Cross-Country Output Convergence and Growth: Evidence from Varying Coefficient Nonparametric Method

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Cross-Country Output Convergence and Growth: Evidence from Varying Coefficient Nonparametric Method

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Abstract

This article uses a nonparametric varying coefficient panel data model to study the convergence of real GDP per capita among 120 world economies for the sample period of 1980-2010. The estimates show that the indirect contribution of initial income via the control variables is important. The mediating effect of control variables to affect growth is positive. The conditional speed of convergence is larger than the absolute counterpart at all levels of initial income. The convergence hypothesis does not hold for economies with extremely low level of development. The conclusion is robust for regional sub-samples of Europe, Asia, Latin America and Africa.

Keywords: convergence, growth, varying coefficient model, nonparametric

JEL Classifications: C14, F43, O11, O40

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I Introduction

The world economy since the turn of the 21st century has been troubled by financial crises among the developed countries and terrorist attacks originated from the unstable 'fragile' states (Fund for Peace, 2015). These events have led to a reiteration in the discussion and debate on growth and convergence among world economies. Having noted the multifaceted nature of convergence, Spence (2011) for example, argued that economies are moving in a "multispeed" world. Income convergence which simply argues that low income countries will catch up with the richer countries has given rise to numerous theoretical and empirical studies (Islam, 2003).

In the literatures on income convergence, the two prominent areas concerned the definition and process through which convergence can be achieved. In the definition of income convergence, Bernard and Durlauf (1995) defined convergence within a group of countries that show "identical long-run trends", while Sala-i-Martin (1994) and Quah (1996a, 1996b) considered the importance of cross-sectional distribution of economies. Sala-i-Martin (1996a, 1996b) considered the relevance of speed, absolute and conditional features of convergence. Chatterji (1992), Quah (1997) and Fischer and Stirböck (2006) employed "club-convergence" that concentrated on regional income growth.

With reference to the process of income convergence, there are studies that relate convergence to endogenous growth, while others considered the relevance of technological adaptation, carbon dioxide emissions, legal aspects, use of neoclassical growth models with steady-state characteristics and wage distribution hypothesis (Tamura, 1991; Zind, 1991; Barro and Sala-i-Martin, 1992; Kocherlakota and Yi, 1995; Caselli *et al*., 1996; Durlauf, 1996; Maasourmi *et al*., 2007; Hashemi, 2013; Chen *et al*., 2014; Yang *et al*., 2016). There are also studies based either on a region prospective or a particular country (Cárdenas and Pontón, 1995; Quah, 1996c; Dobson and Ramlogan, 2002; King and Ramlogan-Dobson, 2015).

The empirical literature using parametric regression analysis has concentrated on convergence of per capita income growth when structural differences across economies are considered. Parametric regression analyses show that a negative estimate of the initial income coefficient is interpreted as evidence of convergence. The methodology used included construction of stochastic, dynamic panel and Bayesian spatial models and autoregressive dynamic structures. Other studies have conducted panel unit root test on the convergence hypothesis, and used the system-generalized method of moments for the dynamic panel data model to show that earlier results might be seriously biased due to weakness of the instruments in the first-differenced generalized method of moments approach (Baumol, 1986; Mankiw *et al*., 1992; Levin and Lin, 1993; Quah, 1994; Islam, 1995; Evans and Karras, 1996; Im *et al*., 2003; Bond *et al*. 2001; Evans and Kim, 2005; Ho, 2006; Ucar and Guler, 2010; Seya *et al*., 2012).

A key assumption in parametric models is that cross-country growth is linear with identical rate of convergence and the test of convergence is based on the parametric estimate of the income coefficient. However, new growth theories have shown that cross-country growth can be non-linear and is characterized by multiple steady states. As such, the implied rates of convergence could differ between different groups of economies (Azariadis and Drazen, 1990; Durlauf and Johnson, 1995). Consequently, nonparametric approaches that pre-specify neither the income distribution form nor the functional form of the regression function have been applied to the study of convergence (Bianchi, 1997; Wang, 2004; Juessen, 2009). However, these nonparametric analyses have concentrated on absolute convergence and excluded other steady state growth determinants.

To control for structural differences across countries in the steady state, recent empirical research used semiparametric methods to test the conditional convergence hypothesis and estimated the implied rate of convergence as a function of the initial income. Kumer and Ullah (2000) developed a local linear instrumental variable method with a kernel weight function, and applied the smooth varying coefficient function to estimate the per capita output convergence of a panel of countries. Both Dobson *et al.* (2003) and Azomahou *et al.* (2011) presented semiparametric analysis on the cross-country convergence and provided evidence for nonlinear convergence.

The strength of nonparametric estimation approaches stems from their ability to relax functional form assumptions in regression model and let the data to determine the convergence process. The nonlinearity and heterogeneity in structural economies can be accounted for even though there is little prior knowledge on a particular convergence process. Nonparametric models can be more flexible than parametric models in describing the nonlinearity in the convergence process and the multiple steady states in the economy (Henderson *et al.*, 2008; Chambers and Dhongde, 2011).

In light of the nonlinearity in the convergence process and the heterogeneity of cross-country structural economies, this article proposes the use of nonparametric panel data models to study and compare the two cases of absolute convergence and conditional convergence. By using an unbalanced panel data set of 120 world economies over the period 1980-2010, this article examines whether differences in macroeconomic and institutional factors, endowments, and other country characteristics have played a role in per capita income growth and convergence among world economies. Panel data analysis on income convergence can incorporate heterogeneity across economies. The fixed and random effects are specified in the growth model for unobservable heterogeneity in the economies. There is no agreement as to which kind of effects is more suitable to use.[1] However, in order to obtain consistent estimates for the nonparametric function of the lagged output and the speed of convergence, no matter whether the individual effect is random or fixed, fixed effects specification are applied in the nonparametric and semiparametric models (Henderson *et al*., 2008).

Section II presents the theory on growth and convergence and specifies the varying coefficient model to estimate the convergence speed. Section III describes the data and variables. Section IV presents the estimation of the varying coefficient nonparametric models and the model specification test with unbalanced panel data. Section V reports the empirical results and analysis, while Section VI shows the results based on regional performances. Section VII concludes the paper.

II Speed of Convergence and Nonparametric Estimation

By employing the neoclassical growth model as in Rassekh (1998), the assumption of diminishing returns implies that the economy will eventually reach the steady state values of output per capita. Using the output specification in Mankiw *et al*. (1992) and Islam (1995), we specify:

$$Y_{it} = K_{it}^{\alpha_1} H_{it}^{\alpha_2} (A_{it} L_{it})^{1-\alpha_1-\alpha_2} \tag{1}$$

where Y denotes output, K and H depict physical and human capital, respectively,

[1] When the individual effect is independent of the regressors, the estimation of both the random effects model and the fixed effects model is consistent with each other, except that the random effects estimator is more efficient. However, when the individual effect is correlated with any of the regressors, the random effects estimator is biased and inconsistent whereas the fixed effects estimator still leads to consistent estimates and is appropriate for the estimation of regression functions.

A represents technology, and L denotes labor, we can derive that the steady state value of $y_{it} = Y_{it} / (A_{it} L_{it})$, the output in effective units of labor, is:

$$y^* = \left[\left(\frac{s_K}{x + n + \delta_K} \right)^{\alpha_1} \left(\frac{s_H}{x + n + \delta_H} \right)^{\alpha_2} \right]^{1/(1-\alpha_1-\alpha_2)}$$

or

$$\ln(y^*) = \frac{1}{1-\alpha_1-\alpha_2} \left[\alpha_1 \ln s_K + \alpha_2 \ln s_H - \alpha_1 \ln(x+n+\delta_K) - \alpha_2 \ln(x+n+\delta_H) \right], \quad (2)$$

where s_K and s_H are the fractions of output invested in K and H, x and n are the exogenous constant growth rates of A and L, and δ_K and δ_H are the depreciation rates of K and H, respectively. If all the parameters in (2) are identical across economies, the steady state output per capita in different economies converges to the same value. However, before reaching the steady state, the economies necessarily grow at different rates. The essence of the convergence in the neoclassical model is that the farther the actual values of y_{it} are from y^* the faster the economies with the same initial output y_{i0} will grow. The speed of convergence λ is defined by:

$$e^{-\lambda\tau} = \frac{\ln(y_{i,t_2}) - \ln(y^*)}{\ln(y_{i,t_1}) - \ln(y^*)}, \quad (3)$$

where $\tau = t_2 - t_1$. To estimate the speed in empirical study, we usually set $t_2 = t$ and $\tau = 1$ or some other fixed integer, and transform (3) to its stochastic version:

$$\ln(y_{it}) - \ln(y_{i,t-\tau}) = \beta \ln(y_{i,t-\tau}) - \beta \ln(y^*) + u_i + v_{it}, \quad (4)$$

where $\beta = -(1 - e^{-\lambda\tau})$, u_i is the individual effect allowed to be correlated with $\ln(y_{i,t-\tau})$, and v_{it} is an error term with a zero mean and a finite variance. One can derive from (2) and (4) and obtain:

$$\ln(y_{it}) - \ln(y_{i,t-\tau}) = \beta \ln(y_{i,t-\tau}) + \gamma_1 \ln x_{1,it} + \gamma_2 \ln x_{2,it} + \gamma_3 \ln x_{3,it} + \gamma_4 \ln x_{4,it} + u_i + v_{it}, \tag{5}$$

where

$$\gamma_1 = -\frac{\alpha_1\beta}{1-\alpha_1-\alpha_2}, \gamma_2 = -\frac{\alpha_2\beta}{1-\alpha_1-\alpha_2}, \gamma_3 = \frac{\alpha_1\beta}{1-\alpha_1-\alpha_2}, \gamma_4 = \frac{\alpha_2\beta}{1-\alpha_1-\alpha_2},$$

and

$$x_{1,it} = \ln s_K,\ \ x_{2,it} = \ln s_H,\ \ x_{3,it} = \ln(x+n+\delta_K),\ \ x_{4,it} = \ln(x+n+\delta_H). \tag{6}$$

We distinguish between the case of absolute or unconditional convergence and the case of conditional convergence. In absolute or unconditional convergence, all economies share the same steady state; namely, all variables in (6) are constant and whether economies converge or not will depend only on their initial income level. In conditional convergence, on the contrary, the steady state is conditional on the variables in (6); namely whether economies converge or not will depend on both their initial income level and the control variables in (6).

The negative value of β in (5) shows that the economies with lower initial income will grow faster as implied in the meaning of convergence. If the convergence speed (hence β) is assumed to be a constant, then equation (5) is a linear parametric model with parameters $\beta, \gamma_1, \gamma_2, \gamma_3$ and γ_4. Once the coefficient β is estimated (denoted as $\hat{\beta}$), the speed of convergence λ is calculated as:

$$\hat{\lambda} = -\ln(1+\hat{\beta}). \tag{7}$$

However, equation (5) may have a model misspecification problem. That is, the speed λ may not be identical across economies with different initial income levels. In general, λ (hence β) is a function of the initial income $\ln(y_{i,t-\tau})$ and (5) is generally specified in the following varying coefficient version:

$$\begin{aligned}\ln(y_{it})-\ln(y_{i,t-\tau}) &= \beta(\ln y_{i,t-\tau})\ln(y_{i,t-\tau})+\gamma_1(\ln y_{i,t-\tau})\ln x_{1,it}+\gamma_2(\ln y_{i,t-\tau})\ln x_{2,it} \\ &\quad +\gamma_3(\ln y_{i,t-\tau})\ln x_{3,it}+\gamma_4(\ln y_{i,t-\tau})\ln x_{4,it}+\alpha_i+\varepsilon_{it},\end{aligned} \tag{8}$$

where $\beta,\gamma_1,\gamma_2,\gamma_3$ and γ_4 are functions of $\ln(y_{i,t-\tau})$, α_i are fixed effects, and ε_{it} are the error term. Correspondingly, the speed of convergence is also a function of $\ln(y_{i,t-\tau})$. Once the varying coefficient $\beta(\ln y_{i,t-\tau})$ is estimated (denoted as $\hat{\beta}(\ln y_{i,t-\tau})$), the speed of convergence λ is estimated as a function of the initial income:

$$\hat{\lambda}(\ln y_{i,t-\tau})=-\ln(1+\hat{\beta}(\ln y_{i,t-\tau})). \tag{9}$$

The flexibility specified in model (8) allows the data in the sample economies to determine the functional forms, which avoids the effect of the model misspecification on the estimation of the convergence speed.

III Variables Selection and Data

Though the steady state output $\ln(y^*)$ in (4) is determined by the variables in (2) or (6), it has been debated as to the choice of variables to proxy the steady state in studying growth and convergence. Recent studies distinguished external variables from domestic variables and found that an improvement in the performance of domestic variables can have a bigger impact on growth (Sala-i-Martin, 1997; Durlauf *et al*., 2005, Li and Zhou, 2010). The empirical analysis in this paper includes a total of eleven control variables in the vector of characteristics in order to reflect differences in the steady state equilibrium and to capture a variety of external and domestic variables.

The two external variables that examined economic openness include percentage share of trade in GDP and percentage share of net foreign direct investment in GDP. As an indication of economic openness, trade has always been seen as an important catalyst for economic growth, while foreign direct investments could generate increasing returns in production through positive externalities and spillover effects (Frankel and Romer, 1999; Dollar and Kraay, 2001; Makki and Somwaru, 2004).

The nine domestic variables include government expenditure share of real GDP per capita, investment share of real GDP per capita, annual percentage of GDP deflator, life expectancy, share of urban to total population, domestic credit to private sector as a percentage of GDP, carbon dioxide emission per capita, labor participation rate and enrollment rate for primary school.

The government size is used to proxy an institutional indicator and to test if a larger government size was likely to harm growth, as shown in Iradian (2003, 2005). The inclusion of investment as a control variable is important because it has been one of the determinants in the conventional Solow growth model. The rate of inflation acts as a proxy for macroeconomic stability with the intention to test the hypothesis of the negative effect to income growth (Fischer, 1993; Barro, 2013). Health in the form of life expectancy has appeared in many cross-country growth regression analyses and has been generally found to have a significant positive effect on the rate of economic growth (Bloom and Canning, 2000; Bloom *et al.*, 2004). Life expectancy is thus used to indicate whether increased expenditures on health are justified on the grounds of their impact on economic growth. Urbanization has been viewed necessary for achieving high growth, high income, increased productivity and efficiency through specialization, diffusion of knowledge, size and scale (Annez and Buckley, 2009; Duranton, 2009; Quigley, 2009). However, urbanization may also deter firms from locating in larger cities due to negative spillovers including congestion and high land rents, leading to dampening effect on economic growth. Urbanization is included in our analysis to provide evidence if its progress supports income growth. Carbon dioxide emission and private credit share are used to capture the environmental issue and level of financial development, respectively. Labor participation rate reflects the engagement of workers in the economy. The enrollment rate for primary school captures the human capital development which acts as an input in the production and growth (see for example, Zhou *et al*., 2011).

The data are sourced from the Penn World Tables, World Development Indicators and the United Nations. The real GDP per capita (gdpc) are expressed in 2005 constant price derived from the growth rates of consumption, government expenditure and investment. The unbalanced panel dataset contains 1,338 observations on 120 world economies for the period 1980-2010 (see Appendix). Table 1 presents the simple statistics of the variables and Table 2 reports their correlation.

(Table 1 about here)

(Table 2 about here)

IV Nonparametric Models and Specification Test

The motivation discussed in Section II makes it necessary to use varying coefficient nonparametric panel data models to examine income convergence. Nonparametric models (see (8) and (9)) relax the assumption of an identical speed of convergence specified in parametric models and allow convergence to be related to the initial level of economic development. The generated flexibility allows the data in the sample economies to determine the functional form. Specification tests will be conducted to justify the chosen model.

Corresponding to (8), the varying coefficient nonparametric panel data model with country-specific fixed effects is specified as:

$$y_{it} = \gamma_0(z_{it}) + x_{it}'\gamma_1\left(z_{it}\right) + \alpha_i + \varepsilon_{it},\ t = 1,2,\cdots,m_i;\ i = 1,2,\cdots,n, \tag{10}$$

where $y_{it} = \ln(gdpc_{it}) - \ln(gdpc_{i,t-1})$, $z_{it} = gdpc_{i,t-1}$, $\gamma_0(z_{it}) = \beta(z_{it})\ln(z_{it})$, $\ln(gdpc)$ is the logarithm of real GDP per capita, and x_{it} is the vector of the variables to proxy the steady state in Section II. Equation (10) shows an unbalanced panel data model, where each country i in the sample may have different years (m_i) of data. The individual effects α_i are fixed effects allowed to be correlated with the regressors. The error term ε_{it} is assumed to be i.i.d. with a zero mean and a finite variance, and $E(\varepsilon_{it} \mid x_{it}, z_{it}) = 0$. Once $\gamma_0(\cdot)$ is estimated as $\hat{\gamma}_0(\cdot)$, we can compute $\hat{\beta}(z) = \hat{\gamma}_0(z)/\ln(z)$ and apply (9) to estimate the speed of convergence as $\hat{\lambda}(z) = -\ln(1+\hat{\beta}(z))$. Corresponding to the case of conditional convergence, $\hat{\lambda}(z)$ is the speed of estimated conditional convergence. If there are no control variables in (10), the model becomes $y_{it} = \beta(z_{it})\ln(z_{it}) + \alpha_i + \varepsilon_{it}$, and $\lambda(z) = -\ln(1+\beta(z))$ shows the speed of absolute or unconditional convergence.

Model (10) can be estimated by generalizing the nonparametric method as in Sun *et al*. (2009) to the case of unbalanced varying coefficient panel data. For simplicity, we still use x_{it} to denote $(\ln(z_{it}), x_{it}')'$ and $\gamma\left(z_{it}\right) = (\beta(z_{it}), \gamma_1'(z_{it}))'$, and write (10) as $y_{it} = x_{it}'\gamma\left(z_{it}\right) + \alpha_i + \varepsilon_{it}$, or in matrix form:

$$Y = B(X, \gamma(Z)) + D_0\alpha_0 + E \tag{11}$$

where

$$B(X,\gamma(Z)) \equiv (x_{11}'\gamma(z_{11}),\cdots,x_{1m_1}'\gamma(z_{1m_1}),\cdots,x_{n1}'\gamma(z_{n1}),\cdots,x_{nm_n}'\gamma(z_{nm_n}))',$$

$Y \equiv (Y_1', Y_2', \cdots, Y_n')'$, $Z \equiv (Z_1, Z_2, \cdots, Z_n)'$, $E \equiv (E_1', E_2', \cdots, E_n')'$,

$Y_i' \equiv (y_{i1}, y_{i2}, \cdots, y_{im_i})$, $Z_i' \equiv (z_{i1}, z_{i2}, \cdots, z_{im_i})$, $E_i' \equiv (\varepsilon_{i1}, \varepsilon_{i2}, \cdots, \varepsilon_{im_i})$,

$\alpha_0 \equiv (\alpha_1, \alpha_2, \cdots, \alpha_n)'$ with $\sum_{i=1}^n \alpha_i = 0$,

$D_0 \equiv diag(e_{m_1}, e_{m_2}, \cdots, e_{m_n})$ with $e_{m_i}' = (1, 1, \cdots, 1)_{1\times m_i}$ and $i = 1, 2, \cdots, n$.

Further, by $\alpha_1 = -\sum_{i=2}^n \alpha_i$, we have $D_0\alpha_0 = D\alpha$, where

$$\alpha \equiv (\alpha_2, \cdots, \alpha_n)' \text{ and } D = \begin{pmatrix} E_{-1} \\ diag(e_{m_2}, \cdots, e_{m_n}) \end{pmatrix}$$

and E_{-1} is an $m_1 \times (n-1)$ matrix with elements -1. Then (11) is written as

$$Y = B(X, \gamma(Z)) + D\alpha + E. \tag{12}$$

Denote

$$W_h(z) = diag\left\{ K\left(\frac{z_{11}-z}{h}\right), \cdots, K\left(\frac{z_{1m_1}-z}{h}\right), \cdots, K\left(\frac{z_{n1}-z}{h}\right), \cdots, K\left(\frac{z_{nm_n}-z}{h}\right) \right\},$$

where h is the bandwidth of z. Model (12) can nonparametrically be estimated by solving the following minimization problem:

$$\min_{\theta(Z),\alpha} \left(Y - B(X, \gamma(Z)) - D\alpha\right)' W_h(z) \left(Y - B(X, \gamma(Z)) - D\alpha\right). \tag{13}$$

The first order condition with respect to α gives $D' W_h(z)\left(Y - B(X, \gamma(Z)) - D\hat{\alpha}\right) = 0$, or $\hat{\alpha} = \left(D' W_h(z) D\right)^{-1} D' W_h(z)\left(Y - B(X, \gamma(Z))\right)$. Then the concentrated minimization problem for $\theta(Z)$ is:

$$\min_{\gamma(\cdot)} \left(Y - B(X, \gamma(Z))\right)' S_h(z) \left(Y - B(X, \gamma(Z))\right), \tag{14}$$

where $S_h(z) = M_h(z)' W_h(z) M_h(z)$, $M_h(z) = I - D(D' W_h(z) D)^{-1} D' W_h(z)$ and I is an $\left(\sum_{i=1}^n m_i\right) \times \left(\sum_{i=1}^n m_i\right)$ identity matrix.

Denote $\theta(z) \equiv \left(\gamma(z)', \left(\partial\gamma(z)/\partial z\right)'\right)'$. By a Taylor expansion, (14) is equivalent to

$$\min_{\theta(\cdot)} \left(Y - R(z,h)\theta(z)\right)' S_h(z) \left(Y - R(z,h)\theta(z)\right), \tag{15}$$

where

$$R(z,h) = \left(G_{11}(z,h) \otimes x_{11}, \cdots, G_{1m_1}(z,h) \otimes x_{1m_1}, \cdots, G_{n1}(z,h) \otimes x_{n1}, \cdots, G_{nm_n}(z,h) \otimes x_{nm_n}\right)'.$$

The solution to (15) is $\hat{\theta}(z) = \left[R(z,h)' S_h(z) R(z,h)\right]^{-1} \left[R(z,h)' S_h(z) Y\right]$, by which the estimator for $\gamma(z)$ is:

$$\hat{\gamma}_{FE}(z) = \left[X' S_h(z) X\right]^{-1} \left[X' S_h(z) Y\right]. \tag{16}$$

It can be shown that $\sqrt{nh}\left(\hat{\gamma}_{FE}(z) - \gamma(z) - \psi^{-1}(z)\Lambda(z)\right) \to N\left(0, \Sigma_{\theta(z)}\right)$, where

$$\Lambda(z) = O(h^2), \quad \psi(z) = h^{-1} n^{-1} \sum_{i=1}^{n} \sum_{t=1}^{m_i} E\left[(1-\omega_{it}) k((z_{it} - z)/h) x_{it} x_{it}'\right],$$

$$\Sigma_{\theta(z)} = \sigma_v^2 \, p\lim_{n\to\infty} \psi^{-1}(z) \Gamma(z) \psi^{-1}(z),$$

$$\Gamma(z) = h^{-1} n^{-1} \sum_{i=1}^{n} \sum_{t=1}^{m_i} E\left[(1-\omega_{it})^2 k^2((z_{it} - z)/h) x_{it} x_{it}'\right],$$

$$\omega_{it} = k((z_{it} - z)/h) / \sum_{t=1}^{m_i} k((z_{it} - z)/h).$$

To incorporate a data driven procedure for model selection, we further modify the specification test between parametric and nonparametric varying coefficient models for unbalanced panel data (see Henderson *et al*., 2008). The null hypothesis H_0 is the parametric model:

$$y_{it} = \gamma_0 + x_{it}'\gamma_1 + \alpha_i + \varepsilon_{it}, \; t = 1, 2, \cdots, m_i; \, i = 1, 2, \cdots, n. \tag{17}$$

The alternative model is the varying coefficient model (10). The test statistic for testing this null is:

$$I_n = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m_i}\sum_{t=1}^{m_i}(\hat{\gamma}_0(z_{it}) + x_{it}'\hat{\gamma}_1(z_{it}) - \tilde{\gamma}_0 - x_{it}'\tilde{\gamma}_1)^2 , \tag{18}$$

where $\tilde{\gamma}_0$ and $\tilde{\gamma}_1$ are consistent estimators in the parametric panel data model; $\hat{\gamma}_0(\cdot)$ and $\hat{\gamma}_1(\cdot)$ are the varying-coefficient nonparametric estimator of model (10). For the empirical study, we apply bootstrap procedures to approximate the finite sample null distribution of test statistics and obtain the bootstrap probability values for the test statistics.

V Empirical Results

For comparison with the varying coefficient nonparametric model (10), we also present parametric estimation results for the conditional convergence model. Table 3 reports the parametric estimation results from the pooled OLS, fixed effects and random effects models. For comparison, the results for without control variables are also reported. The OLS estimator and the within-groups (fixed effects) estimator are used to establish an upper and a lower bound, respectively, for the estimated coefficient of the initial income term. This would mean that a consistent estimate of the initial income term coefficient can be expected to lie between the OLS levels and within-groups estimates (Bond *et al*., 2001).

The Hausman test for random and fixed effects in parametric models shows that random effects model is rejected. The more reliable linear conditional convergence model with fixed effects gives an average conditional convergence rate of 0.091, while the absolute speed is 0.026. The estimates on coefficients of the control variables reflect the differences in the steady state equilibrium.

Investment, urbanization, pollution, trade, life expectancy, FDI, employment, and enrollment have positive impacts on economic growth, consistent with other finding in the literature. For example, the positive and significant effect of life expectancy on growth agrees with the empirical evidence that health plays an important role in determining economic growth (Bloom and Canning, 2000; Bloom *et al.*, 2004). On the contrary, government consumption, inflation and private credit share produce a negative impact to economic growth. The significant negative coefficient estimates for government size and inflation support the fact that inefficient government expenditure and high inflation rates would hinder growth (Iradian, 2003, 2005; Fischer, 1993; Barro, 2013).

Since the theoretic discussion focuses on the varying coefficient specification, we concentrate on the varying coefficient nonparametric estimation. The kernel is chosen as the Gaussian function and the bandwidth is chosen according to the rule of thumb: $h = 1.06 \times stdc(z) \times N^{-1/5}$, where $stdc(z)$ is the standard deviation of z, the logarithm of the initial GDP per capita and N is the sample size. The varying coefficient estimates at the sample mean of z and the corresponding t statistic values (in parentheses) calculated by the bootstrap approach (with 1000 replicates) are reported in the last two columns of Table 3. The model specification test (see (18)) for parametric model against the varying coefficient models is conducted (Henderson *et al.*, 2008) and we find that the probability value for the test is 0.024. So we should reject the parametric model at 5% significant level. This evidence justifies our varying coefficient model specification.

The last two columns of Table 3 present the varying coefficient estimates at the sample mean of the initial GDP per capita. Most coefficient estimates are consistent in direction with those in other parametric models. The world economy on average converges in both the unconditional and conditional ways since the coefficients of the initial GDP per capita are negative and significant. The convergence speed λ in the conditional case at the mean of the initial GDP per capita is calculated as 0.22, which is quite a large convergence rate. The coefficient estimates of the control variables except life expectancy in the varying coefficient conditional case are identical in direction to those in the parametric models with random or fixed effects. Investment, urbanization, carbon dioxide emission, trade and foreign direct investment contribute positively to economic growth, while government size, inflation, and private credit share exert negative effects.

Table 4 shows the estimation of the varying coefficient function and the implied speed of convergence at some quartile points of the logarithm of initial real GDP per capita. It can be seen that the estimates of the speed $\lambda(\cdot)$ near the mean and median of the initial income ln(gdpc) are larger than those at the other quartile points of ln(gdpc). It seems that either a low level or a high level of initial income deduces a slower speed of convergence.

(Table 3 about here)

(Table 4 about here)

Figures 1 and 2 illustrate the estimated varying coefficient function $\beta(\cdot)$ and the convergence speed $\lambda(\cdot)$, respectively, as functions of initial log income ln(gdpc), where lower and upper bounds of 95% confidence intervals are also drafted. The estimates are acceptable though the estimation has boundary effects. Figure 1 shows that except low initial income where $\beta(\cdot)$ has positive values, the economies with fairly high initial income will converge at a positive speed. This is justified in Figure 2 where $\lambda(\cdot)$ is positive when the log initial income is greater than 6.4. Figure 2 also shows that the high average convergence speed (0.22) estimated from the varying coefficient model in Table 3 is mainly determined by the high speed among the economies with high initial income. This finding shows that the "fragile" states or those extremely underdeveloped economies with low initial development level will not converge to the steady state, and their situation will get worse in comparison to the world economy, whereas fast developing economies have a higher convergence speed. Among the various causes of underdevelopment, especially in those "fragile" states, stability is obviously the pre-condition before they can converge.

(Figures 1 to 4 about here)

Figure 3 compares the estimates of the varying coefficient function $\beta(\cdot)$ in the conditional case with controls and the unconditional case without controls. The vertical difference between the two curves shows the contribution of control variables in enhancing growth. The gross (direct and indirect) effect of initial development on growth is illustrated by the dashed line (without controls), which is above the direct or net effect of initial development illustrated by the solid line (having controls). The integrated indirect effect of initial development through control variables is positive in enhancing growth.

Figure 4 compares the estimates of the convergence speed function $\lambda(\cdot)$ in the two cases with (having) control and without control variables. Contrary to the comparison of effects in Figure 3, the convergence speed in the "without controls" case is smaller than the case with controls; that is, the conditional speed of convergence is larger than the absolute speed of convergence at all levels of initial income. This fact can be directly explained by the relationship $\lambda(z) = -\ln(1+\beta(z))$ since the model with controls has suppressed the gross effect of initial income on growth in the model without controls (see Figure 3). The economic intuition is that since the control variables in (10) are used as proxies for the steady state of the economies, the speed of convergence conditional on these control variables can be regarded as the speed at which the economy converges to its own steady state, which is larger than the speed of unconditional (or absolute) convergence at which the economy converges to the common steady state of all the economies. Hence the speed of absolute convergence embodies the effect from the common steady state. In other words, an economy would conditionally converge to its particular steady state more easily than it converges to the common steady state of all the economies.

VI Comparing Different Regions

Table 5 reports the estimation results of the varying coefficient models for growth at their sample average of initial GDP per capita with subsamples from Asia, Africa, Europe and Latin America. The four regions are ranked as Europe, Asia, Latin America and Africa in terms of their average income with Europe the highest income and Africa the lowest. Absolute convergence is insignificant in each region (in Latin America the economy even diverges) and conditional convergence is significant in Europe, Asia and Latin America while insignificant in Africa, which implies that controls play important roles in growth convergence and the initial income level matters in this process. This confirms the result in previous section.

(Table 5 about here)

Figure 5 through Figure 8 present the comparison of absolute convergence and conditional convergence in the four regions. For Europe, Asia and Latin America in Figure 5, 6 and 7, respectively, the conditional convergence speed is larger than the absolute convergence speed at all levels of initial income, implying that each of the four economies conditionally converges to its own particular steady state more easily than it converges to the common steady state of all the economies of the region. However, this result does not hold for Africa (see Figure 8), which is the lowest-income economy in our sample. This is consistent with the result in Table 5 that the convergence hypothesis does not hold for economies with extremely low level of initial development (since the estimate of β is insignificant for the subsample of Africa), so securing a stable economic condition is the pre-requisite to those 'fragile' states before their growth can converge.

(Figures 5 to 8 about here)

VII Conclusion

The multiple steady state growth states confirm that there is nonlinearity and that implied non-constant rates of convergence among different groups of economies in the convergence process. By using the varying coefficient nonparametric unbalanced panel data model with fixed effects, this paper investigates the two cases of absolute (without controls) and conditional (with controls) convergence of real GDP per capita among 120 world economies over the period 1980-2010.

Our econometric estimation on growth convergence can be evaluated with reference to a number of parametric empirical studies that have chosen similar variables in their analysis of the conditional convergence issue. However, the specification test in the data driven model justifies the use of varying coefficient nonparametric model to study both the absolute and conditional convergence processes. The nonparametric estimation results show that the proxy variables of the steady state, such as investment, urbanization, carbon dioxide emission, trade and foreign direct investment, contributed positively to economic growth, while the other determinants, such as government size, inflation and private credit share exerted negative effects.

The comparison between absolute and conditional convergence shows that the indirect contribution of initial income to growth via the control variables is an important part in the gross contribution of initial income to economic growth. The total effect of control variables on growth is positive whereas the total effect on the convergence speed is negative. The convergence hypothesis does not hold for the economies that have extremely low level of initial development. This suggests that securing a stable economic condition is the pre-requisite to those 'fragile' states before their income can converge.

Initial income level can affect economic growth either directly or indirectly via controls. Our finding is that the indirect contribution of initial income to growth via the control variables is important in the gross (direct and indirect) contribution of initial income to economic growth. The total mediating effect of control variables for initial income to affect growth is positive. These regression estimates are supported by regional evidences when data from different world geographical regions are used.

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Table 1 Simple Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
growth	1,338	0.02	0.04	-0.18	0.21
$gdpc_{-1}$	1,338	15,766.75	16,353.70	124.10	86,127.23
ki	1,338	23.73	7.15	3.11	54.26
kg	1,338	8.42	4.26	2.82	45.39
urban	1,338	63.67	19.90	8.53	100.00
co_2	1,338	6.24	5.43	0.04	37.93
deflator	1,338	19.79	226.66	-26.30	5,018.19
trade	1,338	79.48	42.98	13.75	432.95
life	1,338	72.66	6.71	40.94	82.98
credit	1,338	64.02	49.91	2.41	311.06
fdi_in	1,338	3.80	12.91	-57.43	430.64
laborate	1,338	60.26	8.94	18.00	94.30
enroll	1,338	93.38	9.83	19.21	100.00

Table 2 Correlation of Variables

	gdppc	ki	kg	urban	co2	deflator	trade	life	credit	fdi_in	labor
ki	0.08	1.00									
kg	-0.29	-0.08	1.00								
urban	0.57	0.03	-0.38	1.00							
co2	0.59	0.11	-0.22	0.42	1.00						
deflator	-0.06	-0.04	0.29	-0.03	-0.06	1.00					
trade	0.11	0.13	0.01	0.00	0.11	-0.01	1.00				
life	0.65	0.12	-0.31	0.65	0.43	-0.08	0.09	1.00			
credit	0.68	0.19	-0.22	0.41	0.40	-0.06	0.12	0.55	1.00		
fdi_in	0.13	0.05	-0.03	0.06	0.11	-0.01	0.32	0.07	0.11	1.00	
labor	0.24	-0.07	-0.02	0.03	0.11	0.00	-0.06	-0.01	0.15	0.00	1.00
enroll	0.33	0.09	-0.29	0.44	0.32	-0.13	0.07	0.63	0.31	0.06	-0.02

Table 3 Estimation results for conditional convergence models

	Pool-OLS		Random Effects		Fixed Effects		Varying coefficients	
ln(gdppc$_{-1}$)	-0.0031***	-0.0116***	-0.0048***	-0.0228***	-0.0204***	-0.0872***	-0.0259	-0.1996***
	(-4.32)	(-6.57)	(-3.28)	(-6.72)	(-4.06)	(-10.13)	(-1.46)	(-3.12)
ki		0.0011***		0.0016***		0.0019***		0.0029***
		(7.90)		(8.40)		(8.81)		(2.42)
kg		-0.0009***		-0.0020***		-0.0038***		-0.0070***
		(-3.46)		(-4.48)		(-6.21)		(-2.33)
urban		0.0001		0.0002		0.0010***		0.0018**
		(1.31)		(0.99)		(2.79)		(1.95)
ln(co2)		0.0039*		0.0077**		0.0360***		0.0616
		(1.82)		(2.30)		(5.23)		(1.16)
$(\ln(co2))^2$		0.0012*		0.0029***		0.0060***		0.0216***
		(1.91)		(2.86)		(3.15)		(1.41)
inflation		-0.0000*		-0.0000		0.0000		-0.0004**
		(-1.66)		(-0.70)		(0.43)		(-2.00)
trade		0.0001**		0.0002***		0.0005***		0.0010***
		(2.40)		(3.61)		(6.46)		(3.33)
life		0.0010***		0.0015***		0.0018***		-0.0007
		(3.69)		(3.75)		(2.93)		(-0.27)
credit		-0.0001***		-0.0003***		-0.0002***		-0.0001
		(-5.12)		(-7.85)		(-4.59)		(-1.25)
fdi_in		0.0001		0.0001*		0.0001		0.0006
		(1.60)		(1.66)		(1.48)		(0.86)
labor_rate		0.0002		0.0002		-0.0002		-0.0001
		(1.41)		(0.86)		(-0.84)		(-0.11)
enroll		0.0002		0.0003		0.0004		0.0007
		(1.07)		(1.46)		(1.63)		(0.78)
_cons	0.0509***	-0.0028	0.0641***	0.0306	0.2044***	0.4741***		
	(7.75)	(-0.14)	(5.15)	(0.97)	(4.58)	(7.36)		
obs	1338	1338	1338	1338	1338	1338	1338	1338
R^2	0.014	0.125			0.013	0.244		
Hausman			10.61***	145.09***				
			(0.001)	(0.000)				
λ	0.003	0.012	0.005	0.023	0.021	0.091	0.026	0.223

Notes: The dependent variable is $\ln(gdpc_{it}) - \ln(gdpc_{i,t-1})$. The numbers in the parentheses except in the last two columns are t-values of the coefficient estimates. The numbers in the parentheses in the last two columns are bootstrapping t-values. *, ** and *** indicate 10%, 5%, and 1% significant levels, respectively. The null hypothesis H_0 for Hausman test is random effects model. λ is the implied speed of convergence, which is calculated by (7).

Table 4 Estimation of varying-coefficient functions $\beta(\cdot)$ and $\lambda(\cdot)$

Percentile of ln(gdpc): z		$\beta(\cdot)$	speed $\lambda(\cdot)$
2.5%	6.0767	0.0101	-0.010
25%	7.8810	-0.0632	0.065
50%	8.9381	-0.2079	0.233
75%	10.1874	-0.1236	0.132
95%	10.7542	-0.1040	0.110
97.5%	10.8695	-0.1053	0.111
mean of ln(gdpc):	8.8899	-0.1996	0.223

Table 5 Estimation results for convergence models with subsamples of different regions

	Europe		Asia		Latin America		Africa	
$\ln(gdppc_{-1})$	-0.0140	-0.1993***	-0.0140	-0.2241**	0.0335	-0.2114***	-0.0001	-0.0711
	(-0.68)	(-3.44)	(-0.42)	(-2.25)	(0.76)	(-2.63)	(-0.01)	(-0.57)
ki		0.0052***		0.0036**		0.0060***		0.0010
		(3.25)		(2.12)		(6.00)		(0.83)
kg		-0.0014*		-0.0077		-0.0018		-0.0044
		(-1.87)		(-0.96)		(-0.40)		(-0.38)
urban		0.0043*		0.0201		0.0072		0.0005
		(1.69)		(1.18)		(1.29)		(0.22)
ln(co2)		-0.0940		0.0201		0.0078		0.0511
		(-0.45)		(0.18)		(1.13)		(0.94)
$(\ln(co2))^2$		0.0358		0.0175		-0.0422		0.0002
		(0.70)		(0.47)		(0.70)		(0.01)
inflation		-0.0019*		-0.0006*		-0.0001		-0.0009
		(-1.73)		(-1.75)		(-0.50)		(-0.53)
trade		0.0012***		0.0009*		-0.0002		0.0002
		(3.06)		(1.80)		(-0.33)		(-0.40)
life		0.0017		0.0036		-0.0008		-0.0006
		(0.36)		(0.42)		(-0.12)		(-0.21)
credit		-0.0003***		-0.0008		-0.0015***		-0.0005
		(-3.00)		(-1.14)		(-2.50)		(-0.63)
fdi_in		0.0002		0.0022		0.0033		0.0041***
		(0.18)		(0.71)		(1.43)		(2.73)
labor_rate		0.0005		0.0034		0.0007		-0.0006
		(0.38)		(1.31)		(0.64)		(-0.60)
enroll		0.0011		-0.0005		0.0004		0.0007
		(0.79)		(-1.16)		(0.33)		(0.88)
obs	526	526	296	296	275	275	138	138
λ	0.014	0.222	0.014	0.254	-0.033	0.237	0.0001	0.074

Notes: The dependent variable is $\ln(gdpc_{it}) - \ln(gdpc_{i,t-1})$. The numbers in the parentheses are bootstrapping t-values. *, ** and *** indicate 10%, 5%, and 1% significant levels, respectively. λ is the implied speed of convergence, which is calculated by (7).

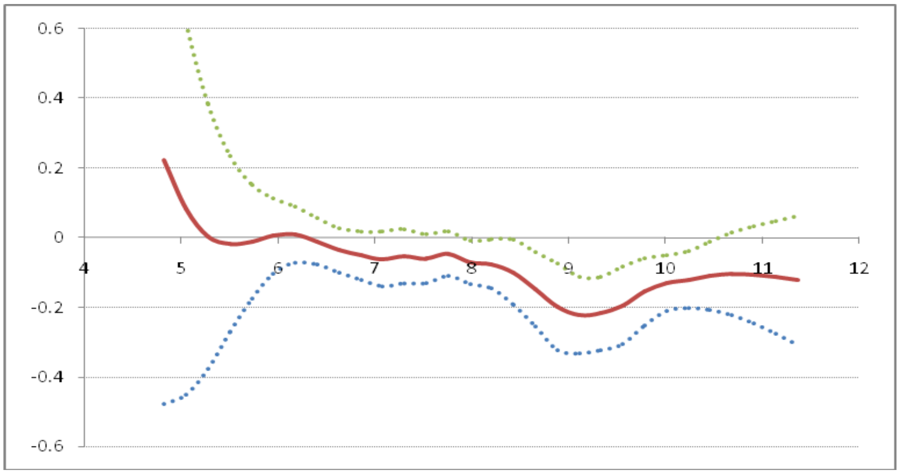


Figure 1 The varying coefficient function $\beta(\cdot)$ varies with ln(gdpc)

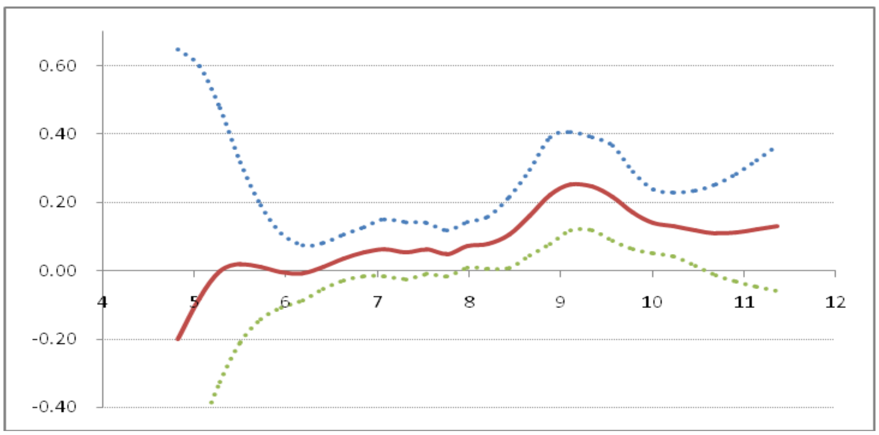


Figure 2 The convergence speed function $\lambda(\cdot)$ varies with ln(gdpc)

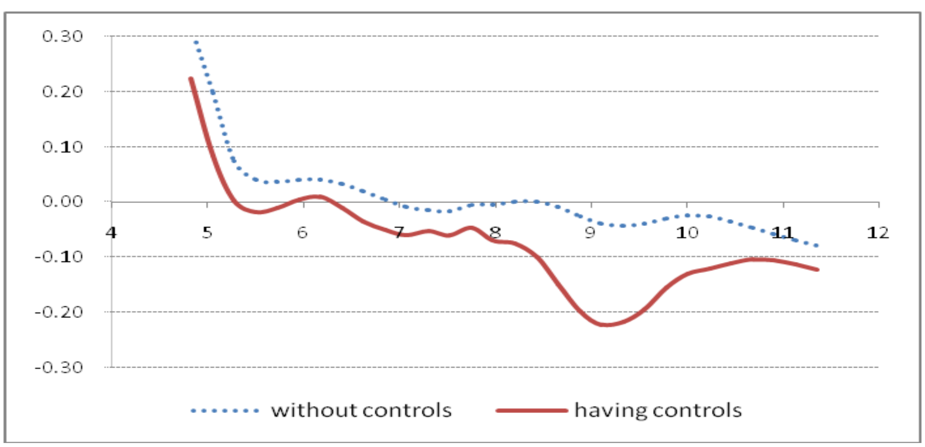


Figure 3 Comparing the varying coefficient $\beta(\ln(gdpc))$

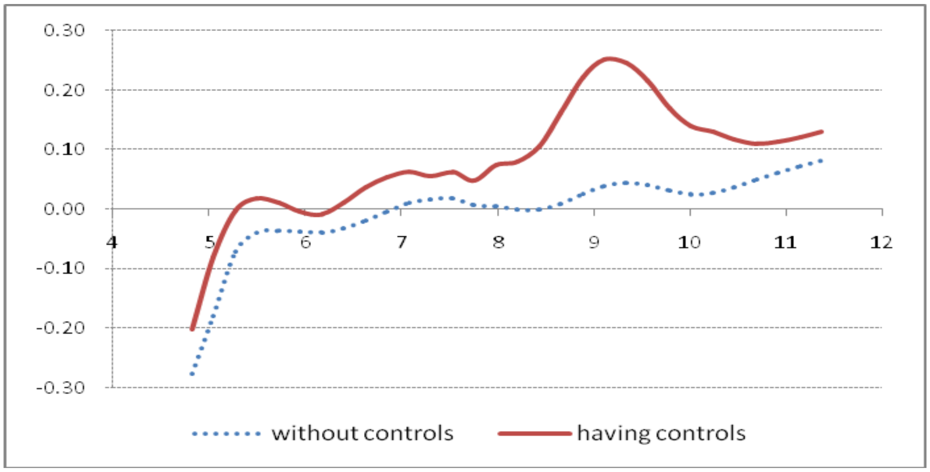
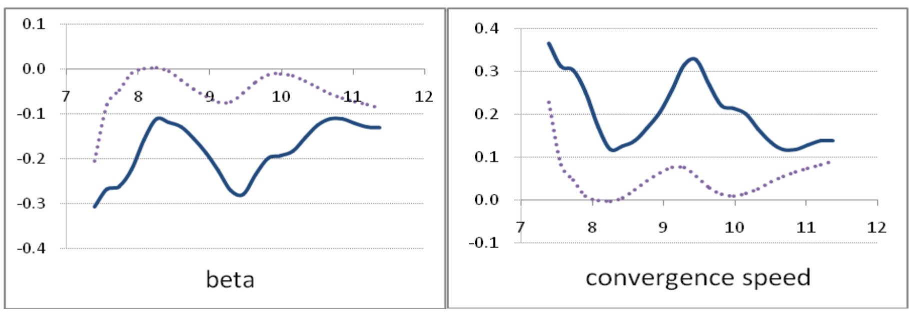
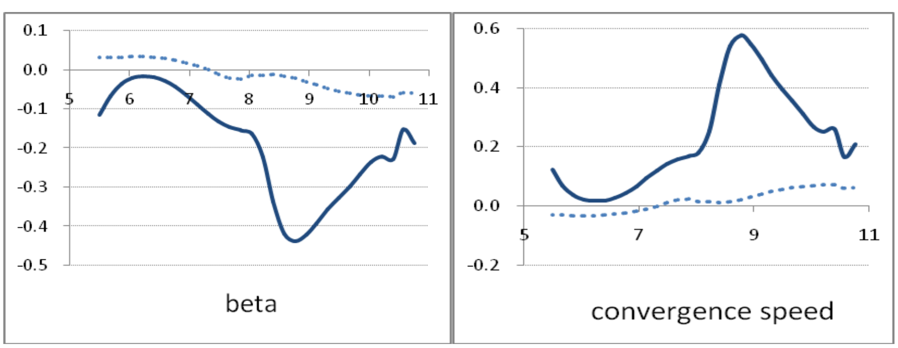


Figure 4 Comparing the convergence speed $\lambda(\ln(gdpc))$



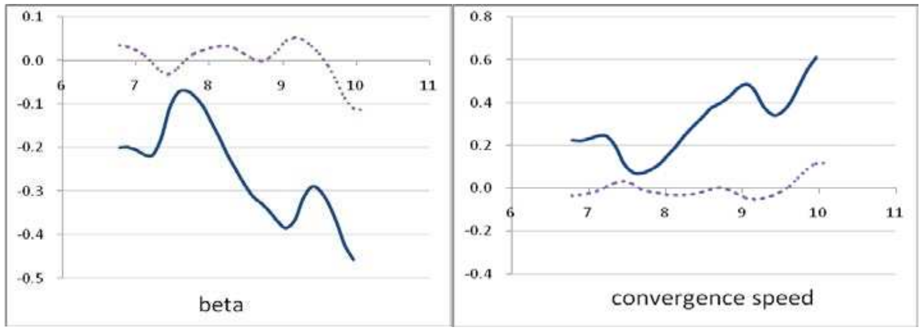
--- without controls; — having controls

Figure 5 $\beta(\ln(gdpc))$ and $\gamma(\ln(gdpc))$ for Europe



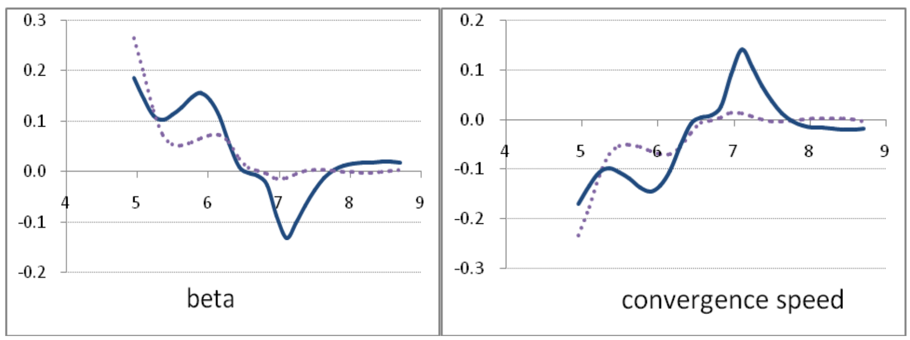
--- without controls; — having controls

Figure 6 $\beta(\ln(gdpc))$ and $\gamma(\ln(gdpc))$ for Asia



--- without controls; — having controls

Figure 7 $\beta(\ln(gdpc))$ and $\gamma(\ln(gdpc))$ for Latin American



--- without controls; — having controls

Figure 8 $\beta(\ln(gdpc))$ and $\gamma(\ln(gdpc))$ for Africa

Appendix: Sample of 120 countries and years:

Albania, 1999-2001, 2003. Algeria, 1983-85, 87, 96-97, 2000-2001, 2008-2010. Argentina, 1987, 91, 97-99, 2003-2005. Australia, 1980-2010. Azerbaijan, 2007-2010. Bahamas, The, 1980, 92-94, 99, 2004-2009. Bahrain, 1981, 91-99. Bangladesh, 1981, 84-86, 89, 2005. Barbados, 1983, 89-90, 92, 99-2004, 2009. Belarus, 2001-2005, 2007, 2009. Belgium, 2002-2010. Belize, 1999, 2003-2005. Benin, 1986, 92, 2003. Bhutan, 2005-2006, 2009-2010. Bolivia, 2000-2003, 2006-2009. Botswana, 1981, 85, 91, 94, 96, 98, 2000-2001, 2003, 2006. Bulgaria, 1997, 2000-2010. Burkina Faso, 1985, 91, 94, 2006. Cambodia, 1998, 2000, 2008, 2010. Canada, 1982-96, 98-2000. Chile, 2007-2010. China, 1987, 90, 95-97. Colombia, 1985, 87, 95, 2001-2002, 2004-2010. Congo, Republic Of, 1984, 2005. Costa Rica, 1980, 82, 85-87, 89-96. Croatia, 2000-2003, 2005-2010. Cyprus, 1984-85, 87-92, 95, 2000-2010. Denmark, 1981, 83-96, 98-2002, 2004-2010. Dominican Republic, 2000, 2002-2007, 2009-2010. Ecuador, 1980, 94-2003, 2005-2007, 2009-2010. Egypt, 1994, 99, 2001-2003, 2005-2007, 2009. El Salvador, 1998, 2000-2003, 2005-2006, 2008, 2010. Estonia, 1996, 98-2010. Ethiopia, 1994-95, 99, 2005. Fiji, 1992, 96, 2004, 2007-2009. Finland, 1993-2010. France, 1983, 85-86, 91-97, 99-2010. Gambia, The, 1983, 93. Georgia, 2004-2007, 2009. Germany, 1999-2010. Ghana, 1999-2000, 2006. Greece, 1983-97, 99-2007, 2010. Guatemala, 1980-81, 99-2000, 2002, 2004, 2006, 2010. Honduras, 1980, 82-84, 91, 2000, 2004-2010. Hong Kong, 2008-2010. Hungary, 1994-2010. Iceland, 1994, 96-2010. India, 2000-2001, 2010. Indonesia, 1982, 85-86, 88-90, 92, 94-97, 2001-2006, 2008-2010. Iran, Islamic Rep. Of, 1986, 2005, 2007. Ireland, 1981, 83, 86-2010. Israel, 1999-2010. Italy, 1985, 95-97, 99-2010. Japan, 1980-92, 94-95, 98-2010. Jordan, 2000, 2002-2003, 2010. Kazakhstan, 2002-2004, 2007-2010. Kenya, 1999, 2005. Korea, South, 1980-2010. Kuwait, 2003, 2005, 2007. Kyrgyz Republic, 2002, 2004, 2006. Laos, 2003, 2005. Latvia, 1999, 2008-2010. Lebanon, 2004, 2007. Lithuania, 1998-2010. Luxembourg, 2002-2008, 2010. Macao, 1990, 92. Macedonia, 1998, 2000-2001, 2006-2010. Malaysia, 1998-2005. Mali, 2004, 2006. Malta, 1980-81, 83, 85-90, 93-97. Mauritius, 1983-84, 87, 89-91, 93-95, 2000-2001, 2004-2010. Mexico, 1988, 90-2010. Moldova, 2000-2010. Mongolia, 1998, 2000, 2002-2010. Morocco, 1982, 90, 94-95, 98-2010. Namibia,1994, 97, 2000-2001, 2004, 2008, 2010. Nepal, 1999, 2003. Netherlands, 1980-97, 99-2010. New Zealand, 1981, 86-92, 94-2010. Nicaragua, 1985, 89-91, 95-96, 99-01, 2004-2008, 2010. Niger, 2001, 2005. Norway, 1980-82, 84-2006. Oman, 1996, 2000, 2003. Pakistan, 2002, 2004-2007. Panama, 1980, 82-90, 99-2002, 2004-2010. Paraguay, 1991-96, 99-2010. Peru, 1980-82, 95, 97-2010. Philippines, 1983, 85, 87-90, 92-94, 96, 98-99, 2001-2009. Poland, 1999-2010. Portugal, 1980-81, 84-87, 90-95, 2000, 2002, 2004-2006, 2010. Romania, 1997-2010. Russia, 1994-95, 2006-2009. Senegal, 1983-85, 88. Serbia, 2006-2010. Slovenia, 1996-2010. South Africa, 1994-95, 98-2005. Spain, 1980-81, 83-97, 99-2010. Sri Lanka, 1986, 2001-2010. St. Lucia, 2000-2001, 2003-2007. Sweden, 1982, 87-97, 99-2010. Switzerland, 1985-86, 88-96, 99-2010. Syrian Arab Republic, 1981, 83-84, 93, 95, 97-2003, 2006-2007. Tajikistan, 2003-2004. Tanzania, 1991, 2001-2002, 2006. Thailand, 2006-2009. Togo, 1980, 2006. Tonga, 1984, 86, 90. Trinidad And Tobago, 1980-81, 83, 85-93, 96-97, 99-2005, 2007-2008. Tunisia, 1980, 84, 89, 94, 97, 2003, 2005-2010. Turkey, 1985, 88-95, 97, 99-2010. Ukraine, 2002-2006, 2009-2010. United Arab Emirates, 2005, 2009. United Kingdom, 1983-92, 98-2010. United States, 1986-87, 90-91, 93-96, 99-2010. Uruguay, 1984-85, 91-96, 2005-2010. Venezuela, 1999-2002, 2004-2010. Vietnam, 1998-2002, 2009-2010. Yemen, 1999, 2004-2005. Zambia, 1980-81, 84, 98, 2000, 2005, 2008. Zimbabwe, 1982, 99, 2002.