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Growth path heterogeneity across provincial economies in China: the role of geography versus institutions

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Abstract
This paper investigates whether China's provincial economies follow the same growth path by adopting a finite mixture model in which provinces are sorted into groups according to the similarity in the conditional distribution of their growth rates. The method is flexible in that it accounts for (i) endogenous classifications other than given priori, (ii) heterogeneous marginal effects of determinants, (iii) the possibility of growth path transformation, and (iv) the roles of geographic location and institutions in the growth path. The results reveal that all provinces do not follow a common growth process, but rather two distinct growth regimes. Particularly, one is dominated by foreign direct investment and financial depth, while the other is dominated by trade openness. The growth process of provinces in the central region evolves around the year 2004 from the former to the latter. More importantly, geography and institutions help sort provinces into groups, and institutions are more predominant.

Keywords Multiple regimes · Finite mixture model · Geography–institutions debate · Growth path · China

JEL Classification C33 · O11 · O47

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1 Introduction

Substantial attention over the past few decades has targeted the logic about why some countries are more productive than others. The majority of previous research studies assume that there is a universal growth model for each country, such as the econometric specification of Mankiw et al. (1992) derived from the Solow (1956) growth model. In other words, no matter for developed or developing countries, the same variable has the same effect on economic growth. However, the validity of treating all countries as a group with the same growth regime seems increasingly questionable (Brock and Durlauf 2001). If the growth paths of different countries diverge, then the average effects are not representative for providing less information about the growth sources of a particular country (Solow 1994), and policy recommendations based on the one-size-fits-all model are thus misleading (Bos et al. 2010).

To deal with heterogeneity in growth regimes, traditional empirical works commonly adopt the manner of dummy variables and subsample analysis (Shen and Lee 2006). For example, we can add country-specific effects into the regression and select geographic locations or income levels to divide the full sample into several groups. Nevertheless, the former does not consider the different marginal effects of growth fundamentals, while the latter neglects the diverse growth paths of countries within the same group and the number of groups is unknown (Owen et al. 2009). Therefore, although most growth economists affirm the significance of growth regime heterogeneity worldwide, conventional methods are unsatisfactory.

How to identify and distinguish the heterogeneity of growth paths across economies is an unknown “black box.” Using a series of advanced methodologies, many recent papers have found parameter heterogeneity across countries.[1] These findings are contradictory to the homogeneous assumption of the standard regression model, which does not allow for heterogeneity among countries.[2] Among these studies, however, there is huge discrepancy in the number of regimes and group membership, even with the same econometric specification.[3] The subtle disparity in these works implies that the concomitant variables, which are used to sort countries into groups, are critical. Although using cross-country data can enlarge the sample size, the diversity of historical experiences and cultural norms across different countries may distort the estimations (Lee and Liu 2017). Moreover, the growth paths of different regional economies in an individual country also exhibit heterogeneous

[1] For example, Durlauf and Johnson (1995), Durlauf et al. (2001), Papageorgious (2002), Bloom et al. (2003), Canova (2004), Paap et al. (2005), Alfo et al. (2008), Owen et al. (2009), Bos et al. (2010), Lee et al. (2014), Flachaire et al. (2014), and Lee et al. (2017).

[2] These methods include regression tree analysis, panel threshold regression, varying coefficient model, latent class model, and finite mixture models.

[3] For example, with the framework of finite mixture models, Owen et al. (2009) and Flachaire et al. (2014) adopt the mixture model with two groups, while Alfo et al. (2008) employ the mixture model with four groups. Furthermore, using similar data, Owen et al. (2009) find that Australia and Colombia are classified into different groups, but Flachaire et al. (2014) point out that these same two countries are sorted in the same group.

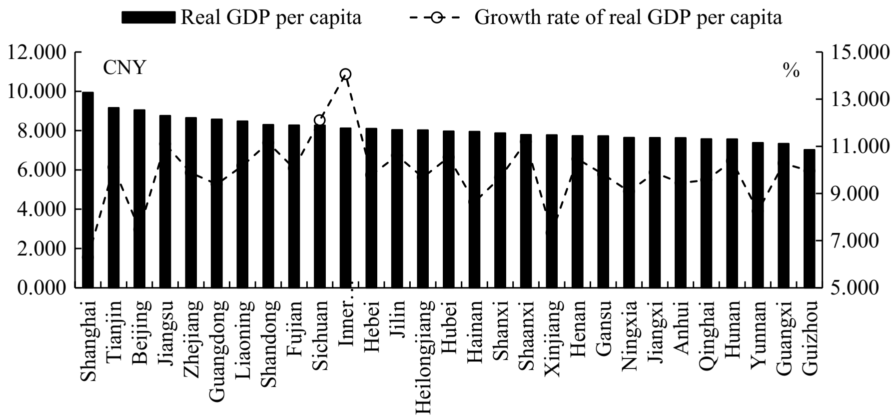

Fig. 1 Real GDP per capita and the growth rates across China's provinces over 1979–2015

patterns, especially for large countries. It is thus helpful to understand the unbalanced regional development inside one particular country via exploring the heterogeneity of growth regimes across regions. Within one country, different regions confront the same circumstance, such as the political system and culture norms, and so it is an ideal condition to justify whether one variable is conducive to sort regions into groups. These ideas prompt the initial motivation of this study, where we investigate growth path heterogeneity in China's provincial economies and the roles that geography and institutions play.

Ever since the reform and opening-up policy in 1978, China has been growing rapidly at a rate of about 10% for the past few decades and becoming the second largest economy in the year 2010. At the same time, there has been an impressive rise in the imbalance across China's provincial economies. As Fig. 1 illustrates, during the period 1979–2015, for provinces with lower income levels, their growth rate of real GDP per capita has not necessarily been very high. This stylized fact indicates that the convergence hypothesis may be inadequate to depict the growth process of China's provinces; or at least there are two or more growth regimes, in which the convergence hypothesis is not always true. More importantly, the effects of growth determinants in different provinces should manifest diverse patterns, such as the role of trade openness in the process of economic growth for coastal and central regions.

With respect to China, this paper is designed to answer the following questions. First, do the provincial economies in the central and western regions follow the same growth path with that in the eastern region? If not, then how many growth regimes can be summarized to describe the heterogeneous provincial economies? Second, is there a significant difference in the marginal effects of economic determinants across regimes? If yes, then which one dominates in different growth paths? Third, is there some evidence of convergence in China or not? Even if there is no monolithic convergence, does the convergence hypothesis exist in any group? Fourth, differing from the traditional debate on the direct effects of geography and institutions on economic growth, are there any indirect effects of geography and institutions through group membership?[4] In other words, this paper's aim is to investigate whether there is an identical growth path applicable for China's provincial economies and to specifically explore the roles of geography and institutions in determining the growth regime.

To achieve this goal, we employ the finite mixture model that allows for heterogeneous growth paths, and the number of groups is endogenously determined using several criteria. The method is a novel econometric framework combining the latent class regression model with the standard multinomial logit model, and we relax the hypothesis that the growth path of one province is constant. In particular, we model the growth rate of each economy as a function of growth determinants. Based on the similarity of the conditional distributions of growth rates, China's provinces are sorted into different groups. Furthermore, the variables of geography and institutions are introduced into the regression, in order to examine the geography–institutions debate from the view of growth regime classifications. In addition, we conduct a series of robust checks, including alternative econometric specification, possible endogeneity, and different production function estimations across regimes.

Our paper contributes to a growing number of different studies in the literature on the heterogeneity of growth across countries. First, based on a panel data consisting of developed and developing countries, the bulk of empirical studies explore the heterogeneity of growth regimes.[5] Focusing on provincial economies in China, we also provide some evidence for the existence of multiple regimes within a particular country. Second, under the assumption that the growth path of each country does not switch, the majority of previous studies adopt latent class models and finite mixture models to test the existence of multiple equilibria, such as Owen et al. (2009), Konte (2013) and Flachaire et al. (2014). Following Bos et al. (2010), we introduce additional flexibility into the model by permitting the growth regimes of countries to switch between regimes over time.

Our study also contributes to the researches on heterogeneous growth patterns of China's provinces. Using geographic locations and income levels as classification criteria, previous studies divide China's provinces into different subsamples, such as Lee and Liu (2017), Liu et al. (2017), Zhang (2017), and Liu and Zhang (2018). However, these methods are lack of uniform standards. For example, we can employ the distance from each province to Beijing (China's capital) or the nearest coastline as the sorting variable. Furthermore, based on the Solow decomposition framework, stochastic frontier analysis (SFA) and data envelopment analysis (DEA), series of previous works explore the growth patterns across China's provinces from the perspective of economic efficiency.[6] But, they do not allow for parameter heterogeneity when constructing production frontiers, suggesting a single common frontier.

[4] As the growth determinants, series of factors have direct growth effects, such as technological progress and fixed investment. But, if one factor determines the growth regime that one province belongs to, it plays an indirect role on economic growth.

[5] Such as Bloom et al. (2003), Paap et al. (2005), Alfo et al. (2008), Owen et al. (2009), and Flachaire et al. (2014).

[6] Such as Wang and Feng (2015), Feng et al. (2017), Liu et al. (2018), and Song et al. (2018).

Differing from given priori, in this paper provinces are endogenously classified into groups, and production technologies across growth regimes are provided.

In particular, our paper contributes to the literature on the relative importance of geography and institutions. A series of previous research studies explore their direct effects on economic growth, and no consistent conclusions are provided. For example, Acemoglu et al. (2001), Easterly and Levine (2003), and Rodrik et al. (2004) deem that institutions can promote economic growth, while Bloom et al. (2014) and Andersen et al. (2016) verify the role of geographic variables in economic growth. In our paper, we investigate the indirect effects of geography and institutions on the growth path of one economy. Differing from them, we find that both geography and institutions help sort provinces in China into groups, supporting the combined findings of Bloom et al. (2003) and Alfo et al. (2008).

Apart from the standard growth regression models, several interesting findings emerge from the empirical investigation in our study. First, there is no a common growth process for China's provincial economies, but a finite mixture model with two regimes best describes their heterogeneous growth paths. Second, except for human capital and transport infrastructure, one regime of provinces in the eastern region is dominated by foreign direct investment and financial depth, while another regime of provinces in the western region is dominated by trade openness. Third, the growth path of provinces in the central region evolves from the former to the latter around the year 2004. Fourth, geography and institutions are conducive to sort provinces into different groups, especially the relationship between government and markets.

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature of multiple regime models and the geography–institutions debate. Section 3 presents the methodology, including standard regression models and finite mixture models. Section 4 describes the data and variable definitions and then provides the results. Section 5 conducts several robust checks, and Sect. 6 concludes the paper.

2 Literature review

2.1 Multiple regime models

In order to understand the differences in income levels and growth rates across countries, the existing literature explores the sources of growth from various perspectives, including geographic factors (e.g., location, climate, and malaria risk), financial development, foreign direct investment, the quality of institutions, and trade openness; for more details, see Barro (1991), Sala-i-Martin (1997), and Hall and Jones (1999), among many others. Furthermore, another brand of economic growth literature concerns the convergence hypothesis, which states that "the poor catch up with the rich," while no consistent conclusions are obtained; for more details, see Bianchi (1997), Paap et al. (2005), and Alfo et al. (2008).

Although these studies provide lots of useful information, they neglect the heterogeneous importance of the same variable to economic growth in different economies, even accounting for the country-specific effects. To overcome the drawbacks of traditional methods, some authors commonly use income per capita and geographic location to conduct a series of subsample analysis; for more details, see Shen and Lee (2006), Flachaire et al. (2014), Liu et al. (2018), and Luo and Wen (2017), among many others. However, this ex ante sample division is exogenously determined according to personal experience and especially lacks a uniform standard, and thus, conflict conclusions are always given. Therefore, endogenous group classification is crucial for investigating the heterogeneity of growth rates across countries.

Differing from traditional regression models, based on regression- and distribution-based methods, some newly developed frameworks are employed to explore the existence and characteristics of multiple regimes. On the one hand, some works adopt the regression-based method. For example, Durlauf and Johnson (1995) examine the existence of multiple growth regimes by splitting the data into subsamples on the basis of different control variables and conduct regression tree analysis to identify group membership. Using the data-sorting method on the basis of an asymptotic distribution proposed by Hansen (2000) and Papageorgious (2002) explores the roles of trade openness to endogenously select regimes, while Sirimaneetham and Temple (2009) investigate the threshold effects of macroeconomic stability.

More research studies employ the density-based method. For example, from the perspective of distribution dynamics, Quah (1997) analyzes the patterns of growth across countries and finds two peaks in the cross-country distribution. Bianchi (1997) tests the convergence hypothesis by means of nonparametric density estimation techniques and points out low mobility patterns of intra-distribution dynamics and increasing evidence for bimodality. To account for country-specific heterogeneity in the Solow model, Durlauf et al. (2001) employ the varying coefficient model that permits the parameter to differ across countries and verify the heterogeneity of growth rates in different countries. Based on the predictive density, Canova (2004) proposes a new method to identify the convergence clubs and finds four groups of countries. Nevertheless, these studies are based on predetermined factors, and the results of group membership are continuous and ordered.

The latent class model and its applications have recently attracted more and more attention, and we can specifically detect which factor determines growth regimes. Based on a poverty trap model with two regimes, Bloom et al. (2003) investigate the role of each economy's geography in income differences across countries. Employing a latent class panel time series model, Paap et al. (2005) suggest that three groups are sufficient to describe the growth paths of different countries. Applying the multivariate mixture model, Alfo et al. (2008) present that the explanatory power of the Solow model is enhanced when cross-country heterogeneity is considered. Through estimating a finite mixture model, Owen et al. (2009), Konte (2013), and Flachaire et al. (2014) discover that a model with two regimes is best to describe the growth processes of different countries, while Bos et al. (2010) point out that three regimes exist in production technologies across countries.

The majority of research studies assume that the growth path of each economy is constant, neglecting the possible switch of growth regimes over time, such as Owen et al. (2009), Konte (2013), and Flachaire et al. (2014). In fact, Bianchi (1997), Bloom et al. (2003), and Bos et al. (2010) argue that countries always transform from one equilibrium to another, and it is necessary to take the possibility of growth path transformations into account. As for China, there are huge differences across provinces, and the growth paths may evolve with the development of economy. Thus, we have the first hypothesis as follows.

Hypothesis 1 There are multiple growth paths in China's provinces, and the growth paths of some provinces may switch over time.

2.2 The geography–institutions debate

In the existing literature of economic growth, one of the vital ongoing debates is whether geographic factors or institutions have direct effects on economic growth in the long run or not, and which one is more important (Kourtellos et al. 2010; Luo and Wen 2017). Generally speaking, previous studies can be classified into two strands: one is the geography school, while the other is the institutions school.

The institutions school strengthens the importance of political or economic systems and legal institutions in the process of economic growth, such as property rights and the order of law. Specifically, fine institutions are conducive to physical capital accumulation, human capital investment, and technical innovations and help promote the improvement of economic efficiency and income per capita (North 1981). Using different kinds of macro- and micro-data, many empirical works support the institutions view, including Acemoglu et al. (2001), Johnson et al. (2002), Easterly and Levine (2003), Rodrik et al. (2004), and Banerjee and Iyer (2005), among other papers.

Among the above research, the most remarkable paper is Acemoglu et al. (2001). To overcome potential endogeneity, they employ the settlement mortality rate in the colonial period as an instrumental variable of modern institutions and find that institutions explain almost three-quarters of income differences across former colonies. However, they suggest that geographic factors have no direct effects on economic performance once institutions are controlled for and argue that geography affects economic growth through the quality of institutions. In fact, Hall and Jones (1999) deem that the distance to the equator measures the effect of western countries, which is appropriate to as the instrumental variable of institutions, and then cause the income differences across countries. Following the instrumental variable approach, various works support the institutions school (e.g., Easterly and Levine 2003; Rodrik et al. 2004; Luo and Wen 2017).

The geography school argues that geographic factors are the fundamentals of economic growth, such as geographic locations and climate, and institutions are ultimately shaped by geography (Diamond 1997). Aside from the transport costs of trade openness and the availability of natural resources for production, geography also affects human health, technology diffusions, and life expectancy. For example, Diamond (1997) and Sachs (2001) emphasize the role of geographic environment in technology imitation, while Sachs and Malaney (2002) point out that malaria risk negatively influences human health and is positively related to the degree of civil violence, which then impedes economic growth. Barrios et al. (2010) and Dell et al. (2012) examine the effects of temperature shocks and rainfall on economic growth. In addition, Bloom et al. (2014) and Andersen et al. (2016) explore the relationships between initial sanitary condition as well as ultraviolet radiation intensity and economic growth.

Some studies confirm the combination of the geography and institutions views. Bloom and Sachs (1998) explore the deep underlying factors that impede African growth over the entire modern period and find that various aspects of tropical geography, demography, and public health are dominant factors rather than economic policy and governance. Based on their estimates, "non-economic" conditions can explain two-thirds of African growth, while economic policy and institutions only contribute to one-thirds. Sachs (2003) suggests that the quality of institutions and the malaria risk have significant effects on income per capita, and Kourtellos et al. (2010) discover substantial heterogeneity in the geography–institutions debate using a structural threshold regression methodology.

With regard to the former colonies of 95 countries, Auer (2013) verifies the importance of legal origins and institutions and especially points out that the estimates in previous studies are biased for mixing the effect of the historical determinants of institutions with the sizeable direct impact of geographic endowments on development. McCord and Sachs (2013) strengthen that the development of one economy is a complex process driven by economic, political, social, and biophysical forces. In fact, the sources of economic growth include geography, institutions, and technology, and none of these alone is sufficient to account for the diverse patterns of global growth. Luo and Wen (2017) deem that the importance of growth fundamentals varies with the stage of development and confirm that non-institutional factors largely account for the income variation among agrarian countries, while institutional factors predominantly explain the income differences across industrialized countries.

Numerous works focus on the direct effects of geography and institutions in the process of economic growth, but neglect their indirect roles. Recently, a few research studies have examined the impacts of geography and institutions on the growth paths in different countries. Persson (2004) and Acemoglu et al. (2005) argue that political institutions determine the stage of economic development, which then affect the roles of growth sources in economic growth. Bloom et al. (2003) point out that countries with a favorable geography have relatively high income in the low-level equilibrium and find it easy to jump to the high-level equilibrium. Alfo et al. (2008) deduce that institutions matter for the growth regimes across countries, and Konte (2013) and Flachaire et al. (2014) prove the prediction. Owen et al. (2009) provide no evidence that geographic variables play a role in determining group memberships, but the quality of institutions helps sort countries into different regimes. With respect to China, the provinces located in coastal regions and with fine institutions tend to have higher growth rates, and some economic indicators (e.g., trade openness, foreign direct investment) are more active. Therefore, we propose the second hypothesis as follows.

Hypothesis 2 Geography and institutions play important roles in sorting provinces into different groups in China.

3 Model and methodology

3.1 Standard growth regression model

To compare with the previous research, we consider the following standard growth regression model (Shen and Lee 2006; Shen et al. 2011; Zhang et al. 2015; Lee and Lin 2018):

$$eg_{it} = \beta_0 + \beta_1 \ln gdp_{i0} + \beta_2 trade_{it} + \beta_3 gov_{it} + \beta_4 fd_{it} + \beta_5 edu_{it} + \beta_6 fdi_{it} + \beta_7 trans_{it} + \beta_8 geo_i + \beta_9 ins_{it} + \gamma_t + \varepsilon_{it} \quad (1)$$

Here, the dependent variable is the annual growth rate of real GDP per capita (eg) of province i in year t, and the explanatory variables include initial GDP per capita ($\ln gdp_0$), trade openness ($trade$), government consumption (gov), financial depth (fd), human capital (edu), foreign direct investment (fdi), and transport infrastructure ($trans$). Furthermore, in order to investigate whether geography and institutions have a significantly direct effect on economic growth, geography (geo) and institutions (ins) are also added into the regression. In addition, the year-fixed effects γ_t are introduced to capture the time-varying economic conditions in China, but the province-fixed effects are not taken into account for investigating the convergence hypothesis.

Equation (1) assumes that all provinces follow the same growth path. However, the growth path across China's provinces may be heterogonous. Recently, some empirical research studies have provided strong evidence for multiple equilibria across countries.[7] Specifically, China's unbalanced regional development is now widely known. While the provinces in the eastern region are developed, the provinces in the western region are less developed. In fact, the gap among different regions has been increasing over the past few decades. Thus, we conjecture that there may be several different growth regimes for the provincial economies.

Geography and institutions have a direct effect on economic growth in Eq. (1), as argued by a series of previous works. For example, Bloom et al. (2014) and Andersen et al. (2016) find a significant direct impact of geographic indicators on economic growth, and Acemoglu et al. (2001) and Rodrik et al. (2004) insist that institutions directly affect a regional economy, although the geographic features of the economy are controlled for. Nevertheless, their theoretical analyses are based on the logic that geography and institutions affect growth through several channels, such as the disease environment, human health, trade openness, capital accumulation, and labor productivity.

[7] Owen et al. (2009) and Flachaire et al. (2014) find that the growth path of international countries is best described by an econometric model with two growth regimes, while Paap et al. (2005) and Bos et al. (2010) identify that global countries follow three growth regimes.

It is possible that the impacts of geography and institutions on economic growth are not direct, but rather determine the growth process of the economy. Some variables are the fundamentals of growth, while others may be considered "deeper" determinants through shaping the overall environment in which growth happens (Rodrik et al. 2004).[8] With respect to China's provinces, we predict that geography and institutions also play important roles in determining a province's growth process and that they have an indirect effect on economic growth. In order to test our prediction, we account for the possibility that the provinces follow several different growth paths using an advanced econometric framework. In particular, differing from the previous research focusing on the direct effects of geography and institutions on growth, their indirect effects are discussed through determining the growth regimes, which provide some new evidence for the geography–institutions debate.

3.2 Finite mixture model

To overcome the drawback of the standard growth regression model that assumes a common and unique growth process for all provinces, we introduce a newly developed model that takes the possibility of multiple growth regimes into account. Specifically, the finite mixture approach is a semi-parametric framework for modeling unobserved heterogeneity across economies. This method is an application of latent class regression models to estimate a latent discrete distribution of growth regimes, which is not priori and exogenously imposed, but rather endogenously estimated. Compared to traditional approaches, the mixture models have three remarkable features. First, two or more growth processes are allowed, and the growth determinants are assumed to have different marginal effects across regimes. Second, based on the conditional distribution of the growth rate, the group membership that each economy belongs to is endogenously determined with concomitant variables, and the resulting classification is in terms of posterior probabilities. Third, the parameters of the growth regression for each regime and the distribution of the latent regimes are estimated jointly via maximum likelihood.

To illustrate the approach, we consider the following finite mixture model with the joint normal distribution in which two groups are not generated by the same data-generating process (Konte 2013; Flachaire et al. 2014):

$$\begin{cases} Group1 : y = x\beta_1 + \varepsilon_1 \;\; \varepsilon_1 \sim N\left(0, \sigma_1^2\right) \\ Group2 : y = x\beta_2 + \varepsilon_2 \;\; \varepsilon_2 \sim N\left(0, \sigma_2^2\right) \end{cases}, \tag{2}$$

where y is the dependent variable; x denotes the vector of covariates; and ε_1 and ε_2 are independent and identical normally distributed error terms within each group with variances σ_1^2 and σ_2^2, respectively. Specifically, the sets of coefficients β_1 and β_2 must be significant and not equal at the 10% level, in order to explore the different

[8] For example, Owen et al. (2009) find that institutions rather than geographic characteristics are the deep causes of growth, and Flachaire et al. (2014) also point out that political institutions are the "deeper" determinants of growth.

roles of covariates x in explaining the differences between observations y in each group.

The reason why we use the finite mixture model is that at least one explanatory variable does not explain identical growth discrepancies within the two groups. Specifically, for economies with different income levels, the effects of financial development on economic growth should be different (Shen and Lee 2006; Liu et al. 2017). Note that we also can add a 0–1 dummy variable that specifies group membership into Eq. (1), such as 1 for developed provinces and 0 for other provinces. However, the groups have to be defined priori according to the experience of some researchers, which may incur misleading results. Differing from traditional methods, group memberships in the finite mixture approach are estimated in terms of the relationship between y and x, and the number of groups is endogenously determined using several econometric criterions.

In Eq. (2), one economy's probability of being in the two regimes only depends on the observations of growth rates y and growth determinants x. In other words, provinces are allocated to the regime that best fits the data. Furthermore, a set of additional covariates, called concomitant variables, can be added into Eq. (2) to characterize group profiles. More importantly, the roles of standard covariates and of concomitant variables are different: the former help to explain the variations within groups, while the latter explain the variations between groups—that is to say, aside from growth rates y and the covariates x, the concomitant variables partly determine the probability that one province belongs to which group.

A general version of the finite mixture model for a given economy is:

$$f(y|x, z, \Theta) = \sum_{k=1}^{K} \pi_k\left(z, \alpha_k\right) f_k\left(y|x, \beta_k, \sigma_k\right), \tag{3}$$

where the integer K is the number of groups; z denotes the vector of concomitant variables with the coefficients α_k; $\pi_k\left(z, \alpha_k\right)$ denotes the probability of being in the group k with z; $f_k\left(y|x, \beta_k, \sigma_k\right)$ represents the distribution of growth rates y conditional on belonging to group k and on standard covariates x with the coefficients β_k; and the parameters σ_k are the standard deviations of the error term in group k. If we treat f_k as a normal distribution, then the finite mixture Eq. (3) reduces to Eq. (1) with $K = 1$ and reduces to Eq. (2) with $K = 2$.

The probability of being in a given group membership m is then assumed to follow a multinomial logit model, or specifically:

$$\pi_m\left(z, \alpha_m\right) = \frac{\exp\left(\alpha_m + z\alpha_m\right)}{\sum_{k=1}^{K} \exp\left(\alpha_k + z\alpha_k\right)}, \tag{4}$$

and this assesses the likelihood that a given economy's observed growth rates are generated by the process described by parameters β_m and σ_m, given the values of x and z. Intuitively, the finite mixture approach allows us to endogenously determine the groupings of provinces by including province characteristics that do not affect growth directly, but may influence growth by determining the probability of group membership.[9]

Under the assumption that the error term in the growth rate equation comes from a normal distribution, the log-likelihood function is:

$$\log L = \sum_{i=1}^{N} \log f(y|x, z, \Theta) = \sum_{i=1}^{N} \log \left[\sum_{k=1}^{K} \pi_k(z, \alpha_k) \prod_{t=1}^{T} f_k(y|x, \beta_k, \sigma_k) \right]. \tag{5}$$

Using the empirical Bayes rule, the province-specific posterior membership probabilities for a given province i belonging to group m are obtained:

$$\hat{\pi}(m|z_i, y_i) = \frac{\pi_m(z_i, \hat{\alpha}_m) f_m(y_i|x_i; \hat{\beta}_m, \hat{\sigma}_m)}{\sum_{k=1}^{K} \pi_k(z_i, \hat{\alpha}_k) f_k(y_i|x_i; \hat{\beta}_k, \hat{\sigma}_k)}. \tag{6}$$

Furthermore, provinces are classified into the groups with the largest posterior probability, and we can get the size of each class (% of observations):

$$p_m = \frac{\sum_{i=1}^{N} \hat{\pi}(m|z_i, y_i)}{N}. \tag{7}$$

Once we get the probabilities of being in different group memberships for each province, each province is classified into the group in which it has the largest posterior probability. Note that even though for the majority of provinces the classification occurs with the posterior probability very close to 1, the classification is probabilistic. In particular, the conditional probability of misclassification for a given province i is $1 - \max \hat{\pi}(m|z_i, y_i)$, and then, the overall misclassification error for the finite mixture model (3) is:

$$E = 1 - \frac{\sum_{i=1}^{N} \max \hat{\pi}(m|z_i, y_i)}{N}, \tag{8}$$

where N is the number of provinces.

In summary, we redefine the growth paths as a latent class trajectory characterized by a system of equations: K groups with heterogeneous growth paths and a multinomial logit model with additional covariates (geography and institutions) that account for the sorting of provinces into each of the K regimes. It is worth noting that previous studies assume that one economy is not allowed to switch regimes, and then, the concomitant variables must be constant over time (e.g., Owen, et al. 2009; Konte 2013; Flachaire et al. 2014). In contrast, following Bloom et al. (2003) and Bos et al. (2010), we allow provinces to switch regimes across periods. For example,

[9] For example, the legal system may affect the economic environment in which growth occurs and then indirectly determine the effect of financial structure on growth.

for a given province moving from t to $t + 1$, the province is treated as a different unit i at different periods and can switch regimes.

Because the number of groups is priori unknown, we start with a one-class model and then estimate subsequent models that increase the number of groups by one each time. For a given number of groups K, finite mixture models are often estimated by maximum likelihood with the EM algorithm of Dempster et al. (1977). Since the log-likelihood function can be highly nonlinear and a global maximum can be difficult to obtain, we use three information criteria to select the model that best fits the data: the Bayesian information criteria (BIC), the corrected Akaike information criteria (CAIC), and the Akaike information criteria 3 (AIC3).[10]

More importantly, the reasons we do not control the province-fixed effects in the regressions are as follows. First, China's provinces are classified into different growth regimes based on the conditional distribution of growth rates, indicating that the individual fixed effects are similar in the same group, consistent with a series of previous works, such as Bos et al. (2010), Owen et al. (2009), Konte (2013), and Flachaire et al. (2014). Second, we allow each province to be in different regions at different times. In some cases, there is only one observation for some provinces within a group, suggesting that the individual fixed effects cannot be accounted. Third, the initial level of real GDP per capita (ln gdp_0) is introduced to test the convergence hypothesis, which is collinear with the province-fixed effects. Of course, we can break the data in 5-year intervals to have time-varying initial GDP levels. However, the period is set from 1997 to 2009 limited to the data of institutions, revealing that this method is not suitable in our paper.

4 Empirical results

4.1 Data and variable definitions

In order to investigate the heterogeneity of growth paths across provinces in China, we collect panel data consisting of 29 provinces. Considering the availability of data, Tibet is not included in the regression, and we merge the data of Chongqing into the Sichuan province. Limited to the data for institutions, the period is set from 1997 to 2009.[11] The raw data are retrieved from two sources. The data for the dependent and explanatory variables are obtained from China's official publications, the Provincial Statistical Yearbooks (PSY hereafter), and the data for measuring the quality of institutions are obtained from the National Economic Research Institute (NERI hereafter) Index of the marketization of China's provinces 2011 Report developed by Fan et al. (2011).

[10] All the criteria are decreasing along with the value of the log likelihood LL and increasing in the number of parameters J estimated. Specifically, with the number of observations n, we can obtain $BIC = -2LL + J \log n$, $CAIC = -2LL + J \log (N + 1)$, and $AIC3 = -2LL + 3J$.

[11] With respect to the data of institutions, the NERI index developed by Fan et al. (2011) only provides the time period 1997–2009. Wang et al. (2017) update the data for China's provinces. However, the calculation methods are different, and so the data are inconsistent.

Table 1 provides the definitions and sources of variables used in the regression. As in standard growth regression models, the dependent variable is the growth rate of real GDP per capita, measured by the log difference of total real GDP over total population. The explanatory variables include the natural logarithm of initial real GDP per capita in 1996 ($\ln gdp_0$), the ratio of exports and imports to total GDP (*trade*), the ratio of government consumption to total GDP (*gov*), the natural logarithm of loans and deposits in financial institutions to total GDP (*fd*), the natural logarithm of average education years per capita (*edu*), the ratio of actual usage of foreign direct investment to total GDP (*fdi*), and the natural logarithm of highway length to total population (*trans*).

In order to eliminate the effects of inflation and obtain real GDP, nominal GDP is converted into 1978 PPP-adjusted CNY. To calculate the weighted average education years per capita across provinces, we assign 2, 6, 9, 12, and 16 to those people that have education degrees/levels corresponding to illiteracy, primary school, junior school, senior school, and above. To obtain the measurement of foreign direct investment, we convert the original value provided by PSY using the average exchange rate of the US dollar against CNY at the same year.

As for the concomitant variables, the geographic location of each province is treated as the proxy of geography. According to the 2007 China Statistical Yearbook, the 29 provinces are classified into the eastern, central, and western regions. The eastern region includes 10 provinces: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes 11 provinces: Shanxi, Liaoning, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi. The western region includes 8 provinces: Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. We denote 1, 2, and 3 as the provinces in the eastern, central, and western regions, respectively. The smaller the value is, the more favorable the geographic location is. Thus, provinces with higher values have greater distance to coastlines.

To measure the quality of institutions across the provinces, following Ang et al. (2015) and Zhang et al. (2016), we use the marketization indices constructed by Fan et al. (2011). The logic lies in the fact that along with the reform of China's economic system, the mode of economic development has turned from a planned economy to a market economy, which has improve resource allocations in the factor and product markets and promoted economic growth for the past three decades (Hsieh and Klenow 2009; Liu et al. 2018). Fan et al. (2011) use arithmetic average method to generate an overall indicator and five secondary indicators: the relationship between government and markets, the development of the non-state economy, the marketization of product markets, the marketization of factor markets, and the order of intermediary organizations and law.[12] Table 2 summarizes the descriptive statistics for variables and provides an average numerical impression of the variables used in our empirical analysis.

[12] With respect to each secondary indicator, Fan et al. (2011) propose several specific proxies. For example, they propose five proxies to measure the relationship between government and markets, including resource allocated by markets, government intervention for enterprises, tax burden of farmers, non-tax burden of firms, and government size. In addition, they also use principal component analysis to generate these indicators, and the data are very similar.

Table 1 Definitions and sources of variables used in the regression analysis

Variable	Definition	Measurement	Source
Dependent variable	Economic growth ***eg***	Log difference of total GDP to total population	Author's calculation using PSY
Explanatory variable	Initial GDP per capita **ln** $\boldsymbol{gdp_0}$	Natural logarithm of total GDP to total population in 1996	Author's calculation using PSY
	Trade openness ***trade***	Ratio of exports and imports to total GDP	Author's calculation using PSY
	Government consumption ***gov***	Ratio of government consumption to total GDP	Author's calculation using PSY
	Financial depth ***fd***	Natural logarithm of ratio of loans and deposits in financial institutions to total GDP	Author's calculation using PSY
	Human capital ***edu***	Natural logarithm of weighted average education years per capita	Author's calculation using PSY
	Foreign direct investment ***fdi***	Ratio of actual usage of foreign direct investment to total GDP	Author's calculation using PSY
	Transport infrastructure ***trans***	Natural logarithm of highway length to total population	Author's calculation using PSY
Concomitant variable	Geography ***geo***	1, 2, and 3 for provinces in the eastern, central, and western regions	Author's definition using PSY
	Institutions ***ins***	Natural logarithm of marketization value	Fan et al. (2011)

Table 2 Descriptive statistics

Variable	Obs.	Mean	Min.	Max.	Std.
eg	377	0.1150	0.0491	0.2382	0.0261
ln gdp_0	377	7.4258	6.4602	9.1544	0.5624
trade	377	0.3206	0.0325	1.7996	0.4092
gov	377	0.1524	0.0534	0.4532	0.0644
fd	377	0.7884	-0.2917	1.8621	0.3238
edu	377	2.0845	1.7084	2.4189	0.1113
fdi	377	0.0355	0.0010	0.1653	0.0315
trans	377	2.8024	1.1099	4.7145	0.6438
geo	377	1.9310	1.0000	3.0000	0.7859
ins	377	1.6819	0.2546	2.4681	0.3863

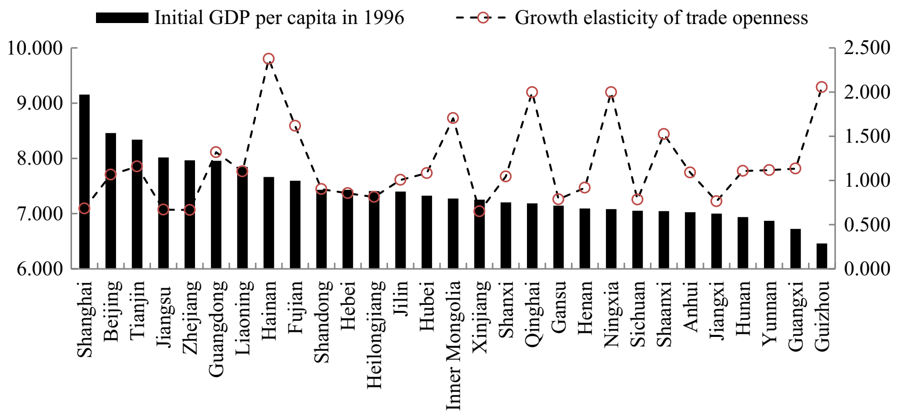

Fig. 2 Initial GDP per capita in 1996 and growth elasticity of trade openness across China's provinces over 1997–2009

Further, to present the existence of different regimes across the provinces, we take trade openness as an example. In particular, we employ the ratio of the growth rate of real GDP per capita over the growth rate of exports and imports to simply measure the marginal effects (growth elasticity) of trade openness on economic growth. Figure 2 depicts the initial value of real GDP per capita in 1996 and growth elasticity of trade openness across China's provinces over 1997–2009. It is obvious that trade openness has a greater role in the provinces with lower income per capita, suggesting the heterogeneous importance of trade openness across provincial economies. Thus, it is crucial to account for growth path heterogeneity when understanding the growth sources in the provinces.

Table 3 Standard regression models

Variable	Full sample analysis				Subsample analysis		
	(i)	(ii)	(iii)	(iv)	Eastern	Central	Western
ln gdp_0	−0.0132***	−0.0135***	−0.0075*	−0.0034	−0.0078	−0.0121	−0.0146
	(0.0043)	(0.0045)	(0.0040)	(0.0043)	(0.0073)	(0.0118)	(0.0118)
edu	0.1080***	0.1072***	0.0556***	0.0572***	0.0899***	0.0090	0.0519*
	(0.0147)	(0.0151)	(0.0152)	(0.0151)	(0.0282)	(0.0465)	(0.0290)
trade	0.0169***	0.0166***	−0.0003	0.0008	0.0046	0.0409	−0.0097
	(0.0052)	(0.0053)	(0.0053)	(0.0053)	(0.0062)	(0.0424)	(0.0485)
fdi	0.2119***	0.2106***	0.1520***	0.1582***	0.1153*	−0.0923	0.4241***
	(0.0459)	(0.0462)	(0.0432)	(0.0430)	(0.0606)	(0.1570)	(0.0819)
fd	−0.0225***	−0.0221***	−0.0124**	−0.0150***	−0.0227***	−0.0068	0.0482**
	(0.0050)	(0.0052)	(0.0048)	(0.0049)	(0.0079)	(0.0078)	(0.0196)
gov	0.0309	0.0340	0.0522*	0.0238	−0.0478	−0.2060**	0.0166
	(0.0285)	(0.0312)	(0.0266)	(0.0287)	(0.0586)	(0.1034)	(0.0453)
trans	0.0130***	0.0130***	0.0097***	0.0097***	0.0001	0.0401***	0.0083
	(0.0025)	(0.0025)	(0.0024)	(0.0024)	(0.0045)	(0.0064)	(0.0055)
geo		−0.0007		0.0069**			
		(0.0028)		(0.0027)			
ins			0.0311***	0.0346***	0.0366***	0.0346***	0.0166**
			(0.0040)	(0.0042)	(0.0083)	(0.0094)	(0.0075)
Obs.	377	377	377	377	130	143	104
R^2	0.3047	0.3029	0.4012	0.4097	0.3235	0.5539	0.5296

Growth regression estimations include intercepts and time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

4.2 Standard growth regression model

Table 3 reports the pooled OLS estimation results of the standard growth regression model (1). Columns (i)–(iv) present the estimation results based on the full sample. Geographic location has a significantly positive role in economic growth when institutions are added into the regression; otherwise, it has an insignificant role. In all regressions, the significantly positive effect of institutions on economic growth does not change. Combining with the coefficients, it is easy to deduce that institutions play a more important role than geography.

The coefficients of human capital, foreign direct investment, and transport infrastructure are significantly positive, which are consistent with theoretical expectations. Trade openness is positively and significantly related to the growth rate of real GDP per capita with the geographic locations added into the regression, but loses significance once institutions are controlled for. Even though government consumption has a positive effect on economic growth, it is insignificant at the 10% level. In addition, there is a significantly negative relationship between initial GDP per capita and the growth rate of real GDP per capita, supporting the convergence hypothesis.

Table 4 Wald tests for the heterogeneous coefficients across regions

Variable	Eastern versus Central		Eastern versus Western		Central versus Western	
	Statistic	p value	Statistic	p value	Statistic	p value
ln gdp_0	0.14	0.713	0.28	0.595	0.03	0.860
edu	3.47*	0.062	0.95	0.331	0.80	0.372
trade	0.91	0.341	0.08	0.775	0.66	0.416
fdi	2.19	0.139	7.13***	0.008	9.53***	0.002
fd	1.84	0.175	8.72***	0.003	5.29**	0.021
gov	1.76	0.185	0.56	0.455	4.95**	0.026
trans	17.85***	0.000	1.16	0.281	11.54***	0.007
ins	0.03	0.867	3.57*	0.059	2.80*	0.094

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Contrary to the expected sign, the coefficient of financial depth is significantly negative. This finding is seemingly controversial, but is essentially consistent with the reality in China. On the one hand, Chinese banks are keen on providing loans to state-owned and large enterprises, and the services provided by China's financial system concentrate on these enterprises. However, it is widely known that the efficiency of state-owned enterprises is relatively low. On the other hand, small- and medium-sized enterprises with high productivity cannot obtain sufficient financial services from banks and other financial institutions. Consequently, there is a serious mismatch between financial services and the real economy, and hence, it is not surprising to see that financial development plays a negative role in China's economic development.

The last three columns report the estimation results using the subsample in different regions. Obviously, institutions have significantly positive impacts on the growth rate of real GDP per capita across regions, but other explanatory variables play heterogeneous roles in different regions. With respect to the same variable, Table 4 provides the Wald tests for the heterogeneous coefficients in the eastern, central, and western regions. The results reveal that the differences in the marginal effects of covariates (except initial GDP per capita and trade openness) in different regions are significant, and so the average effects provided by standard regression models using a full sample may be misleading.

Differing from the results of full sample, the negative coefficient of initial GDP per capita is not significant in the subsample, which more importantly suggests that the convergence hypothesis is not proved for different regions. This is likely to be a result of parameter heterogeneity due to the fact that group membership classified by geographic location is not appropriate. In other words, the growth paths of provinces within the same geographic location may be heterogeneous, which make the subsample estimations of standard regression models confusing.

Table 5 Standard regression models with disaggregated components of institutions

Variable	Different components of institutions				
	ins1	*ins2*	*ins3*	*ins4*	*ins5*
ln gdp_0	−0.0037	−0.0039	−0.0085*	−0.0091**	−0.0131***
	(0.0045)	(0.0044)	(0.0045)	(0.0043)	(0.0044)
edu	0.0794***	0.0673***	0.0860***	0.0842***	0.0744***
	(0.0148)	(0.0150)	(0.0153)	(0.0148)	(0.0165)
trade	0.0057	0.0089*	0.0121**	0.0042	0.0077
	(0.0053)	(0.0051)	(0.0053)	(0.0054)	(0.0056)
fdi	0.1836***	0.1348***	0.1956***	0.1555***	0.2168***
	(0.0438)	(0.0443)	(0.0451)	(0.0448)	(0.0452)
fd	−0.0182***	−0.0143***	−0.0192***	−0.0196***	−0.0212***
	(0.0050)	(0.0050)	(0.0051)	(0.0050)	(0.0051)
gov	0.0210	−0.0007	0.0616**	0.0262	0.0420
	(0.0295)	(0.0295)	(0.0309)	(0.0297)	(0.0305)
trans	0.0129***	0.0110***	0.0120***	0.0109***	0.0088***
	(0.0024)	(0.0024)	(0.0025)	(0.0024)	(0.0027)
geo	0.0044	0.0075***	0.0005	0.0036	0.0008
	(0.0027)	(0.0028)	(0.0027)	(0.0027)	(0.0027)
ins	0.0326***	0.0156***	0.0153***	0.0171***	0.0146***
	(0.0048)	(0.0021)	(0.0033)	(0.0027)	(0.0034)
Obs.	377	377	377	377	377
R^2	0.3797	0.3931	0.3409	0.3707	0.3352

The variables ins1, ins2, ins3, ins4, and ins5 refer to different components of institutions, including: (i) the relationship between government and markets; (ii) the development of the non-state economy; (iii) the marketization of product markets; (iv) the marketization of factor markets; and (v) the order of intermediary organizations and law. Growth regression estimations include intercepts and time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

As for the five disaggregated components of institutions, Table 5 reports the results of standard growth regression models.[13] The convergence hypothesis exists in most cases, and each element of institutions is conducive to promote economic growth. However, geographic location has no significant coefficients, except for the case with the development of the non-state economy, suggesting that geographic location does not directly influence real GDP per capita. Overall, our finding is consistent with Acemoglu et al. (2001), Easterly and Levine (2003), and Rodrik et al. (2004), supporting the institutions school.

[13] When adding the five disaggregated components of institutions into the regression, the estimation results (not reported) show that the coefficient of geography is insignificant, while the coefficients of most elements of institutions are significantly positive.

4.3 Finite mixture model

From the previous vein, the results based on standard regression models show that there are significantly direct effects of institutions on economic performance in China even through the factor of geography. More importantly, the marginal effects of growth determinants vary with groups, and the traditional subsample classification according to geographic location is inadequate. In fact, when we conduct the subsample analysis using income per capita as the categorical variable, similar results are also given (not reported). Therefore, it is critical to identify the heterogeneity of growth paths across provincial economies in China and sort provinces into different groups. In particular, whether geography and institutions indirectly affect economic growth via the growth regime is worth investigating.

Table 6 provides the specification tests of finite mixture models. We estimate four cases: (i) the first one is the model in which geography and institutions only have direct effects on growth; (ii) the second one is the model in which geography has a direct effect on growth, while institutions act as a concomitant variable; (iii) the third one is the model in which the quality of institutions has a direct effect on growth, while geography acts as a concomitant variable; and (iv) the fourth one is the model in which both geography and institutions act as concomitant variables, but have no direct effects on growth. The results show that the BIC and CAIC criteria are minimized for 2-class regression for all cases, while the AIC3 criterion is minimized for 1-class regression. Therefore, a finite mixture model with two groups best describes the data.

Table 7 reports the results of finite mixture models, where the coefficients of standard regressors are shown in the upper half and the coefficients of concomitants relative to class one are shown in the bottom half. For the case I in which geography and institutions only act as covariates, the coefficients of institutions in each regime are significant and positive, but geographic location in regime B plays a significant role, while no significant effects exist in regime A. Furthermore, the Wald test verifies the significant differences of geography across regimes, but the differences of institutions are insignificant.

For the case II in which geography acts as a concomitant variable and the quality of institutions acts as a covariate, institutions directly promote growth in regime A, but have no significant effects in regime B. Moreover, the Wald test shows that the marginal effects of institutions in different regimes are significantly heterogeneous. Specifically, the coefficient of geographic location is significantly negative, indicating that geography has an indirect impact on growth by determining the group membership, in accordance with Bloom et al. (2003). The more favorable the geographic location of one province is, the higher probability the province belongs to regime B.

For the case III in which geography acts as a covariate and the quality of institutions acts as a concomitant variable, geographic location has a direct role in growth in regime B, while its coefficient is insignificant in regime A. Moreover, the Wald test verifies the significant differences of geography across regimes. Particularly, the significantly positive coefficient of institutions indicates that institutions help sort provinces into groups, supporting the conjecture of Alfo et al. (2008). The better the quality of institutions is, the greater probability the

Table 6 Specification tests for finite mixture models

Hypothesized no. of regimes	Obs.	Log likelihood	Degrees of freedom	*AIC3*	*BIC*	*CAIC*	Optimal regimes
Case I: No concomitant variable; geography and institutions as covariate variables							
1-class regression	377	943.743	11	−1854.486	−1822.231	−1822.202	No
2-class regression	377	984.691	23	−1900.382	*−1832.940*	*−1832.879*	Yes
3-class regression	377	1016.433	35	*−1927.866*	−1825.237	−1825.145	No
4-class regression	377	1025.482	47	−1909.964	−1772.148	−1772.024	No
Case II: Geography as a concomitant variable; institutions as a covariate variable							
1-class regression	377	940.515	10	−1851.030	−1821.708	−1821.681	No
2-class regression	377	978.930	22	−1891.860	*−1827.351*	*−1827.292*	Yes
3-class regression	377	1004.828	34	−1907.656	−1807.960	−1807.870	No
4-class regression	377	1026.071	46	*−1914.142*	−1779.259	−1779.137	No
Case III: Institutions as a concomitant variable; geography as a covariate variable							
1-class regression	377	911.887	10	−1793.774	−1764.452	−1764.425	No
2-class regression	377	978.454	22	−1890.908	*−1826.399*	*−1826.340*	Yes
3-class regression	377	1004.113	34	*−1906.226*	−1806.530	−1806.440	No
4-class regression	377	1021.423	46	−1904.846	−1769.963	−1769.841	No
Case IV: Geography and institutions as concomitant variables							
1-class regression	377	911.856	9	−1796.712	−1770.322	−1770.298	No
2-class regression	377	959.064	21	−1855.128	*−1793.551*	*−1793.495*	Yes
3-class regression	377	989.653	33	−1880.306	−1783.542	−1783.454	No
4-class regression	377	1018.602	45	*−1902.204*	−1770.253	−1770.134	No

Table 7 Results of finite mixture models

Variable	Mixture (i): Case I		Wald test (p value)	Mixture (ii): Case II		Wald test (p value)	Mixture (iii): Case III		Wald test (p value)	Mixture (iv): Case IV		Wald test (p value)
	Regime A	Regime B		Regime A	Regime B		Regime A	Regime B		Regime A	Regime B	
ln gdp_0	−0.0079*	−0.0175	3.21*	−0.0108**	0.0176*	6.29**	0.0022	−0.0043	0.61	−0.0250***	−0.0019	6.42**
	(0.0047)	(0.0122)	(0.0734)	(0.0047)	(0.0095)	(0.0121)	(0.0050)	(0.0065)	(0.4338)	(0.0067)	(0.0060)	(0.0113)
edu	0.0492***	0.1165***	1.65	0.0499***	0.0870**	0.73	0.0332**	0.0854***	3.01*	0.0882***	0.0813***	0.04
	(0.0170)	(0.0452)	(0.1989)	(0.0184)	(0.0358)	(0.3930)	(0.0169)	(0.0247)	(0.0827)	(0.0181)	(0.0283)	(0.8370)
trade	0.0014	0.0090	0.18	−0.0154	0.0311***	10.10***	0.0069	0.0064	0.00	−0.0234	0.0162***	1.79
	(0.0058)	(0.0151)	(0.6717)	(0.0101)	(0.0053)	(0.0015)	(0.0096)	(0.0064)	(0.9670)	(0.0290)	(0.0057)	(0.1812)
fdi	0.0127	0.4153***	12.14***	0.1943***	0.0851	0.74	0.0332	0.1725***	2.35	0.4859***	−0.0277	36.43***
	(0.0570)	(0.0991)	(0.0005)	(0.0538)	(0.1017)	(0.3899)	(0.0634)	(0.0637)	(0.1254)	(0.0606)	(0.0595)	(0.0000)
fd	0.0016	−0.0868***	30.09***	0.0127**	−0.1067***	72.79***	−0.0098*	−0.0141*	0.21	0.0143*	−0.0317***	21.43***
	(0.0049)	(0.0152)	(0.0000)	(0.0062)	(0.0150)	(0.0000)	(0.0058)	(0.0072)	(0.6497)	(0.0076)	(0.0065)	(0.0000)
gov	0.0303	−0.0003	0.09	0.0247	0.1604**	3.09*	0.1308***	−0.0799	13.63***	0.0443	0.0205	0.13
	(0.0319)	(0.0882)	(0.7616)	(0.0289)	(0.0690)	(0.0787)	(0.0319)	(0.0493)	(0.0002)	(0.0358)	(0.0540)	(0.7142)
trans	0.0035	0.0175***	4.28**	0.0050*	0.0224***	7.68***	−0.0035	0.0173***	19.78***	0.0105***	0.0151***	0.78
	(0.0027)	(0.0058)	(0.0386)	(0.0029)	(0.0054)	(0.0056)	(0.0026)	(0.0038)	(0.0000)	(0.0040)	(0.0036)	(0.3760)
geo	0.0015	0.0330***	8.49***				0.0003	0.0107**	3.60*			
	(0.0030)	(0.0097)	(0.0036)				(0.0032)	(0.0045)	(0.0577)			
ins	0.0410***	0.0246**	1.67	0.0395***	0.0041	9.58***						
	(0.0046)	(0.0117)	(0.1960)	(0.0043)	(0.0103)	(0.0020)						
Concomitant variables												
geo					−0.6927*						−26.0336	
					(0.3547)						(4583.442)	
ins								13.7942***			19.9898**	
								(3.8818)			(9.7783)	

Table 7 (continued)

Variable	Mixture (i): Case I		Wald test (p value)	Mixture (ii): Case II		Wald test (p value)	Mixture (iii): Case III		Wald test (p value)	Mixture (iv): Case IV		Wald test (p value)
	Regime A	Regime B		Regime A	Regime B		Regime A	Regime B		Regime A	Regime B	
Class size	75.4%	24.6%		75.8%	24.2%		48.7%	51.3%		45.5%	54.5%	
Obs.	377			377			377			377		
Classification error	17.77%			18.22%			6.68%			2.36%		

Growth regression estimations include intercepts and time dummies, while logit models include intercepts, but not time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Table 8 Province classifications: year 1997 versus year 2009

Year 1997				Year 2009			
Regime A		Regime B		Regime A		Regime B	
Province	Probability	Province	Probability	Province	Probability	Province	Probability
Shanxi	1	Beijing	1	Sichuan	1	Beijing	1
Inner Mongolia	1	Tianjin	1	Guizhou	1	Tianjin	1
Liaoning	0.93	Hebei	1	Yunnan	1	Hebei	1
Jilin	1	Shanghai	1	Shaanxi	1	Shanghai	1
Heilongjiang	1	Jiangsu	1	Gansu	1	Jiangsu	1
Anhui	0.71	Zhejiang	1	Qinghai	1	Zhejiang	1
Jiangxi	0.97	Fujian	1	Ningxia	1	Fujian	1
Henan	0.74	Shandong	1	Xinjiang	1	Shandong	1
Hubei	0.75	Guangdong	1			Guangdong	1
Hunan	0.74	Hainan	1			Hainan	1
Guangxi	0.98					Shanxi	1
Sichuan	1					Inner Mongolia	1
Guizhou	1					Liaoning	1
Yunnan	1					Jilin	1
Shaanxi	1					Heilongjiang	0.99
Gansu	1					Anhui	1
Qinghai	1					Jiangxi	1
Ningxia	1					Henan	1
Xinjiang	1					Hubei	1
						Hunan	1
						Guangxi	0.99

The classification is obtained from the mixture model with geography and overall institutions as concomitant variables. Provinces are sorted into the group if the posterior probability of belonging to a group is higher than 0.5

province belongs to regime B—that is to say, institutions can have indirect effects on growth via the group classification.

For the case IV in which both geography and institutions act as concomitant variables, the concomitant coefficients suggest that the latent variable sorting provinces into different regimes is the quality of institutions rather than geography, which is consistent with Owen et al. (2009). In fact, the quality of institutions may be affected by geography. Compared to the mixture models without institutions as a concomitant variable (see case II), it is obvious that the significance of geography increases. Therefore, the fact that geographic location is no longer significant when institutions are controlled for indicates that geography may play a role in sorting provinces into growth regimes through its effect on institutional development.

Fig. 3 Growth path heterogeneity of China's provinces in 1997

Fig. 4 Growth path heterogeneity of China's provinces in 2009

Table 9 Province's regime switch over 1997–2009

Province	Regime	Year	Province	Regime	Year	Province	Regime	Year
Beijing	B	–	Shanxi	A–B	2003	Sichuan	A	–
Tianjin	B	–	Inner Mongolia	A–B	2004	Guizhou	A	–
Hebei	B	–	Liaoning	A–B	2001	Yunnan	A	–
Shanghai	B	–	Jilin	A–B	2004	Shaanxi	A	–
Jiangsu	B	–	Heilongjiang	A–B	2004	Gansu	A	–
Zhejiang	B	–	Anhui	A–B	2003	Qinghai	A	–
Fujian	B	–	Jiangxi	A–B	2004	Ningxia	A	–
Shandong	B	–	Henan	A–B	2004	Sinkiang	A	–
Guangdong	B	–	Hubei	A–B	2004			
Hainan	B	–	Hunan	A–B	2004			
			Guangxi	A–B	2004			

The classification is obtained from the mixture model with geography and overall institutions as concomitant variables. Provinces are sorted into the group if the posterior probability of belonging to a group is higher than 0.5

The misclassification error of the finite mixture model (iv) is minimized with 2.36%, and so we select this model rather than the other three models. With respect to the growth determinants, initial GDP per capita, foreign direct investment, and financial depth are significantly different across regimes, and the differences are affirmed by the Wald test. Specifically, the convergence hypothesis only exists in regime A rather than for B, verifying the existence of the convergence clubs in China. There is a positive relationship between foreign direct investment and growth in regime A, and financial development has a positive role in regime A, but a negative role in regime B. In addition, both human capital and transport infrastructure significantly promote growth in the two regimes, while trade openness is conducive to economic growth in regime B rather than in A, even though the difference does not go through the Wald test. In other words, we conclude that regime A is dominated by foreign direct investment and financial depth, while regime B is dominated by trade openness.

In the selected mixture model with two growth regimes, the class sizes of regimes A and B are 45.5% and 54.5%, respectively. On the basis of the similarity of the conditional distribution of growth rates, Table 8 and Figs. 3 and 4 display the classification of the provinces with their group membership posterior probabilities in the years 1997 and 2009 (for time-varying posterior probabilities across provinces, see Table 18 in "Appendix"). Obviously, the certainty of classification is high for the majority of provinces, and the lowest probability is 0.74. At the beginning of the sample period, the provinces located in the eastern region are classified into regime B, while the other provinces are classified into regime A. At the end of the sample period, the provinces located in the eastern and central regions are classified into regime B, while the other provinces are classified into regime A. In particular, according to the development status across Chinese

Table 10 Descriptive statistics of key variables by groups

Variable	Regime A			Regime B			Difference	Paired-samples *T* test	
	Obs.	Mean	*Std.*	*Obs.*	Mean	*Std.*		Statistic	*p* value
eg	174	0.1034	0.0230	203	0.1249	0.0245	−0.0215	−8.7533***	0.0000
ln gdp_0	174	7.0806	0.2619	203	7.7217	0.5826	−0.6411	−13.3983***	0.0000
edu	174	2.0222	0.0892	203	2.1379	0.1001	−0.1157	−11.7574***	0.0000
trade	174	0.0964	0.0551	203	0.5128	0.4781	−0.4164	−11.4192***	0.0000
fdi	174	0.0213	0.0227	203	0.0478	0.0329	−0.0265	−8.9616***	0.0000
fd	174	0.7878	0.2405	203	0.7890	0.3816	−0.0012	−0.0337	0.9731
gov	174	0.1792	0.0748	203	0.1293	0.0421	0.0499	8.1209***	0.0000
trans	174	2.9330	0.6444	203	2.6905	0.6235	0.2425	3.7063***	0.0002
geo	174	2.5977	0.4918	203	1.3596	0.4811	1.2381	24.6567***	0.0000
ins	174	1.3866	0.2999	203	1.9351	0.2473	−0.5486	−19.4614***	0.0000

The classification is obtained from the mixture model with geography and overall institutions as concomitant variables. Provinces are sorted into the group if the posterior probability of belonging to a group is higher than 0.5. The descriptive statistics of key variables are calculated for each group

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

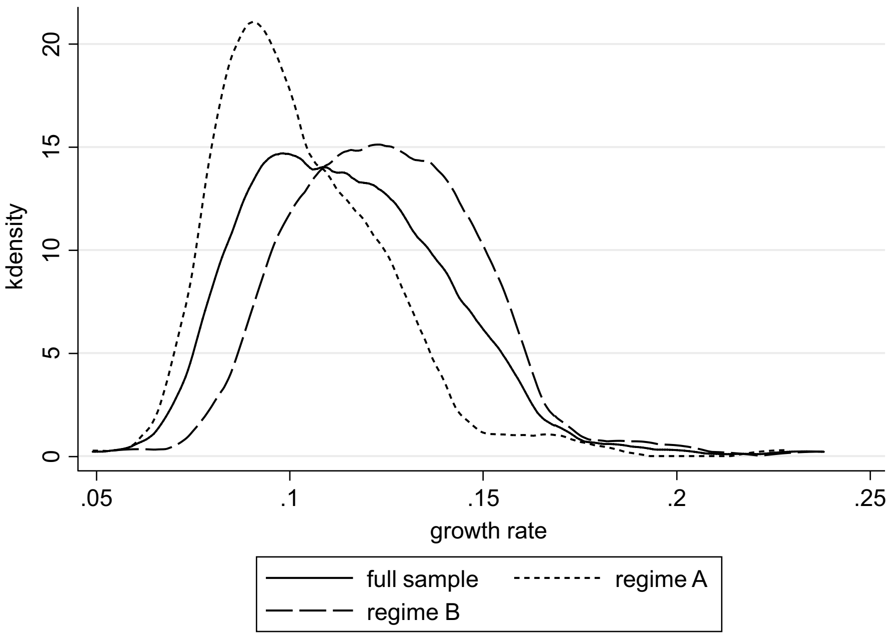

Fig. 5 The Kernel density of growth rate across regimes

provinces, we can conclude: the provinces belonging to regime A are industrial-oriented, while the provinces in regime B are agricultural-oriented.

The results reveal that the growth paths of China's provinces transform during the period 1997–2009, which leads to the inference that neglecting the switch of regimes will bring about misleading results. Table 9 reports the switch year of a province's group membership over 1997–2009. A few points are worth noting. First, the growth paths of provinces in the eastern and western regions do not change. Second, the growth regimes of provinces in the central regime transform from A to B, and the structural change is commonly around the year 2004 (except for Shanxi and Anhui in 2003 and Liaoning in 2001).

These results suggest that the provinces within regimes A and B do not share the same observable characteristics, such as geographic location and income per capita, that are typically used to conduct subsample analysis. Furthermore, Table 10 summarizes the descriptive statistics of key variables by group. The paired-samples *T* test suggests that, except financial depth, there are significant differences across regimes in the other variables. The average growth rate of real GDP per capita for regime A is 2.1% higher than that for regime B, but exhibits greater dispersion. Specifically, provinces in regime B tend to be with more favorable geographic locations and better institutions.

The core point in finite mixture modeling is that the observed full sample consists of several distinct unobserved subsamples. To illustrate the issue, as shown in Fig. 5, we plot the observed distribution of growth rates of the provinces as a whole (solid line) and the two unobserved densities of growth rates in the two underlying regimes A and B (dashed lines). The observed distribution performs with slight asymmetry, because of more values above the expectation. This asymmetry occurs since the distribution is a mixture of two different density functions, and the density of regime B with higher growth rates skews the distribution to the right. Therefore, it is necessary to take into account the heterogeneity of growth rates in different provinces when exploring the sources of growth in China and to provide some explanation for the existence of multiple regimes.

We overall can conclude that provincial economies in China do not follow a universal growth path, while a finite mixture model with two groups best depicts the process of economic development—that is, there are multiple growth regimes across China's provinces, thus supporting Hypothesis 1. More importantly, differing from the direct impacts of geography and institutions in traditional research, they also play important roles in sorting provinces into groups, providing some new evidence for Hypothesis 2. In particular, our findings are consistent with the combination of Bloom et al. (2003) and Alfo et al. (2008), but differ from the argument of Acemoglu et al. (2001) and Owen et al. (2009). In other words, the indirect effect of geography on the growth regime is not only through the quality of institutions, but there are also other channels that directly affect the growth rate and the group membership.

Table 11 Finite mixture models with disaggregated components of institutions

Variable	Mixture (i): ins1		Wald test (*p* value)	Mixture (ii): ins2		Wald test (*p* value)	Mixture (iii): ins3		Wald test (*p* value)	Mixture (iv): ins4		Wald test (*p* value)
	Regime A	Regime B		Regime A	Regime B		Regime A	Regime B		Regime A	Regime B	
ln gdp_0	−0.0313***	0.0030	14.58***	−0.0259***	−0.0009	8.16***	−0.0267***	−0.0004	7.53***	−0.0267***	0.0021	8.96***
	(0.0069)	(0.0056)	(0.0001)	(0.0065)	(0.0059)	(0.0043)	(0.0072)	(0.0063)	(0.0061)	(0.0077)	(0.0056)	(0.0028)
edu	0.0846***	0.0851***	0.00	0.0887***	0.0830***	0.03	0.0987***	0.0849***	0.16	0.0872***	0.0739***	0.14
	(0.0195)	(0.0270)	(0.9874)	(0.0171)	(0.0282)	(0.8625)	(0.0184)	(0.0296)	(0.6933)	(0.0252)	(0.0275)	(0.7120)
trade	−0.0247	0.0153***	2.23	−0.0189	0.0152***	3.95**	−0.0069	0.0175***	2.48	0.0062	0.0160***	0.05
	(0.0260)	(0.0057)	(0.1357)	(0.0162)	(0.0056)	(0.0469)	(0.0141)	(0.0058)	(0.1150)	(0.0454)	(0.0056)	(0.8302)
fdi	0.5780***	−0.0288	32.94***	0.4996***	−0.0247	39.80***	0.4598***	−0.0120	28.36***	0.5151***	−0.0213	38.39***
	(0.0876)	(0.0611)	(0.0000)	(0.0583)	(0.0590)	(0.0000)	(0.0636)	(0.0615)	(0.0000)	(0.0668)	(0.0599)	(0.0000)
fd	0.0185**	−0.0333***	26.80***	0.0178**	−0.0299***	23.58***	0.0117	−0.0344***	22.21***	0.0222	−0.0285***	14.75***
	(0.0073)	(0.0065)	(0.0000)	(0.0078)	(0.0065)	(0.0000)	(0.0073)	(0.0069)	(0.0000)	(0.0153)	(0.0079)	(0.0001)
gov	0.0161	0.0177	0.00	0.0416	0.0107	0.24	0.0486	0.0114	0.30	0.0548	0.0137	0.38
	(0.0359)	(0.0526)	(0.9801)	(0.0341)	(0.0534)	(0.6266)	(0.0365)	(0.0567)	(0.5834)	(0.0381)	(0.0549)	(0.5363)
trans	0.0126***	0.0188***	1.51	0.0113***	0.0162***	0.97	0.0088**	0.0164***	1.77	0.0098**	0.0193***	2.39
	(0.0038)	(0.0033)	(0.2194)	(0.0036)	(0.0035)	(0.3251)	(0.0039)	(0.0038)	(0.1832)	(0.0044)	(0.0040)	(0.1218)
Concomitant variables												
geo		−4.2782*			−18.6083			−10.7591			−18.8093	
		(2.5827)			(11.7879)			(7.0383)			(404.7017)	
Ins		10.5630**			25.0451			25.3341			6.5265	
		(4.2542)			(16.1315)			(26.1449)			(5.0041)	
Class size	40.1%	59.9%		44.3%	55.7%		46.7%	53.3%		37.4%	62.6%	
Obs.	377			377			377			377		
Classification error	5.32%			1.60%			2.58%			3.64%		

The variables ins1, ins2, ins3, and ins4 refer to different components of institutions, including: (i) the relationship between government and markets; (ii) the development of the non-state economy; (iii) the marketization of product markets; and (iv) the marketization of factor markets. Growth regression estimations include intercepts and time dummies, while logit models include intercepts, but not time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

5 Robustness analysis

5.1 Alternative measure of institutions

In order to test the robustness of our results, we conduct a series of alternative estimations. First, to explore the heterogeneous roles of disaggregated components of institutions, Table 11 presents the results of the finite mixture model with two classes for each of these components.[14] We note that the specification tests also show that the BIC and CAIC criteria are minimized in 2-class regression (not reported). The heterogeneous coefficients of growth fundamentals across regimes are similar to the overall index of institutions, as shown in Table 7. Nevertheless, as for disaggregated components, the relationship between government and markets (rather than other indices) is conducive to classify provinces into different groups, and geographic location also performs a similar role.[15]

5.2 Alternative measure of geography

Second, the categorical variable taking 1–3 for geographic locations across provinces is relatively crude. To overcome the drawback, we employ the distance between each province and China's capital (Beijing) as an alternative measure of geography.[16] The specification tests also show that the BIC and CAIC criteria are minimized in 2-class regression (not reported), and Table 12 reports the estimation results of finite mixture models. Particularly, we consider three specific cases as follows: (i) geography acts as a concomitant variable (see case I); (ii) geography and the overall index of institutions act as two concomitant variables (see case II); (iii) geography and one disaggregated component of institutions (referring to the relationship between government and markets) act as two concomitant variables (see case III). Obviously, the coefficients of standard regressors are heterogeneous across the two regimes A and B, and geography and institutions significantly help sort provinces into groups. In detail, the farther the distance from one province to Beijing, the larger the probability of the province belongs to regime A.

5.3 Alternative econometric specification

Third, consistent with Owen et al. (2009), Konte (2013), and Flachaire et al. (2014), we consider the following standard Solow model:

$$eg_{it} = \beta_0 + \beta_1 \ln gdp_{i0} + \beta_2 \ln pop_{it} + \beta_3 \ln inv_{it} + \beta_4 \ln edu_{it} + \varepsilon_{it}, \qquad (9)$$

[14] Because the finite mixture model measuring the quality of institutions with the order of intermediary organizations and law does not converge, we only provide the estimations results for the other four disaggregated components of institutions.

[15] When considering the disaggregated components of institutions together in the sorting logit model, the results of 2-class finite mixture models (not reported) are similar to Table 11.

[16] When using two dummy variables to measure the geographic locations across provinces, the estimation results (not reported) are similar.

Table 12 Finite mixture models with the distances between provinces and China's capital (Beijing)

Variable	Mixture (i): Case I		Wald test (*p* value)	Mixture (ii): Case II		Wald test (*p* value)	Mixture (iii): Case III		Wald test (*p* value)
	Regime A	Regime B		Regime A	Regime B		Regime A	Regime B	
ln gdp_0	−0.0035	−0.0228	2.61	0.0006	−0.0101*	1.74	−0.0033	−0.0051	0.05
	(0.0164)	(0.0211)	(0.1059)	(0.0049)	(0.0061)	(0.1876)	(0.0045)	(0.0063)	(0.8203)
edu	0.0512	0.0851***	0.32	0.0364**	0.0536**	0.32	0.0344**	−0.0077	1.29
	(0.0525)	(0.0269)	(0.5714)	(0.0143)	(0.0269)	(0.5962)	(0.0157)	(0.0326)	(0.2569)
trade	0.0307***	0.0200	0.26	0.0156*	0.0106	0.22	0.0136*	0.0126*	0.01
	(0.0075)	(0.0159)	(0.6111)	(0.0085)	(0.0065)	(0.6411)	(0.0076)	(0.0067)	(0.9184)
fdi	0.0886	0.2790***	2.33	0.0101	0.2002***	5.82**	0.1146*	0.1680***	0.39
	(0.1571)	(0.0841)	(0.1269)	(0.0569)	(0.0557)	(0.0158)	(0.0596)	(0.0590)	(0.5309)
fd	−0.0322**	−0.0089	2.39	−0.0045	−0.0149**	1.45	−0.0099*	−0.0101	0.00
	(0.0139)	(0.0090)	(0.1223)	(0.0057)	(0.0067)	(0.2292)	(0.0054)	(0.0064)	(0.9879)
gov	0.1584**	−0.0884	8.88***	0.1383***	0.0181	4.69**	0.1430***	0.1170**	0.16
	(0.0672)	(0.1100)	(0.0029)	(0.0253)	(0.0483)	(0.0304)	(0.0256)	(0.0592)	(0.6853)
trans	−0.0010	0.00279**	11.12***	−0.0027	0.0187***	21.68***	−0.0025	0.0221***	32.07***
	(0.0050)	(0.0117)	(0.0009)	(0.0026)	(0.0036)	(0.0000)	(0.0035)	(0.0035)	(0.0000)
Concomitant variables									
geo		−2.2867**			−2.2741***			−5.7646***	
		(0.9663)			(0.7367)			(1.6270)	
Ins					9.2572***			29.2189***	
					(1.8947)			(8.2865)	
Class size	43.6%	56.4%		40.9%	59.1%		51.1%	48.9%	
Obs.	377			377			377		
Classification error	19.40%			7.47%			3.82%		

Growth regression estimations include intercepts and time dummies, while logit models include intercepts, but not time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Table 13 Finite mixture models with geography and institutions as concomitant variables

Variable	Case I: Neglect technology and capital depreciation			Wald test (p value)	Case I: Account for technology and capital depreciation			Wald test (p value)
	Full sample	Regime A	Regime B		Full sample	Regime A	Regime B	
ln gdp_0	0.0018	−0.0137*	−0.0007	3.20*	0.0017	−0.0124	−0.0010	2.66
	(0.0028)	(0.0076)	(0.0034)	(0.0738)	(0.0028)	(0.0075)	(0.0035)	(0.1032)
pop	−0.0031**	−0.0021	−0.0038***	0.58	−0.0065*	−0.0121*	−0.0032	1.83
	(0.0012)	(0.0022)	(0.0014)	(0.4474)	(0.0034)	(0.0064)	(0.0039)	(0.1758)
invest	0.3497***	0.3092***	0.3157***	0.01	0.3473***	0.3272***	0.3125***	0.06
	(0.0247)	(0.0504)	(0.0310)	(0.9165)	(0.0249)	(0.0493)	(0.0317)	(0.8115)
edu	0.0664***	0.0760***	0.0557***	0.71	0.0662***	0.0765***	0.0514***	1.11
	(0.0141)	(0.0222)	(0.0185)	(0.3993)	(0.0142)	(0.0217)	(0.0191)	(0.2928)
Obs.	377	174	203		377	174	203	
R^2	0.4784	0.2719	0.4544		0.4588	0.2962	0.4200	

Growth regression estimations include intercepts and time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Table 14 Standard growth regression models with instrument variables

Variable	*ins*	*ins1*	*ins2*	*ins3*	*ins4*	*ins5*
ln gdp_0	−0.0100**	−0.0094*	−0.0097**	−0.0115**	−0.0162***	−0.0187***
	(0.0047)	(0.0049)	(0.0048)	(0.0050)	(0.0048)	(0.0048)
edu	0.0759***	0.0967***	0.0800***	0.0923***	0.1084***	0.0834***
	(0.0175)	(0.0170)	(0.0178)	(0.0182)	(0.0172)	(0.0198)
trade	−0.0011	0.0037	0.0065	0.0076	0.0054	0.0029
	(0.0057)	(0.0057)	(0.0055)	(0.0058)	(0.0060)	(0.0062)
fdi	0.1798***	0.2040***	0.1510***	0.2170***	0.1820***	0.2303***
	(0.0509)	(0.0512)	(0.0528)	(0.0536)	(0.0540)	(0.0532)
fd	−0.0048	−0.0085	−0.0041	−0.0084	−0.0100*	−0.0097*
	(0.0056)	(0.0056)	(0.0057)	(0.0060)	(0.0058)	(0.0058)
gov	0.0160	0.0087	−0.0084	0.0763**	0.0094	0.0270
	(0.0303)	(0.0308)	(0.0309)	(0.0341)	(0.0317)	(0.0324)
trans	0.0111***	0.0145***	0.0118***	0.0130***	0.0131***	0.0093***
	(0.0025)	(0.0025)	(0.0025)	(0.0026)	(0.0026)	(0.0029)
geo	0.0043	0.0026	0.0057*	−0.0009	0.0009	0.0002
	(0.0028)	(0.0028)	(0.0030)	(0.0029)	(0.0029)	(0.0029)
ins	0.0343***	0.0333***	0.0173***	0.0254***	0.0132***	0.0197***
	(0.0049)	(0.0057)	(0.0028)	(0.0047)	(0.0033)	(0.0045)
Obs.	348	348	348	348	348	348
R^2	0.4364	0.4181	0.4205	0.3566	0.3837	0.3622

The variables ins1, ins2, ins3, ins4, and ins5 refer to different components of institutions, including: (i) the relationship between government and markets; (ii) the development of the non-state economy; (iii) the marketization of product markets; (iv) the marketization of factor markets; and (v) the order of intermediary organizations and law. The estimator is OLS-IV, where first lags of *edu*, *fdi*, *fd*, and *ins* are used as instruments. Growth regression estimations include intercepts and time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

where *pop* denotes the growth rate of total population, *inv* denotes the ratio of investment to output, and the definitions and measures of other variables are shown in Table 3. Note that model (9) neglects technology progress and capital depreciation. To account for this issue, following Mankiw et al. (1992) and Owen et al. (2009), we assume the growth rate of technology and the ratio of depreciation are constant and sum up to 0.05, and then, the extended population growth equals $pop + 0.05$.

Based on the group classification using finite mixture models with geography and the quality of institutions as concomitant variables, Table 13 reports the estimation results of the Solow model. The coefficient of initial GDP per capita varies in different regimes, and the coefficient in regime A is significantly negative, while that in regime B is insignificant. Specifically, the Wald test verifies the significant differences in the coefficients of initial GDP per capita across regimes. These findings suggest that there is no universal convergence inside of China, but the so-called "convergence clubs" exists. The results are consistent with Table 10. In addition,

Table 15 Instrument variable estimations across regimes

Variable	Mixture (i): ins		Mixture (ii): ins1		Mixture (iii): ins2		Mixture (iv): ins3		Mixture (v): ins4	
	Regime A	Regime B	Regime A	Regime B	Regime A	Regime B	Regime A	Regime B	Regime A	Regime B
ln gdp_0	−0.0286***	−0.0063	−0.0350***	−0.0003	−0.0298***	−0.0043	−0.0303***	−0.0041	−0.0264***	−0.0021
	(0.0067)	(0.0067)	(0.0067)	(0.0062)	(0.0066)	(0.0066)	(0.0069)	(0.0068)	(0.0082)	(0.0063)
edu	0.1143***	0.0901**	0.1072***	0.1074***	0.1151***	0.0972***	0.1327***	0.0906**	0.1042***	0.0845**
	(0.0204)	(0.0347)	(0.0198)	(0.0332)	(0.0201)	(0.0339)	(0.0207)	(0.0352)	(0.0248)	(0.0331)
trade	−0.0239	0.0163***	−0.0268	0.0135**	−0.0268*	0.0145**	−0.0202	0.0184***	0.0132	0.0163***
	(0.0296)	(0.0062)	(0.0261)	(0.0061)	(0.0152)	(0.0062)	(0.0147)	(0.0062)	(0.0411)	(0.0061)
fdi	0.5175***	−0.0746	0.6214***	−0.0613	0.5311***	−0.0596	0.4915***	−0.0522	0.5631***	−0.0543
	(0.0608)	(0.0788)	(0.0621)	(0.0746)	(0.0608)	(0.0779)	(0.0636)	(0.0790)	(0.0666)	(0.0769)
fd	0.0253***	−0.0225***	0.0283***	−0.0247***	0.0299***	−0.0199***	0.0268***	−0.0266***	0.0374***	−0.0185***
	(0.0069)	(0.0077)	(0.0067)	(0.0075)	(0.0073)	(0.0076)	(0.0072)	(0.0078)	(0.0093)	(0.0071)
gov	0.0569	−0.0277	0.0237	−0.0513	0.0497	−0.0450	0.0535	−0.0279	0.0607	−0.0324
	(0.0355)	(0.0578)	(0.0336)	(0.0557)	(0.0348)	(0.0570)	(0.0366)	(0.0595)	(0.0397)	(0.0557)
trans	0.0090**	0.0168***	0.0116***	0.0213***	0.0101***	0.0191***	0.0082**	0.0184***	0.0084*	0.0221***
	(0.0038)	(0.0037)	(0.0035)	(0.0034)	(0.0035)	(0.0036)	(0.0037)	(0.0038)	(0.0046)	(0.0034)
Obs.	157	191	139	209	152	196	156	192	131	217
R^2	0.5167	0.2776	0.5775	0.3510	0.5273	0.2943	0.4914	0.2932	0.5089	0.3341

The variables ins1, ins2, ins3, and ins4 refer to different components of institutions, including: (i) the relationship between government and markets; (ii) the development of the non-state economy; (iii) the marketization of product markets; and (iv) the marketization of factor markets. The estimator is OLS-IV, where first lags of *edu*, *fdi*, *fd*, and *ins* are used as instruments. Growth regression estimations include intercepts and time dummies. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

there are no significant differences in the marginal effects of population growth, investment, and human capital on growth.

5.4 Possible endogenous problems

Fourth, to overcome possible endogenous problems in the growth regression, we perform instrumental variable approaches. It is widely known that financial depth, education attainment, and foreign direct investment also can be determined by economic growth, and the quality of institutions can be shaped in the process of economic development. Using the first lags of human capital, financial depth, foreign direct investment, and the quality of institutions, Table 14 provides the results of standard regression growth models with instrumental variables. In all regressions, the coefficients of the explanatory variables are similar to Table 3.

As argued by Konte (2013), there is no feasible procedure of finite mixture models that allows for dealing with potential endogeneity in instrumental variables. Based on the earlier group classification using finite mixture models with two groups for overall and disaggregated institutions, we perform instrument variable estimations for each regime. Using the first lags of human capital, financial depth, and foreign direct investment, Table 15 reports the instrumental variable estimations of standard regression models across regimes. It is obvious that the coefficients are close to those reported in Tables 7 and 11.

5.5 Different production technologies across regimes

Fifth, based on the group classifications with geography and the quality of institutions as concomitant variables, we estimate the logarithmic version of the Cobb–Douglas production function across regimes as the following form:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \varepsilon_{it}, \tag{10}$$

where the dependent variable is total GDP (Y) of province i in year t and the explanatory variables include total physical capital stock (K) and labor force (L).[17]

Table 16 presents the estimation results of production technologies across regimes. In the case I in which the Cobb–Douglas functions exhibit constant returns to scale, the coefficients of physical capital stock per labor are significantly positive at 0.474 and 0.596 in regimes A and B, respectively. In the case II in which the Cobb–Douglas functions show variable returns to scale, the coefficients of labor force are significantly positive at 0.609 and 0.403 in regimes A and B, respectively, and the coefficients of physical capital stock are significantly positive at 0.563 and 0.595 in regimes A and B. These results indicate that provinces in regime A heavily depend on the labor force, while provinces in regime B mainly rely on physical capita stock. In addition, the Wald test verifies that the differences of the coefficients

[17] To estimate China's provincial physical capital stock, we use the perpetual inventory method; for more details, see Zhang (2008). Note that, to eliminate the impacts of inflation, GDP and physical capital stock are converted into 1978 PPP-adjusted CNY.

Table 16 Production function estimation across regimes

Variable	Case I: Constant returns to scale			Wald test (*p* value)	Case II: Variable returns to scale			Wald test (*p* value)
	Full sample	Regime A	Regime B		Full sample	Regime A	Regime B	
Capital	0.6361***	0.4744***	0.5958***	9.20***	0.6719***	0.5634***	0.5951***	0.56
	(0.0176)	(0.0275)	(0.0291)	(0.0024)	(0.0173)	(0.0308)	(0.0290)	(0.4534)
Labor					0.4634***	0.6087***	0.4030***	12.49***
					(0.0217)	(0.0254)	(0.0333)	(0.0004)
Obs.	377	174	203		377	174	203	
R^2	0.7770	0.5935	0.7717		0.9147	0.9287	0.8788	

Growth regression estimations include intercepts. For the case I, capital denotes total physical capital stock divided by total labor. Standard errors are shown in parentheses

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Table 17 Growth sources across regimes

Components	Case I: Constant returns to scale		Case II: Variable returns to scale	
	Regime A	Regime B	Regime A	Regime B
Panel A: growth components				
TFP growth	0.0336	0.0226	0.0220	0.0227
Factor endowment growth	0.0690	0.1014	0.0807	0.1013
GDP per capita growth	0.1016	0.1240	0.1027	0.1240
Panel B: the contribution of growth components				
TFP growth	0.3307	0.1823	0.2142	0.1831
Factor endowment growth	0.6693	0.8177	0.7858	0.8169
GDP per capita growth	1.0000	1.0000	1.0000	1.0000

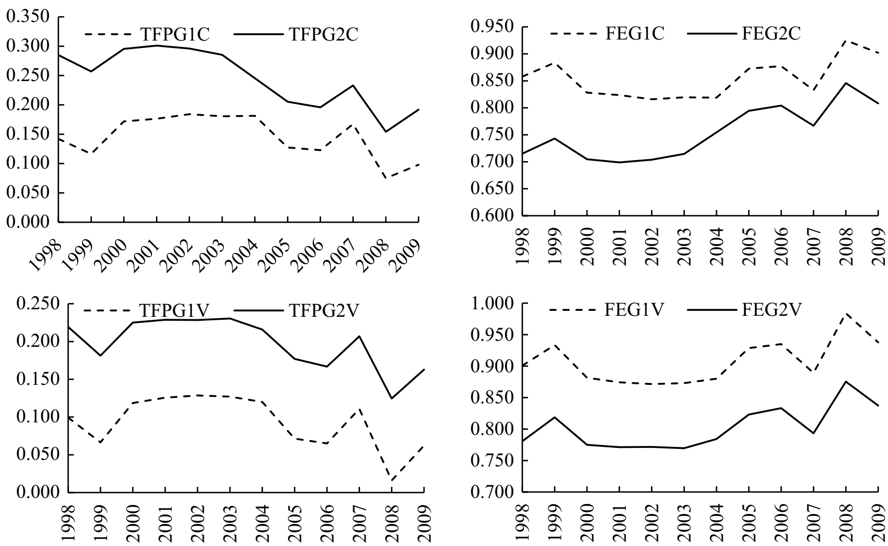

Fig. 6 Growth decompositions in traditional methods versus finite mixture models. *Notes* 1C (1V) refers to the results of traditional methods with constant (variable) return to scale, while 2C (2V) refers to the results of finite mixture models with constant (variable) return to scale

are significant in different regimes. Therefore, the production technologies across regimes are heterogeneous, and the results of standard regression models are biased.

Using the Solow residual method, we can obtain total factor productivity in each province, and then, the growth rate of real GDP (*EG*) can be decomposed into two parts: one is total factor productivity growth (*TFPG*), and the other is factor endowment growth (*FEG*), or specifically:

$$\underbrace{\frac{\Delta y_{it}}{y_{it}}}_{EG} = \underbrace{\frac{\Delta A_{it}}{A_{it}}}_{TFPG} + \underbrace{\beta_1 \frac{\Delta k_{it}}{k_{it}} + \left(\beta_1 + \beta_2 - 1\right) \frac{\Delta L_{it}}{L_{it}}}_{FEG} \tag{11}$$

Here, variable A denotes total factor productivity obtained through the Solow residual method, and Δ represents the amount of change.

Table 17 reports the components of growth in Panel A and their contribution ratios in Panel B. In the two cases I and II, no matter if one province belongs to regime A or B, factor endowment growth dominates the overall growth, followed by total factor productivity growth. In particular, the contribution ratio of factor endowment growth in regime B is greater than that in regime A, and that of total factor productivity growth in regime A is higher than that in regime B. More importantly, the two-side T test reveals that the differences across regimes are significant. These results suggest that the sources of growth across regimes are significantly different. As shown in Table 8 and Figs. 3 and 4, we detect that the growth rate in China tends to rely on capital accumulation after 2004.

Furthermore, to uncover the importance of growth regime heterogeneity in the growth decomposition, we compare the estimation results of traditional methods with those of finite mixture models. It is worth noting that the decomposition results of finite mixture models are weighted with posterior probabilities. Figure 6 depicts the contribution rates of *TFPG* and *FEG* to the overall growth rate over the period 1998–2009. Obviously, no matter under the framework of constant return to scale or variable return to scale, neglecting the existence of heterogeneous growth paths underestimates the role of total factor productivity by 10% and overestimates the role of factor endowment by 10%. Especially, the estimation bias is almost constant from 1998 to 2009, and the paired-samples T test verifies the significance of the differences. Therefore, it is necessary to take into account heterogeneous growth paths across provincial economies in China.

6 Conclusions

Differing from previous studies focusing on global countries, this paper investigates heterogeneous growth paths inside a particular country using panel data of 29 provincial economies in China. Considering unbalanced regional development in China, the growth paths across its provinces should be heterogeneous. The first hypothesis (Hypothesis 1) is that there are multiple growth regimes in which the marginal effects of growth fundamental vary across regimes. We thus shed new light on the debate concerning the impacts of geography and institutions. The second hypothesis (Hypothesis 2) is that geography and institutions have indirect roles in economic growth via determining the growth path of each economy.

On the basis of finite mixture models with more flexibility, the results suggest that the growth paths across provinces are not same, and a finite mixture with two regimes best describes the data. One regime exhibits higher but greatly dispersed growth rates at about 2.1%, while another regime shows lower growth rates. More importantly, geographic location and the quality of institutions help sort provinces into different groups, suggesting that both of them are deep determinants of growth and hence set the growth regime in which standard growth fundamentals affect growth.

With respect to the determinants of growth within regimes, except for the commonly positive roles of human capital and transport infrastructure, the first one is characterized by foreign direct investment and financial depth, while the second one is characterized by trade openness. Furthermore, the growth paths of some provinces switch over the sample period, while those of other provinces remain unchanged. In particular, China's provinces can be classified into three types: (i) provinces in the western region belong to the former group (switch); (ii) provinces in the eastern region belong to the latter group (unchanged), and (iii) the growth paths of provinces in the central region evolve from the former to the latter around the year 2004.

The growth paths of provincial economies in China are overall heterogeneous and switch over time during the process of the country's market-oriented reform. The marginal effects of growth determinants vary across regimes, and this is remarkable to understand the income variation of provinces within the same regime. We also provide some new evidence for the roles of geography and institutions on growth and find that they also are deep determinants of economic growth. Given the fact that geographic locations are exogenous, one province can achieve a transformation of its growth path through improving the quality of institutions.

This paper provides some useful insights for modeling and policy implementation. For empirical modeling, the average effects provided by standard growth regression models (which assume a common growth path) are biased for the existence of multiple regimes, and hence, it is necessary to take into account growth path heterogeneity and switching over time. In particular, when we decompose the overall growth rate, ignoring growth path heterogeneity will overestimate the importance of factor endowment (physical capital and labor force) and underestimates that of total factor productivity. For macroeconomic policy, human capital and transport infrastructure are conducive to promote growth in each regime, and so the government should pay more attention to them for pursuing higher growth rates. Moreover, increasing the added value of international trade benefits provincial growth in the eastern and central regions, while attracting more foreign direct investment and broadening financial sector depth are critical for provincial growth in the western region.

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Appendix

See Table 18.

Table 18 Posterior probabilities across provinces over 1997–2009

Year/Province	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Beijing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tianjin	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hebei	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shanxi	*1.000*	*0.999*	*1.000*	*1.000*	*1.000*	*0.988*	0.484	0.044	0.147	0.045	0.003	0.042	0.005
Inner Mongolia	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*0.997*	*0.854*	0.001	0.000	0.000	0.000	0.000	0.000
Liaoning	*0.935*	*0.925*	*0.967*	*0.880*	0.273	0.031	0.005	0.000	0.000	0.000	0.000	0.000	0.000
Jilin	*0.999*	*0.999*	*0.994*	*0.995*	*0.994*	*0.924*	*0.882*	0.104	0.020	0.001	0.000	0.000	0.000
Heilongjiang	*1.000*	*1.000*	*0.999*	*0.999*	*0.999*	*0.993*	*0.955*	0.385	0.052	0.004	0.001	0.000	0.012
Shanghai	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jiangsu	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Zhejiang	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Anhui	*0.710*	*0.950*	*0.769*	*0.882*	*0.870*	*0.608*	0.335	0.002	0.001	0.000	0.000	0.000	0.000
Fujian	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jiangxi	*0.971*	*0.969*	*0.997*	*0.997*	*0.996*	*0.864*	*0.513*	0.064	0.007	0.003	0.001	0.000	0.000
Shandong	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Henan	*0.637*	*0.500*	*0.992*	*0.972*	*0.989*	*0.970*	*0.547*	0.006	0.000	0.000	0.000	0.000	0.000
Hubei	*0.753*	*0.965*	*0.999*	*0.999*	*0.999*	*0.975*	*0.608*	0.038	0.001	0.000	0.000	0.000	0.000
Hunan	*0.744*	*0.705*	*0.997*	*0.998*	*0.997*	*0.972*	*0.643*	0.016	0.002	0.001	0.000	0.000	0.000
Guangdong	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Guangxi	*0.980*	*0.967*	*0.951*	*0.974*	*0.996*	*0.801*	*0.619*	0.156	0.007	0.006	0.001	0.010	0.009
Hainan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sichuan	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Guizhou	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Yunnan	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Shaanxi	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*

Table 18 (continued)

Year/Province	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Gansu	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Qinghai	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Ningxia	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*
Xinjiang	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*

The classification is obtained from the mixture model with geography and overall institutions as concomitant variables. The italicized numbers refer to regime A

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