruments: hca_ln_AvereduFL, unv.s$_{2005}$ and others.
2. Bold type, where P (>|t|), ***, ** and * show significance levels of 1%, 5%, and 10%, respectively.
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Table 7.6 Measurement of convergence in 1991–2004 (Dependent variable: Average growth rate of per-capita GRP)

	(1) *OLS*	*(2)* *OLS*	*(3)* *OLS*	*(4)* *OLS*	*(5)* *IV*	*(6)* *2SLS*	*(7)* *GMM*
Const.	0.030	0.152***	0.113**	0.095	−0.020	−0.020	−0.013
	0.368	**0.003**	**0.037**	**0.144**	**0.835**	**0.789**	**0.878**
ln_GRP_$_{91}$	0.010*	−0.014	−0.027**	−0.021	−0.028*	−0.028**	−0.024**
	0.076	**0.155**	**0.038**	**0.214**	**0.064**	**0.012**	**0.023**
G.cons._Y_$_{9104}$		0.047*	0.048**	0.051**	0.044*	0.044**	0.046***
		0.054	**0.043**	**0.043**	**0.077**	**0.017**	**0.000**
I_Y_$_{9104}$		−0.026	−0.026	−0.021	0.002	0.002	−0.002
		0.358	**0.333**	**0.488**	**0.963**	**0.953**	**0.936**
trade_Y_$_{9104}$		0.073	0.104	0.091	0.154*	0.154**	0.158**
		0.353	**0.188**	**0.276**	**0.083**	**0.020**	**0.016**
FDI_Y_$_{9104}$		0.310	0.515	0.528	0.413	0.413	0.469
		0.535	**0.306**	**0.305**	**0.449**	**0.326**	**0.173**
ln_fer_$_{87}$		−0.012	−0.010	−0.009	−0.011	−0.011	−0.009
		0.319	**0.419**	0.481	**0.399**	**0.273**	**0.489**
Dummy_Region		0.019***	0.020***	0.021***	0.017**	0.017***	0.016**
		0.010	**0.005**	0.006	**0.032**	**0.003**	**0.046**
ln_Averedu_$_{2000}$			0.063	0.053*	0.132**		0.116***
			0.119	**0.240**	**0.023**		**0.004**
hca_ ln_AvereduFL_$_{2000}$				−0.002			
				0.638			
Percen.unv_empl_$_{99}$					−0.288	−0.288*	−0.217
					0.206	**0.096**	**0.275**

	(1) OLS	*(2) OLS*	*(3) OLS*	*(4) OLS*	*(5) IV*	*(6) 2SLS*	*(7) GMM*
hac_Percen.unv_empl_9699					0.242 **0.503**	0.242 **0.386**	0.112 **0.705**
unv.s_9500							
VIF (Mean, Max)		2.69, 5.11	3.32, 8.84	4.51, 16.24			
Ramsey RESET test		F(3, 18) = 0.84 Prob > F = 0.488	F(3, 17) = 0.27 Prob > F = 0.846	F(3, 16) = 0.37 Prob > F = 0.775			
Wu-Hausman F test:					7.479 F(1,17) P-value = 0.014		
Durbin-Wu-Hausman chi-sq test:					8.860 Chi-sq(1) P-value = 0.0029		
Underidentification test(Anderson canon. corr. LM statistic)						Chi-sq(3) P-val = 0.000	Chi-sq(3) P-val = 0.0227
Weak identification test(Cragg-Donald Wald F statistic)						33.864	25.543

(continued)

Table 7.6 (continued)

	(1) *OLS*	*(2)* *OLS*	*(3)* *OLS*	*(4)* *OLS*	*(5)* *IV*	*(6)* *2SLS*	*(7)* *GMM*
Sargan statistic						Chi-sq(2) P-val = 0.7268	
Hansen J statistic							Chi-sq(2) P-val = 0.7507
Adj.R^2	0.112	0.386	0.431	0.408	0.382	0.603	0.608
Observations	29	29	29	29	29	29	29

Note
1. Instrumented: ln_Averedu_2000; Instruments: hca_ln_AvereduFL, unv.s_2005 and others
2. Bold type, where P (>|t|), ***, ** and * show significance levels of 1%, 5% and 10%, respectively

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Table 7.7 Measurement of convergence in 1991–2007 (Dependent variable: Average growth rate of per-capita GRP)

	(1) OLS	*(2) OLS*	*(3) OLS*	*(4) OLS*	*(5) IV*	*(6) 2SLS*	*(7) GMM*
const.	0.073**	0.191***	0.134***	0.1324**	−0.0330	−0.0330	−0.0316
	0.050	**0.001**	**0.011**	**0.0480**	**0.7020**	**0.6220**	**0.7000**
ln_GRP_91	0.005	−0.020**	−0.040***	−0.0392**	−0.0283**	−0.0283**	−0.0282***
	0.406	**0.054**	**0.003**	**0.0280**	**0.0390**	**0.0050**	**0.0020**
G.cons._Y_9104		0.079***	0.080***	0.0798**	0.0763***	0.0763***	0.0765***
		0.008	**0.003**	**0.0050**	**0.0040**	**0.0000**	**0.0000**
I_Y_9104		−0.023	−0.022	−0.0214	0.0130	0.0130	0.0126
		0.480	**0.447**	**0.5110**	**0.6810**	**0.5960**	**0.6220**
trade_Y_9104		0.077	0.108	0.1070	0.1756**	0.1756***	0.1739***
		0.325	**0.133**	**0.1640**	**0.0240**	**0.0020**	**0.0010**
FDI_Y_9104		0.745	0.916*	0.9181*	0.5267	0.5267	0.5046
		0.191	**0.079**	**0.0890**	**0.3370**	**0.2110**	**0.1480**
ln_fer_87		−0.016	−0.013	−0.0129	−0.0127	−0.0127	−0.0124**
		0.204	**0.255**	**0.2810**	**0.2440**	**0.1270**	**0.0290**
Dummy_Region		0.015**	0.018***	0.0185**	0.0123	0.0123**	0.0128**
		0.044	**0.010**	**0.0130**	**0.1030**	**0.0290**	**0.0580**
ln_Averedu_9104			0.010**	0.0913**	0.1417***	0.1417***	0.1409***
			0.018	**0.0390**	**0.0040**	**0.0000**	**0.0000**
hca_ ln_AvereduFL_2000				−0.0002			
				0.9730			
Percen.unv_empl_99					−0.3467	−0.3467**	−0.3442*
					0.1650	**0.0660**	**0.0830**
hac_Percen.unv_empl_9699					0.1828	0.1828	0.1802
					0.6490		**0.6490**

(continued)

Table 7.7 (continued)

	(1) *OLS*	*(2)* *OLS*	*(3)* *OLS*	*(4)* *OLS*	*(5)* *IV*	*(6)* *2SLS*	*(7)* *GMM*
VIF (Mean, Max)		2.60, 4.87	3.18, 8.36	4.44,15.99			
Ramsey RESET test		F(3, 18) = 1.14 Prob > F = 0.360	F(3, 17) = 0.04 Prob > F = 0.99	F(3, 16) = 0.04 Prob > F = 0.990			
Wu-Hausman F test:						3.216F(1,17) P-value = 0.091	
Durbin-Wu-Hausman chi-sq test:						4.614 Chi-sq(1) P-value = 0.0317	
Underidentification test(Anderson canon. corr. LM statistic)						Chi-sq(3) P-val = 0.000	Chi-sq(3) P-val = 0.0156
Weak identification test (Cragg-Donald Wald F statistic)						54.891	61.127
Sargan statistic						Chi-sq(2) P-val = 0.997	
Hansen J statistic							Chi-sq(2) P-val = 0.995
R^2 (Adj.R^2; Centered R^2)	0.026	0.333	0.475	0.447	0.530	0.698	0.698
Observations	29	29	29	29	29	29	29

Note
1. Instrumented: ln_Averedu$_{8707}$; Instruments: hca_ln_AvereduFL, unv.s$_{2005}$ and others
2. Bold type, where P (>|t|), ***, ** and * show significance levels of 1%, 5% and 10%, respectively

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significantly measured. We also obtain significant estimates for the government's final consumption expenditure ratio to GRP, regional dummies (coastal region = 1, Midwest region = 0), and average years of education as proxy variables for human capital, and human capital agglomeration effect. However, the estimators for other explanatory variables were not statistically significant.

The OLS estimates in Table 7.4 also test for variable dropout likelihood and multicollinearity for the explanatory variables; the Ramsey RESET test and VIF values are the statistics for these tests. All estimations in columns (2) through (4) indicate no possibility of missing variables and no multicollinearity.

Average years of education is another variable that is suspected to be endogenous. Column (5) in Table 7.4 presents the test for the presence or absence of endogeneity in the mean years of education. Columns (5)–(7) in Table 7.4 summarize the endogeneity test's results and the estimates by the IV method when endogeneity is found. The Wu-Hausman F test and the Durbin-Wu-Hausman chi-sq test are tests of the null hypothesis that the mean year of education is an exogenous estimator. If these hypothesis tests are rejected (i.e., if the exogenous nature of average years of education is rejected), then the average years of education are determined as endogenous variables. As indicated in columns (6) and (7), when the human capital agglomeration effect (hca_ ln_AvereduFL_2000) was considered, the estimates for the trade effect (trade dependence) were also significant. This result indicates conditional convergence after the reform. It suggests that the human capital agglomeration effect (hca_ ln_AvereduFL_2000) is present not only in the validation period (1991–2004) but also in the period after the reform until 2007. Columns (5), (6), and (7) also consider Percen.unv_empl_99 and its human capital agglomeration effect, hac_Percen.unv_empl_9699. Estimation results in columns (6) and (7), with average education, hca_ ln_AvereduFL_2000, is as an endogenous variable and others as manipulated variables, show the same results as in column (4), but with a significant effect of hac_Percen.unv_empl_9699. Given that hac_Percen.unv_empl_9699 is a variable that represents the synergistic effect of the human capital level and labor migration (net immigration rate) of workers in each region, the estimated results can be summarized as follows.

Suppose the human capital agglomeration effect exists. In this case, many workers with high levels of human capital will concentrate in coastal regions (the estimation results of hca_ ln_AvereduFL_2000 and ln_Averedu_2000), which will increase the human capital level (hac_Percen.unv_empl_ 9699 estimates) and promote trade, resulting in high economic growth rates.

Meanwhile, the outflow of workers with high human capital in different regions results in lower trade effects and economic growth rates. This result was confirmed by the 1987–2007 and 1991–2007 estimates.

However, unlike Barro (1997), the estimates of the investment rate in columns (2)–(7) were not significant. Nevertheless, the estimates of the government spending to GRP ratio (positive) were all significant. These results can be attributed to the poor investment efficiency of many regions of China during this period. However, it must be considered that Chinese local government consumption expenditures included infrastructure investments that promoted economic growth during this period.

Second, we discuss the results in Table 7.5 which summarizes the results of our previous analysis of China's interregional convergence when FDI effects are considered.

The estimation results in Table 7.5, taking into account the foreign investment effect, are very similar to those in Table 7.4, including the fact that the foreign investment effect (fdi_Y_9104) is not significant in any of the estimations results. As in Table 7.4, the estimation results in Table 7.5 are all significant (positive) for hac_Percen.unv_empl_9699 (the agglomeration effect on the level of workers' human capital).

Third, we discuss the results in Table 7.6 and 7.7. Table 7.6 presents the estimation results for the period in which the hypotheses of this chapter were tested. The results are similar to those in Tables 7.4 and 7.5 except for the human capital agglomeration effect (hac_Percen.unv_empl_9699), which is not significant. However, if the hypothesized estimation period is extended to 2007, due to the human capital agglomeration effect of migrants (hca_ ln_AvereduFL_2000), the convergence coefficient ($\widetilde{\beta}_i$) is larger than in any other period, as shown in Table 7.7.

7.5 A Comparison with China and Japan During High Economic Growth Era

In Japan and China, high economic growth (the 1960s in Japan and the 1990s in China) experienced widening income disperity among regions. This section investigates the factors that widened income disparities during high economic growth in Japan from the perspective of population movement. We examine the relationship between population movement to large cities and income disperity during this period and compare this relationship with the expanding income disperity in China in the 1990s. This comparison provides a perspective on appropriate policies to resolve income disperity among the regions in China.

Considering the population movement to large city areas in Japan, Tokyo had a major economic scale compared to other large cities. Migration to the Tokyo metropolitan area was prominent; at the peak of population movement in 1962, about twice as many people flowed into the Tokyo metropolitan area as into the Osaka metropolitan area and about six times as many as into the Nagoya metropolitan area. For this reason, we focus on the Tokyo metropolitan area when considering the reasons for population movement in urban areas.

7.5.1 Population Migration and Income Inequality in Japan

We can find some previous studies on the factors of income inequality during Japan's high economic growth. Watanabe (1989) focused on the industrial structure, and Nawata (2008) focused on the scale of public works projects. These studies have pointed out that labor migration to the Tokyo metropolitan area was a significant factor in the income disparity between regions during Japan's rapid economic growth. Looking at the period from 1955 to 1974, the population inflow to the Tokyo metropolitan area rose consistently from 1955, peaked in 1961, and then continued to decline, becoming negative (population outflow) from 1967. When we compare the per capita income of the Tokyo metropolitan area to the national average, the discrepancy is the same as that for population outflow: it increased from 1955 to 1961 and continued to decline after 1961. In other words, population movement in Japan is closely related to income inequality.

Various studies have been conducted on the factors that led to population movement in metropolitan areas during periods of high economic growth. Watanabe (1989) showed that changes in the industrial structure are a major factor in population movement. Watanabe (1989) noted that during the period of high economic growth, the development of the manufacturing industry had a significant impact on changes in population movement. Wang (1994) shows that the population movement between prefectures during high economic growth (1955–1972) was largely influenced by the income level of the place of transfer. Nawata (2008) points out that population inflow to the three metropolitan areas approximates the economic growth rate using data on the economic growth rate and population movement from 1955 to 2006. As the reason for this, Nawata (2008) points out that rapid labor migration to highly productive areas, especially from the 1950s to the 1970s, induced high economic growth. It also indicates that the expansion of public works projects in rural areas under the Comprehensive National Development Plan was the reason for the decline in population inflows to urban areas in the 1970s, which narrowed the income gap between urban and rural areas. During the period of high economic growth, when manufacturing was a significant industry, the location of manufacturing companies in rural areas, due to infrastructure development through public works projects, helped reduce the income gap between rural and urban areas. Hatta and Tamura (2020) also attributed the decline in population movement to large cities in the early 1970s to a decrease in the income gap between urban and rural areas. Similar to Nawata (2008), Hatta and Tamura (2020) show that the decline in income disparity is also attributed to public works policies that are biased toward rural areas based on the concept of "balanced development of the nation's land." The shift in manufacturing bases due to local infrastructure development and the increase in labor demand due to public works projects in rural areas have contributed to the decrease in income inequality between urban and rural areas. This result is consistent with the findings of Nawata (2008).

Based on the above literatures, we can conclude that "job search" was a factor in labor migration during high economic growth. In other words, there was active labor migration to the Tokyo metropolitan area and other urban areas during low unemployment in urban areas and high unemployment in rural areas. Meanwhile, labor migration from urban to rural areas was active during periods when labor demand in rural areas increased due to public works and factory relocations. Therefore, if infrastructure (especially roads, since manufacturing was the main industry during this period) was built in rural areas, factories could be built, and people would stay in those areas. As a result, the wage gap between rural and urban areas narrowed, and population movement subsided. Population movements during Japan's rapid economic growth can be explained by the Todaro model, which shows that labor migration occurs based on expected wages—that is, how much income can be earned in the future and the present.

7.5.2 Population Migration and Income Inequality in China

In this study, we have focused on the human capital agglomeration effect of China's internal migration policy, the *hukou* system, and clarified the causes of income inequality in China by using Barro Regression with regional macro data and the 2000 Chinese Population Census data.

First, absolute β convergence was not significantly measured to summarize the results of the empirical analysis. However, conditional convergence is significantly measured when the human capital agglomeration effect is considered. Furthermore, the coefficient estimates of foreign investment and trade effects on regional economic development are also significant. In other words, when human capital accumulation occurs, workers with high levels of human capital are concentrated in the coastal region, which promotes production activities and the trade of foreign-invested firms and leads to higher economic growth rates. In other regions, workers with high human capital leave the region. The effect of foreign investment is insufficient, and the economic growth rate is low. As a result, the income gap between the regions widened during this period.

We then compared the characteristics of population mobility and income inequality in Japan and China. First, as a commonality, we find that China's interregional income disparities are largely related to population mobility as in Japan's high-growth period. The main reason is that higher-income employment opportunities are more prevalent in urban areas. Meanwhile, during Japan's period of rapid economic growth, population movement reversed as the manufacturing base moved to the countryside, narrowing the income gap between regions and reversing population mobility. A household registration system in China is a factor in widening regional disparities. It creates incentives for people to move to coastal areas, where higher wages are available when jobs are available.

What kinds of policies would effectively reduce interregional income disparities in China? During Japan's period of rapid economic growth, the reduction in regional income disparities and population mobility was the supply of infrastructure to move industrial bases to the countryside. If infrastructure is developed in low-income inland regions and the production and development bases are also located in these regions, and if the infrastructure for information and communication technology is developed in the future to increase incomes in the regions, population movement and income inequality between regions will be reduced.

However, it has been pointed out that the migration of production bases to rural areas has caused a decline in productivity in urban areas, reducing the growth rate (Hatta & Tamura, 2020). The policies should be implemented depending on the country's economic situation.

7.6 Conclusions and Future Issues

In this chapter, using Barro regression, we test the hypothesis that the human capital agglomeration effect can explain income disperity between coastal and internal regions in China. We summarize our results as follows. First, absolute β convergence was not measured significantly during the estimation period from 1991 to 2004. Second, conditional convergence is significant when the human capital agglomeration effect is considered, and the trade effect on regional economic development is also significant. This empirical result implies the following. When human capital agglomeration effect exists, workers with high levels of human capital accumulating in the coastal region promote production activities and the trade of foreign-invested firms in the coastal region, leading to a higher economic growth rate. However, the outflow of workers with high levels of human capital in other regions reduces the effect of foreign investment, resulting in a lower economic growth rate. As a result, the income disperity between the regions widened during this period.

In Sect. 7.5 we compare the drivers of population mobility and interregional income inequality in Japan during its rapid economic growth with population mobility and interregional income inequality in China in the 1990s. The main common factor of population movement in both countries is the expected income of the workers. However, there are differences in income inequality trends after population movement between the two countries. In Japan, infrastructure development in regional cities led to a shift in manufacturing production bases to regional cities, resulting in an influx of population to urban areas and a decline in interregional income inequality. In the 1990s, population movement increased interregional income disperity due to the human capital agglomeration effect.

In the future, we need to test our hypothesis over a more extended period to show the reason for income disperity between regions in China. Thus, further research must be conducted using panel analyses and other methods.

Appendix

The Solow–Swan Model with Human Capital Agglomeration Effect

In the Mathematical Appendix, we discuss the theoretical basis for our empirical analysis. This chapter assumes a theoretical model that introduces labor migration into the Solow–Swan model developed by Barro and Sala-i-Martin (2004, chap. 9). Labor is the only factor of production transferred between regions (between countries). The dynamic equations for capital and labor in region i in this chapter are expressed as follows.

$$\begin{aligned} \frac{dK_{i,t}}{dt} &= \dot{K}_{i,t} = s_i Y_{i,t} - \delta_i K_{i,t} + \mu_j M_{ij} \\ \frac{dL_{i,t}}{dt} &= \dot{L}_{i,t} = n_i L_{i,t} + m_i L_{i,t} \quad (i \neq j) \end{aligned} \tag{7.4}$$

where $Y_{i,t}$, $K_{i,t}$, $L_{i,t}$, and M_{ij} represent the number of outputs, capital, and workers in region i and the number of net migrants from region j to region i. s_i, δ_i and n_i are the savings rate, capital depreciation rate, and population growth rate of region i, respectively. To simplify the model, we assume that the savings, capital depletion, and population growth rates are identical across all regions ($s_i = s_j \equiv s, \delta_i = \delta_j \equiv \delta, n_i = n_j \equiv n$ $for\ \forall i, j$). m_i ($\equiv M_{ij}/L_{i,t}$) represents the net migration rate from region j to region i and μ_j represents the level of education (human capital level) of migrants from region j to region i. We represent the Chinese household registration system by making the following assumptions regarding the relationship between M_{ij} and μ_j. First, if the expected income of region i (Ey_i) is extremely higher than that of region j (y_j), that is $Ey_i \gg y_j$, the number of people moving into region i from region j is $M_{ij} > 0$. Meanwhile, if the income level of region i (y_i) is extremely low compared to the expected income of region j ($y_i \ll Ey_j$), the number of people moving out of region i to region j will be $M_{ij} < 0$. Second, with the Chinese household registration system, the higher the level of education (human capital level) of workers (college graduates or those with high school education or above), the more likely they are to be employed in urban areas, especially in developed areas (coastal areas). Thus, the more likely they are to become residents (obtain household registration) in those areas.

Let λ_{ij} ($0 \leq \lambda_{ij} \leq 1$) be the probability that immigrants from region j can obtain household registration in region i. Now we consider the net number of immigrants when we consider the household registration system. We consider the probability of acquiring a household register λ_{ij} depends on the size of human capital of immigrants μ_j, that is $\lambda_{ij}^{'}(\mu_j) > 0$. The larger the human capital μ_j and the closer its value is to the educational level $\overline{\mu}_i$ of long-term employment in region i ($\mu_j \approx \overline{\mu}_i$), the closer the value of λ_{ij} gets to 1 ($\lambda_{ij} \leq 1$) and most of the immigrants (M_{ij}) have high human capital levels ($\lambda_{ij} M_{ij} = M_{ij}^{high}$). However, the lower μ_j is $\mu_j \approx \mu_j^{low} \approx 0$, the closer λ_{ij} is to zero ($\lambda_{ij} \geq 0$), the lower the human capital level of most of the immigrants and the less they can obtain household registration ($(1 - \lambda_{ij}) M_{ij} = M_{ij}^{low}$). Therefore, the net number of migrants in region i is $\lambda_{ij} M_{ij} + (1 - \lambda_{ij}) M_{ij} = M_{ij}$. Equation (7.5) expresses the relationship.

$$M_{ij} = \begin{cases} M_{ij}^{high} & if\ \lambda_{ij} \leq 1 \Leftrightarrow \mu_{ij} \approx \mu_j^{high} \approx \bar{\mu}_i \\ M_{ij}^{low} & if\ \lambda_{ij} \geq 0 \Leftrightarrow \mu_{ij} \approx \mu_j^{high} \approx 0 \end{cases} \tag{7.5}$$

We now assume that the production technology in region i is a Cobb–Douglas production function ($Y_{i,t} = K_{i,t}{}^{\alpha} \left(A_{i,t} L_i \right)^{1-\alpha} h_i^{\mu_j m_i}; 0 < \alpha < 1$). In the production function, $A_{i,t} = e^{xt}$ represents the level of technology (x is exogenous technological progress) and $h_i^{\mu_j m_i}$ is the productivity effect of immigrants in region i ($\partial Y_{i,t} / \partial h_i^{\mu_j m_i} > 0$). As noted earlier, in the presence of a household registration system, the higher μ_j, the higher the human capital level of migrants; so, the net migration rate becomes $m_i \approx M_{ij}^{high} / L_{i,t}$. In this case, the productivity effect ($h_i^{\mu_j m_i}$) of the immigrants may be even higher because of the synergistic effect of μ_j and m_i. Thus, we can interpret $\mu_j m_i$ as the human capital agglomeration effect under the household registration system. If $\mu_j > 0$ and $m_i > 0$, this represents an influx of workers with high human capital levels from other regions. Therefore, the productivity effect, which is due to the human capital agglomeration effect, is positive (i.e., positive human capital agglomeration effect) in region i. However, if $\mu_j > 0 and m_i < 0$, it expresses the state that workers with high human capital levels are flowing out to other regions, and the productivity effect by human capital agglomeration effect in region i becomes negative (i.e., negative human capital agglomeration effect). Using Eq. (7.4), the per capita output of region i and the dynamic equation of capital when the human capital agglomeration effect occurs is considered are as follows:

$$\begin{aligned} y_{it} &= k_{i,t}^{\alpha} h_i^{\mu_j m_i} \\ \dot{k}_{i,t} &= s k_{i,t}^{\alpha} h_i^{\mu_j m_i} - \left(x + \eta + \delta + \varphi\left(k_{i,t}\right)\right) k_{i,t} \\ \text{where } \varphi\left(k_{i,t}\right) &= m_i\left(k_{i,t}\right)\left(1 - \frac{\tilde{\mu}_j}{k_{i,t}}\right) \end{aligned} \tag{7.6}$$

where $\widetilde{\mu}_j \equiv \mu_j / A_{i,t}$ and y_{it} $(\equiv Y_{i,t}/A_{i,t}L_i)$ and k_{it} $(\equiv K_{i,t}/A_{i,t}L_i)$ represent the GRP per capita and capital per capita, respectively. $\varphi\left(k_{i,t}\right)$ is the emigration function. Barro and Sala-i-Martin (2004) assumed that $\varphi\left(k_{i,t}\right)$ is an increasing function of $k_{i,t}$ $(\varphi'\left(k_{i,t}\right) > 0)$. This is because an increase in per capita physical capital leads to an increase in the wage rate in region i, which in turn leads to an increase in the number of migrants and the migration rate.

Figure 7.3 shows the relationship between steady-state growth rates and capital stock levels for three possibilities with different μ_j and m_i: $\mu_j > 0, m_i > 0$ (denoted as Region 1 below), $\mu_j \approx 0, m_i > 0$ (Region 2 below), and $\mu_j > 0, m_i < 0$ (Region 3 below).

We can derive the relationship shown in Figure A through the following process. From Equation (A3), the steady-state per capita GRP (y_i^*) and capital per capita (k_i^*) are obtained as follows:

$$\begin{aligned} k_i^* &= \left(\frac{s h_i^{\mu_j m_i^*}}{x + \eta + \delta + \varphi\left(k_i^*\right)}\right)^{\frac{1}{1-\alpha}}; \\ y_i^* &= \left(\frac{s h_i^{\frac{\mu_j m_i^*}{\alpha}}}{x + \eta + \delta + \varphi\left(k_i^*\right)}\right)^{\frac{\alpha}{1-\alpha}} \end{aligned} \tag{7.7}$$

According to Eq. (7.7), the relationship between μ_j, m_i^* and y_i^* is as follows:

$$\frac{\partial y_i^*}{\partial \mu_j} = \left(\frac{m_i^*}{\alpha} \ln\ h_i + \frac{m_i^*/k_i^*}{x + \eta + \delta + \varphi\left(k_i^*\right)}\right) \psi > 0$$

$$\frac{\partial y_i^*}{\partial m_i} = \left(\frac{\ln h_i \mu_j/\alpha(x + \eta + \delta) + \left(\ln h_i \mu_j m_i^*/\alpha - 1\right)\left(1 - \frac{\tilde{\mu}_j}{k_i^*}\right)}{x + \eta + \delta + \varphi\left(k_i^*\right)}\right)$$

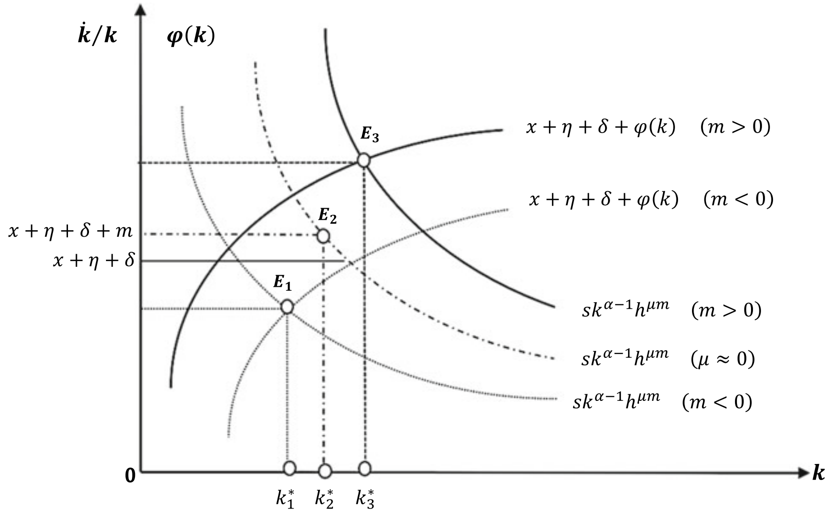

Fig. 7.3 The Solow–Swan Model with human aggregation effect (*Source* Authors' creation)

$$\psi \underset{<}{\overset{>}{-}} 0 \Leftrightarrow \mu_j \underset{<}{\overset{>}{-}} \frac{\alpha}{m_i^* \ln h_i} \tag{7.8}$$

where $\psi \equiv \alpha y_i^*/(1-\alpha)$. As can be seen in Eq. (7.5), if $m_i^* > 0$ and μ_j is high, a positive human capital agglomeration effect in region$i$, by immigrants from region$j$, will occur, resulting in an increase in per capita GRP (GRP(y_i^*)) in region i ($\partial y_i^*/\partial\mu_j > 0$). In contrast, even if m_i^* is high, the human capital level of immigrants must satisfy certain conditions ($\partial y_i^* \big/ \partial m_i - 0 \Leftrightarrow \mu_j\ \alpha \big/ m_i^* \ln h_i$); no increase in per capita GRP (y_i^*) in region i is due to the positive human capital agglomeration effect brought about by immigrants occurs.

Figure 7.2 illustrates the relationship ($y_1^*(k_1^*) < y_2^*(k_2^*) < y_3^*(k_3^*)$) of capital per capita for the three cases in steady state (regions 1 ~ 3). Assuming a Cobb–Douglas production function $y_i^* = \left(k_{i,t}^{\alpha}\right)^* h_i^{\mu_j m_i^*}$, the relationship of per capita GRP for the three cases ($y_1^*(k_1^*) < y_2^*(k_2^*) < y_3^*(k_3^*)$) in steady state is also confirmed similarly.

Considering Figure A and Equation (A4) together, we conclude that: (1) per capita capital (k_3^*) and GRP (y_3^*) in Case 1 ($\mu_j > 0, m_i > 0$) are the highest due to the positive human capital agglomeration effect, while per capita capital (k_3^*) and GRP (y_3^*) in Case 3 ($\mu_j > 0, m_i < 0$) are negative and the lowest due to the effect; (2) Case 2 ($\mu_j \approx 0, m_i > 0$) has higher capital per capita (k_2^*) and per capita GRP (y_2^*) than Case 3 and lower than Case 1 because the increase in the number of migrants is not accompanied by a productivity effect due to immigration ($h_i^{\mu_j m_i^*} \approx 1$).

When the human capital agglomeration effect is considered, the convergence coefficient for capital per capita ($k_{i,t}$) is obtained as follows. First, we rewrite the capital dynamic equation in equation (A3) as $\Gamma\left(\ln k_{i,t}\right) = s h_i^{\mu_j m_i} e^{-(1-\alpha)\ln k_{i,t}} - (x + \eta + \delta) - m_i\left(e^{\ln k_{i,t}}\right)\left(1 - e^{\ln\tilde{\mu}_j - \ln k_{i,t}}\right)$, and using the Taylor expansion of the equation around the steady state ($\ln k_i^*$), we obtain the following equation:

$$
\begin{aligned}
&\frac{\dot{k}_{i,t}}{k_{i,t}} \cong \Gamma'\left(\ln k_i^*\right)\ln\left(\frac{k_{i,t}}{k_i^*}\right) = -(\beta_i + \omega)\ln\left(\frac{k_{i,t}}{k_i^*}\right) \equiv -\underset{i}{\tilde{\beta}}\ln\left(\frac{k_{i,t}}{k_i^*}\right)\\
&\beta_i \equiv (1-\alpha)(x + \eta + \delta);\\
&\omega = \left(1 - \underset{j}{\tilde{\mu}}/k_i^*\right)\partial m_i/\partial \ln k_i^* + (1-\alpha)m_i^* + \alpha\,\underset{j}{\tilde{\mu}}\,m_i^*/k_i^*
\end{aligned}
\tag{7.9}
$$

where β_i is the convergence coefficient in the absence of labor migration, and $\tilde{\beta}$ is the convergence coefficient when labor migration and migration function are introduced, that is, when the human capital agglomeration effect is assumed. The relationship between β_i and $\tilde{\beta}$ is as follows:

$$
\begin{aligned}
&\text{if} \quad m_i^* \geq 0 \quad \text{then} \quad \tilde{\beta}_i \geq \beta_i; \quad \text{if} \quad m_i^* < 0 \quad \text{then } \tilde{\beta}_i < \beta_i;\\
&\text{if} \quad \tilde{\mu}_j \approx 0 \quad \text{and} \quad m_i^* >; 0 \quad \text{then } \tilde{\beta}_i \geq \beta_i
\end{aligned}
\tag{7.10}
$$

Assuming a Cobb–Douglas production function $\left(y_{it} = k_{i,t}^{\alpha} h_i^{\mu_j m_i}\right)$, the convergence coefficient related to per capita GRP and its differential equation solution is as follows:

$$
\begin{aligned}
&\frac{\dot{y}_{i,t}}{y_{i,t}} \cong -(\beta_i + \omega)\ln\left(\frac{y_{i,t}}{y_i^*}\right) \equiv -\tilde{\beta}_i \ln\left(\frac{y_{i,t}}{y_i^*}\right)\\
&\ln y_{i,t} = x + \left(1 - e^{-\tilde{\beta}_i t}\right)\log y_i^* + \left(1 - e^{-\tilde{\beta}_i t}\right)\log y_{i,0}
\end{aligned}
\tag{7.11}
$$

From Eq. (7.11), the Barro Regression [Eq. (17.3) in the main text] that considers the human capital agglomeration effect from period t_0 to period

t_T is obtained as follows:

$$\overline{G}(t_0, t_T)_i = \frac{1}{T}\ln\left(\frac{y_{i,t_T}}{y_{i,t_0}}\right) = x - \left(\frac{1 - e^{-\tilde{\beta}_i T}}{T}\right)\left(\ln y_{i,t_0} - \ln y_i^*\right) + u(t_0, t_T)_i$$

Notes

1. The standard deviation of the logarithm of GRP per capita is one statistical indicator of interregional economic convergence, and if it decreases over time, economic convergence is considered to exist (income inequality decreases). Barro and Sala-i-Martin (2004) call it "sigma convergence."
2. This fact is also confirmed by Jian (1996), World Bank (1997), Chen (2000a, 2002b), Barro and Sala-i-Martin (2004) call it "sigma convergence." Lin and Liu (2003) and others.
3. For economic convergence, see Barro et.al. (1992, 1994).
4. For "club convergence" in economic convergence, see Quah (1996).
5. This may be the reason for the recent "Minkou Roughness" phenomenon (a phenomenon in which there is a shortage of migrant workers (Minkou) in economically developed areas of China, despite the abundance of labor resources in the country).
6. In other words, it quantitatively measures whether there is a process to (convergence on) the long-term equilibrium (steady state) from an initial state, by solving a differential equation obtained from a Solow model or an optimal growth model.
7. See Barro (1997) for choice variables, environmental variables, and state variables in Barro regression.
8. See Barro and Sala-i-Martin (2004), chapter 1.2.10.
9. See Nakazato (1999).
10. Because the data set used in this chapter is insufficient for Qinghai and Tibet, all the following analyses exclude these two regions.
11. Yan (2005, Chapter 3) defines mobility (net immigration) as "net immigration rate = those moving out less those moving in the permanent population" (at the time of the population census).
12. While the graduate ratios of the four regions other than Shaanxi Province (namely, Sichuan, Hubei, Henan, and Hunan Provinces) were among the highest in 2000 (within the top 10, deviation from the nationwide average of 1.63% for the four regions), their graduate employee ratios were among the lowest (within the bottom 12, deviation from the nationwide average for the four regions of −6.79%).
13. The figures −56.81% and −19.04% for net immigration rate mean that those within the permanent population who had moved in minus those

who had moved out has a negative value and that more people moved out than moved in.

14. The net migration rate is -56.81% and -19.04% are negative because the population that went out from the region is grater than the population that come in.
15. Given data limitations in this chapter, we use the average years of education in each region for the year 2000.
16. Due to incomplete consumer price index data for some regions, we use the national consumer price index (1952 = 100).

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