An Alternative Approach to the Analysis of the U.S. Per Capita Income Convergence†

Ming Chien Lo*
Department of Economics, St. Cloud State University

Mark D. Partridge**
Department of Agricultural Economics, University of Saskatchewan

July 27, 2004

Abstract: This paper examines the U.S. per capita income convergence in 1929-2002 using a panel approach based on the assumptions of multiple aggregate structural breaks and growth clubs. One novelty is that our specification explicitly allows for regional conditional convergence to the nation and regional-growth clubs in which states conditionally converge to their regional average. In general, the results support those who argue the entire cross-section of growth dynamics should be examined. In particular, the estimates of convergence speed from previous studies are strongly affected by a post-1982 divergence and a club-growth pattern, which are ignored under simpler econometric specifications.

JEL Code: O47, O18, R11, R12
Keywords: Convergence; Growth Clubs; Panel Time Series Models; Structural Changes

† Previous versions of this paper were presented at the 68th Annual Midwest Economics Association Meetings in Chicago, Illinois and the 79th Annual Western Economics Association International Meetings in Vancouver, BC. We thank James Morley and all session participants for their valuable comments. We also thank Gerry Carlino for his very useful suggestions in framing the question. Ming Chien Lo thanks Eden Yu and the Department of Economics and Finance at the City University of Hong Kong for allowing him to use their facilities to finish part of the paper.

*Assistant Professor, Department of Economics, SH386, St. Cloud State University, 720 Fourth Avenue South, St. Cloud, MN 56301-4498. Phone: (320) 308-0143. Fax: (320) 308-2228. Email: mclo@stcloudstate.edu.

** Canada Research Chair in the New Rural Economy and Professor, Department of Agricultural Economics, University of Saskatchewan, 51 Campus Drive, Saskatoon, SK S7N 5A8, Canada. Phone: (306) 966-4037. Fax: (306) 966-8413. Email: mark.partridge@usask.ca.

1. Introduction

The related questions of whether poor economies eventually catch rich economies and how long this might take have been among the most debated topics in the growth literature for the last two decades. The answers are obviously of great importance to policymakers interested in the plight of poor countries and regions when assessing the need for intervention. The answers also relate to the validity of neoclassical and new-growth models.

While not universal, a consensus emerged from the first wave of convergence studies that countries were conditionally converging after adjusting for factors that affect the steady-state (i.e., β-convergence) (e.g., Mankiw et al., 1992).[1] The general pattern among countries was that β convergence was occurring at about a 2 percent rate per year. For regions *within* countries such as U.S. states, there was an even stronger pattern that economies were converging absolutely at about a 2 percent annual rate to the same steady-state (Barro and Sala-i-Martin, 1991, 1992; Sala-i-Martin, 1996). One favorable implication of absolute convergence is that at least for regions, regional inequalities eventually disappear. However, a 2 percent convergence rate is quite slow in that it would take about 35 years for the poorest economy to catch the economic leader, suggesting policy intervention may be warranted to accelerate the process.

In the second wave of research, the generality of a 2 percent convergence rate was challenged. For example, using data dating back hundreds of years, Pritchett (1997) and Bourguignon and Morrisson (2002) found wide-scale divergence across countries. Such divergence suggests that world incomes are represented by a bi-polar distribution, or by convergence clubs (e.g., Quah, 1993; Durlauf and Johnson, 1995). With growth clubs, the notion of convergence can be misleading because individual members can converge to the club equilibrium, but the clubs themselves may be diverging from one another. There are many possible explanations for the potential emergence of clubs including thresholds in human- and physical-capital (Azariadis and Drazen, 1990), different levels of financial development (Berthelemy and Varoudakis, 1996), and Schumpeterian models of R&D (Howitt and Mayer-Foulkes, 2002).

Growth clubs relate to the whole issue of heterogeneity among regions or countries. Durlauf (2001) and Phillips and Sul (2003) argue that improperly accounting for sample heterogeneity is one of the largest challenges currently facing empirical-growth studies. In illustrating its importance, Lee et al. (1997) found cross-country convergence-rates equaled 4 percent when not accounting for heterogeneity,

[1] Barro and Sala-i-Martin (1991, 1992) and Galor (1996) provide various formal definitions of convergence.

but 30 percent after accounting for heterogeneity (also see Andrés et al., 2004).

Even for a supposed homogeneous group such as U.S. states, there can be unexpected behavior. For one, when considering the standard deviation of per-capita income (σ-convergence), there is evidence that long-running convergence patterns began subsiding in the 1970s (Bernat, 2001). Possible divergence among a relatively homogeneous group such as states raises the notion that there may have been major structural changes. Alternatively, states and broader regions in the U.S. may even represent growth clubs with their own unique dynamics. For instance, regions are composed of states with comparable natural-resource bases, industry mixes, and geographic proximity to oceans and lakes, all of which can produce independent growth trends. A regional-club process would be further reinforced if information spillovers are sometimes localized and labor mobility was constrained by commuting patterns and a reluctance to migrate long distances. Indeed, if relatively-homogeneous U.S. regions did represent clubs, this would be quite suggestive that the club-process is more pervasive than many economists had realized.

While the issue of clubs and heterogeneity is receiving increasing attention, the role of structural change has received much less attention. This omission applies despite the general agreement among economists that structural change is a likely outcome of events such as wars and major technological change. An exception is Carlino and Mills (hereafter, CM) (1993, 1996a, 1996b). CM find scant evidence in support of convergence among eight major regions of the U.S. over the entire 1929-1990 period until they accounted for structural change that they assumed took place in 1946. Yet, the scope of CM's studies did not go beyond the issue of whether structural change affected the general pervasiveness of regional convergence, and more work into structural change's overall effect on growth dynamics is needed.

Even more understudied is the possibility of multiple structural breaks. Besides the turbulent WW II period, the aforementioned rise in cross-regional variation in per-capita income since the 1970s could signal another structural break. There is mounting evidence the structure of the U.S. national economy shifted in the first-half of the 1980s (Kim et al. 2001; Stock and Watson, 2002). With a sea change in the aggregate economy, it seems plausible to expect that regional economies were also profoundly affected. Thus, the possibility of multiple structural breaks is worth exploring given its scant treatment in the past.

A related issue is the possibility of regional spillovers, whether it is among neighboring countries or among regions within a country (Durlauf and Quah, 1999). For instance, growth innovations in one economy could spillover and affect nearby economies. While the vast majority of growth studies have ignored such spatial dependencies, a few studies have found they can affect regional-growth processes.[2]

In sum, growth econometric studies at the international and regional levels are currently grappling with heterogeneity and the prevalence of growth clubs; structural breaks; and regional spillovers. Yet, most studies have either entirely ignored these complications or have only tackled these issues one at a time. To varying extents, such omissions could produce misleading or incomplete pictures of the growth process. Therefore, this study extends the previous literature by *simultaneously* considering whether U.S. state and region growth dynamics are influenced by these factors. Indeed, examining U.S. states is particularly worthwhile because if these factors are significant at the state level, they are likely to be even more pronounced across countries, which would have broad implications across a range of studies. One novelty is we jointly model the growth process as regions converging/diverging to the national average, while states within each region are allowed to converge/diverge to the regional average—i.e., regional growth clubs. To be specific, we use CM's model as a foundation and extend their single-equation analysis into a panel estimation based on the assumption of growth clubs.

To preview the findings, the results suggest significant gains to our approach in which we find that the growth process is considerably richer than what would be ascertained using prior techniques. In particular, the estimates of convergence speed across U.S. states found in previous studies are strongly affected by growth-clubs and a post-1982 divergence, which are ignored under simpler specifications.

2. The Growth and Convergence Process

The standard neoclassical growth approach implies that poor countries catch up to rich countries through a convergence process that follows from diminishing returns to capital and imperfect capital mobility.[3] Poor countries with lower capital-labor ratios have higher capital returns that in turn attract new capital, allowing them to grow faster than the leaders. Yet, there are other reasons for laggards to converge including technological spillovers (Bernard and Jones, 1996) and standard trade effects from factor-price equalization and changing terms of trade (Slaughter, 1997; Acemoglu and Ventura, 2002).

Following various neoclassical approaches, Barro and Sala-i-Martin (1991, 1992) and Mankiw et al.

[2]For instance, Rey and Montouri (1999) found that there were cross-state spatial dependencies when considering state growth rates, while López-Bazo et al. (2004) found similar dependencies when considering regions in the EU. Likewise, using a seemingly unrelated regression (SUR) approach, Andrés et al. (2004) found spatial dependencies when considering OECD countries.

[3]This discussion draws heavily from Barro and Sala-i-Martin (1991, 1992) and Sala-i-Martin (2002).

(1992) derive the following growth relationship for country i that can easily be estimated:

(1) $$\Delta \ln y_{it,t+T} = \beta_0 - \beta \ln y_{it} + \beta \ln y_i^* + e_{it}$$

where $\Delta \ln y_{it,t+T}$ is the growth rate of per-capita income between periods *t* and *t+T*, y_{it} is per-capita income in period *t*, y_i^* denotes the steady-state level of per-capita income, and e_{it} is the error term. β reflects the rate of convergence to the steady state y_i^*, which is negatively related to the capital share (in a Cobb-Douglas formulation), and positively related to the depreciation and population-growth rates.

Empirically implementing (1) requires some assumptions. If the steady state y_i^* is constant across all economies, then a simple pooled model can be estimated with a constant reflecting $\beta_0 + \beta \ln y_i^*$ and the initial income level y_{it} as an explanatory variable.[4] The regression coefficient on the initial-income term (β) provides an estimate of the speed of *absolute* convergence. However, assuming all economies are approaching a common equilibrium is rather strong when examining a heterogeneous group of economies (e.g., a diverse group of countries). Yet, Sala-i-Martin (1996, 2002) contends absolute convergence is an appropriate assumption when applied to regional samples because he argues the initial-income level is uncorrelated with the steady-state income level. Nevertheless, Evans and Karras (1996) contend that even this assumption is strong by showing that there are steady-state income differentials across major U.S. regions, affecting convergence rates (see also Evans, 1997).

Conditional β convergence refers to when economies have similar convergence-rate dynamics, but the steady-state income levels differ due to different initial conditions.[5] In equation (1), this implies $\beta_0 + \beta \ln y_i^*$ varies across economies, which is accounted for by including additional control variables that affect the steady state including country/region fixed effects and industry composition. (See Durlauf

[4]In the literature, variants of equation (1) have been estimated by a variety of approaches including non-linear least squares, cross-sectional techniques, pooled-OLS, panel techniques, and GMM, each with their advantages and disadvantages. To be sure, there are well-known problems with the interpretation of the results from equation (1) (Quah, 1993; Bernard and Durlauf, 1996). In particular, a negative estimate for β may not imply a declining variation in income levels across economies over time (i.e., σ convergence). Instead, it may be consistent with a wide range of behaviors including growth clubs. Hence, despite this approach's widespread use, proper caution should be exercised in interpretation (e.g., see the discussion by Durlauf and Johnson, 1995 and Bernard and Jones, 1996). Similarly, a negative and significant β does not necessarily support neoclassical models, as it is also consistent with more sophisticated endogenous growth models (Sala-i-Martin, 2002).

[5]Another commonly used form of convergence is stochastic convergence (Bernard and Durlauf, 1996). Stochastic convergence between economies i and j in period t occurs when the expected difference between the two economies equals zero as t approaches infinity. Stochastic convergence is a relatively strong concept that is typically tested by examining whether the dynamics of individual economies have a unit root in which shocks have permanent effects (Carlino and Mills, 1996b). Bernard and Durlauf (1996) suggest that cross-section tests such as absolute, β, and σ convergence are more appropriate for examining long-run dynamics when economies are further from their long-run growth paths, while time-series or stochastic-convergence approaches are more appropriate when considering economies close to their equilibrium. Given the lengthy time-span and far-ranging dynamics under consideration in this study, we utilize the more commonly used cross-section approaches.

and Quah 1999 for examples of the conditioning variables that have been used). Therefore, it is important for a model, like the one presented in the next section, to allow for β convergence by allowing for different state fixed effects and regional characteristics.

Aside from concerns expressed above, β convergence is a somewhat vague concept because part of the evolutionary growth process includes convergence of industry composition and of other factors such as human capital (e.g., Barro and Sala-i-Martin 1991). In fact, Caselli and Coleman (2001) contend that a majority of the convergence among U.S. regions since the late 1800s is simple convergence of the farm and nonfarm industry shares and the convergence of relative productivity levels within these two sectors (i.e., not convergence of regional productivity levels to the national average). Hence, when factors such as industry mix are not explicitly controlled for, the resulting convergence-rate estimates should be interpreted as including these other indirect convergence effects.

When there are growth clubs and/or significant heterogeneity, assuming β or absolute convergence is inadequate. For example, Carvalho and Harvey (2003) find that even among what would appear to be a relatively homogenous group of EU countries (at least compared to heterogeneity across the globe); there are two growth clubs of "rich" and "poor" countries. They show that pooling rich- and low-income EU countries obfuscates the underlying dynamics. For one, rich EU countries have similar dynamics as U.S. regions, which is concealed when pooling all EU countries. Similarly, when examining more disaggregated EU regions, Canova (2004) finds that there are four different EU growth clubs. Together, these studies support Quah's (1993) contention that the entire cross section of economies must be examined to accurately capture the underlying growth dynamics.

Even at the U.S. state and region level, there are many possible reasons for states within major regions to form growth clubs that are not simply conditionally converging to the national growth path.[6] One example is that states within a region usually have similar industry mixes and are thus exposed to common industry shocks. Economic spillovers among states in a region would reinforce this coalescence process. Neighboring states typically share a common history including events such as slavery, similar

[6]The eight regions used here are defined by the U.S. Bureau of Economic Analysis (BEA). States in these regions are contiguous and tend to have stronger historical and economic links, and not surprisingly given their geographical proximity, they have similar industry mix, natural-resources, natural amenities, and access to oceans and lakes. Neighborhood externalities could also form the basis of regional club formation (Canova, 2004). Along with major BEA regions, Phillips and Sul (2003) develop more complex algorithms to identify other regional groupings (also see Canova, 2004), but we prefer regions as their contingency better allows for economic spillovers.

natural resource bases/amenities, a mutual initial-settlement period, and comparable government policies that affect "business climate." These commonalities should produce similar migration patterns, leading to comparable human-capital stocks (e.g., see Blanchard and Katz 1992 for an analysis of the persistence of state migration patterns over decades as well as other common regional migration patterns).

There are also reasons to expect that regional convergence/divergence patterns change over time. For instance, Lee et al. (1997) present a model that shows that even among relatively homogeneous economies such as OECD countries or U.S. regions, the eventual dynamics will be such that these economies will almost assuredly begin to diverge if there are technological shocks. Likewise, Howitt and Mayer-Foulkes (2002) (hereafter, HMF) develop a Schumpeterian model that includes three regional groups. First are technologically-leading countries/regions with a high R&D and intellectual capacity. In our case, possible examples could include growth centers such as Silicon Valley, the Puget Sound area around Seattle, and the financial-markets on the East Coast centered near New York.[7] Their second group includes economies that eventually implement or follow the technological leader. A key distinction is the second group has the human capital, institutions, and the absorptive capacity to eventually implement best-practice technology. Examples may include areas in the manufacturing belt of the Midwest. Finally, there are laggard regions without the human-capital to implement the latest developments. These laggards permanently have lower per-capita income and may even have extended periods of lower growth. Possible examples may include areas in the lower South and upper Plains, and less-densely populated rural areas with less human capital.

One of HMF's innovations is to show how a group of regions that have been behaving as if they conditionally converged—i.e., growing at the same rate although they have different income levels—can suddenly experience technological shocks that temporarily give the leading regions an edge in terms of faster growth. The follower region eventually catches up in terms of the growth rate (but not the income level). But the laggard can persistently fall behind because of insufficient absorptive capacity.[8] Growth rates between the three groups may eventually converge, but the follower and especially the laggard find

[7]Using patent citation data, there is growing evidence that regional knowledge spillovers are quite localized in which any externalities or spillovers are spatially limited (Jaffe et al. 1993; Bottazzi, and Peri, 2002; Peri, 2002; AlAzzawi, 2004). While these local effects may decay over time, they are consistent with the notion that certain regions are technology leaders. See Johnson and Takeyama (2001) for more evidence of U.S. regional heterogeneity.

[8]HFM note that laggard regions can benefit from copying and imitating best-practice technology. Yet, if there is an insufficient critical mass of human capital, they will not efficiently absorb this know-how. See Aghion et al. (2004) for an extension of this approach to financial development differences between leading and lagging regions.

themselves further behind the leader than before the shock. Clearly, WW II could be the kind of event that would drastically alter regional dynamics, while macroeconomic changes in the early 1980s or the onset of the "New Economy" technological boom in the mid 1990s are other possibilities.

3. Empirical Implementation

Our empirical implementation begins with CM (1993, 1996a, 1996b). In terms of major U.S. regions, CM assume there are persistent regional-income differentials due to compensating differentials related to factors such as amenities, industry composition, different human- and public-capital stocks, and government policies. For region *i* in period *t*, their approach can be depicted as:

(2) $$RI_{it} = NI_t + CD_{it} + v_{it} = RI_t^* + \varepsilon_{it} \,,$$

where CD_i is region *i*'s steady-state compensating differential, *NI* is national average income, RI^* is the steady-level of income for region *i*, and ε_{it} is an error term that reflects regional deviations from the steady state. Deviations from the steady-state can be rather large if the initial conditions are far from the steady state, to small if they merely reflect transitory shocks.

Using equation (2), CM (1993) investigated whether relative regional incomes--the log difference between the eight BEA regional incomes per capita and the national income per capita--have a unit root. Rejection of the hypothesis implies that regions may be diverging from the national average. CM succeeded in rejecting the unit-root null only when they imposed a structural break of 1946, but this was only for three regions. Yet with other evidence, CM (1993, 1996a, 1996b) argued that after allowing for the 1946 structural break, regions were conditionally converging to their steady-state differential CD_{it} and that individual states had achieved their steady-state equilibrium by 1946.

CM's primary regression approach was an augmented Dickey-Fuller (ADF) type with one-lagged first difference on the right hand side. If we measure the variables in levels and assume one structural break, their regression can be written as:

(3) $$x_{rt} = \sum_{k=1}^{2} (\alpha_{ri} + \beta_{rk} t) D_{kt} + \delta_{r1} x_{r,t-1} + \delta_{r2} x_{r,t-2} + v_{rt}$$

for *r* = Far West, Great Lakes, Mid East, New England, Plains, Rocky Mountains, South East and South West, $D_{1t} = 1$ in period 1 (for years 1929-45 in CM's case) and $D_{1t} = 0$ otherwise, $D_{2t} = 1$ for period two (after 1946 in CM's case) and $D_{2t} = 0$ otherwise, *t* is the deterministic time trend, and x_{rt} represents the difference of per-capita income in region r from the national average.

Equation (3) can be generalized by allowing additional structural breaks

(4) $$\delta_r(L)x_{rt} = \sum_{k=1}^{l+1}(\alpha_{rk} + \beta_{rk}t)D_{kt} + v_{rt},$$

where *l* denotes the number of breaks. This approach uses region as unit of observation and estimates each region individually; we will refer to this as the "equation-by-equation" approach. If we instead allow for the possibility that individual states within each region can be represented as a club, we can write:

(5) $$\gamma_i(L)x_{it} = \sum_{k=1}^{l+1}(\alpha_{ik} + \beta_{ik}t)D_{kt} + \varepsilon_{it},$$

where x_{it} denotes the logarithmic difference between state and regional per-capita income. Following CM, we assume there is a trend component in x_{it} that shares the same break dates of the region. A common break across the country differs from Lowey and Papell (1996) and Strazicich and Lee (2002), who allowed the break date to differ by region.[9]

By summing (4) and (5) for every state *i* in the same region *r,* the following can be derived:

(6) $$y_{it} = TB_i + TB_r + \sum_{j=1}^{J}\gamma_{ij}x_{i,t-j} + \sum_{h=1}^{H}\delta_{rh}x_{r,t-h} + \varepsilon_{it} + v_{rt}$$

for $i = 1,\ldots,N$ where $y_{it} \equiv x_{it} + x_{rt}$, the logarithmic difference between the state and national per-capita income, $TB_i \equiv \sum_{k=1}^{l+1}(\alpha_{ik} + \beta_{ik}t)D_{kt}$, $TB_r \equiv \sum_{k=1}^{l+1}(\alpha_r + \beta_r t)D_{kt}$. Thus, not only does this approach allow for multiple structural breaks, it also allows for significant heterogeneity by allowing separate state *and* regional trends, fixed effects, and convergence coefficients (i.e., γ_{ij} and δ_{rh}). While equation (6) is more general by allowing for factors such as multiple structural breaks, it is consistent with Canova's (2004) approach of allowing for heterogeneous coefficients both within and between regions. Finally, note that

[9]Unlike CM, Lowey and Papell (1996) and Strazicich and Lee (2002) explicitly tested for a break by region, but they did not explicitly test for a common break point. Lowey and Papell found the regional breaks fell between 1942-1945 and Strazicich and Lee found the breaks ranged from 1941-1947. Both are notably close to CM's 1946 break. To be sure, given the close integration and high development of the U.S. economy by 1945, a common structural break across all regions seems plausible. Since structural change in monetary and fiscal policy, adjustments in industry mix, and the wholesale reorganization related to WW II would be common across the nation, any ensuing regional structural changes would likely coincide with the nation (which is consistent with the narrow spread in regional structural breaks in the latter two studies despite different methods). Another practical advantage of assuming a common structural change is that pooling the regions increases the efficiency of the break estimate.

the pairs TB_i and TB_r, and ε_{it} and v_{rt} cannot be estimated simultaneously. In practice, we estimate the system pooled across all states and regions:

(7) $$y_{it} = TB_{ir} + \sum_{j=1}^{J} \gamma_{ij} x_{i,t-j} + \sum_{h=1}^{h} \delta_h x_{r,t-h} + \eta_{irt}$$

for $i = 1, \ldots, N$ where $TB_{ir} \equiv \sum_{k=1}^{l+1} (\alpha_{ik} + \beta_{ik} t + \alpha_r + \beta_r t) D_{kt}$ and $\eta_{irt} \equiv \varepsilon_{it} + v_{rt}$.

To identify TB_i, it is possible to run the pooled regression for (7) and for a restricted model:

(8) $$y_{it} = TB_r + \sum_{j=1}^{J} \gamma_{ij} x_{i,t-j} + \sum_{h=1}^{h} \delta_h x_{r,t-h} + \eta_{irt},$$

in which it is assumed that $\alpha_{ik} = \beta_{ik} = 0$ for all *i*. Then one would compute the estimates of α_{ik} and β_{ik} by taking the difference between TB_{ir} and TB_r. An alternative to using equation (8) to identify TB_r is to use the equation-by-equation approach shown in (4). While there are efficiency gains from pooling as in equation (8), the equation-by-equation approach ensures a weighted average of the regional estimates for TB_r. In practice, with one exception, both methods yield similar results.

While most convergence studies assume that there are no spatial spillovers between regions, besides the cross-equation restriction on the set of coefficients α_r, β_r and δ_{rh}, this model allows for non-zero cross-equation correlation in the residuals. Because each region tends to be composed of similar economies with close linkages, to keep the model manageable, we assume a state's economic shocks affect its neighbors within the region, but they do not affect states in other regions. Thus, with ε_{it} being a state-specific shock and v_{rt} a region-specific shock, then $\lim_{t\to\infty} \text{cov}(\varepsilon_{it}, \varepsilon_{jt}) = 0 \; \forall i \neq j$ and $\lim_{t\to\infty} \text{cov}(\varepsilon_{it}, v_{rt}) = 0 \; \forall i$. Hence, if $\lim_{t\to\infty} \text{var}(\varepsilon_{it}) = \sigma_i^2$ and $\lim_{t\to\infty} \text{var}(v_{rt}) = \sigma_v^2$, then the correlation between η_{irt} and η_{jrt} $\forall i \neq j$ is equal to:

$$\frac{\sigma_v^2}{\sqrt{\sigma_v^2 + \sigma_i^2}\sqrt{\sigma_v^2 + \sigma_j^2}},$$

which is strictly positive. Such a system requires a feasible generalized least-square (FGLS) method that incorporates cross-equation correlation to estimate the parameters. However, in finite samples or when shocks extend outside of a region, it is possible that $\text{cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0 \; \forall i \neq j$ and $\text{cov}(\varepsilon_{it}, v_{rt}) \neq 0 \; \forall i$. Then the correlation becomes:

$$\frac{\sigma_v^2 + \sigma_{ij} + \sigma_{iv} + \sigma_{jv}}{\sqrt{\sigma_v^2 + \sigma_i^2}\sqrt{\sigma_v^2 + \sigma_j^2}}.$$

This coefficient can take a negative value if $\sigma_v^2 < -(\sigma_{ij} + \sigma_{iv} + \sigma_{jv})$.

4. Empirical Results

4.1 Data

Our sample is 1929-2002 per-capita personal income from the U.S. Bureau of Economic Analysis (BEA) website using the lower 48 states. The District of Columbia is also included and is simply treated as a state. Alaska and Hawaii are omitted due to lack of data prior to 1950 and their unique economic conditions. With a couple of exceptions, we pool the relative income data series of all eight BEA regions into one regression system to increase efficiency in estimating coefficients and structural breaks.

4.2 Trends in Between and Within Region Convergence.

We first examine trends in per-capita income variation across states, which is akin to σ-convergence. Panels A and B of Figure 1 respectively report the variance decomposition of the log of per-capita income for 1929-2002 and 1965-2002 across the 49 "states." Panel A shows that while the total variation in log income is considerably smaller at the end of the sample, the vast majority of the decline occurred before the end of WWII. On a basis akin to this decomposition, this dramatic decline over the entire period was offered by Phillips and Sul (2003) as key evidence that regional incomes were converging. Consistent with CM's claim that regions achieved their conditional equilibrium by 1946, most of this convergence was through a decline in the variation between regions, with a much more modest within-region decline.

Compared to dramatic declines in the variation of regional incomes during the Great Depression and WWII, the decline was much more gradual afterwards. Because the scaling in Panel A hides key trends in the last 35 years of the sample, Panel B reproduces the trends since the mid 1960s. Panel B now reveals the increase in income variation across states that began in 1978 and it shows that the increase has been pro-cyclical, peaking with the business cycle in 1989 and 2000. Even with the declining variation as the economy slowed in 2001-2002, regional variation was over 40% greater in 2002 than in 1978. This trend then marks an almost quarter-century reversal of the historic U.S. trend towards convergence.

Another reversal in the last 30 years is the increased role of within-region variation. Panels A and B show that until the early 1970s, most of the convergence across states occurred between regions, with a more modest decline in within-region variation. To more clearly show their roles, Figure 2 reports the share of overall variation in state per-capita income accounted for by between- and within-region variation. Until the late 1960s, the within-region share was generally stable in the 30% range. This stability is consistent with individual regions representing convergence clubs (e.g., see Mayer-Foulkes, 2002 for related discussion). Yet, the within region share began to steadily increase, reaching the 60 percent range by the late 1990s. In regards to the growth in overall-variation since 1978, within-region variation almost doubled its level by 2002, while between-region variation was little changed. Hence, there appears to have been a structural shift in regional dynamics that began sometime around 1980.

4.3 Structural Changes in Relative-Income Growth

The above within- and between-region results suggest a structural change near the end of WW II as hypothesized by CM, Lowey and Papell (1996), and Strazicich and Lee (2002). Yet, unlike their findings, there is evidence of another structural change somewhere around 1980, which nearly coincides with the aggregate structural shifts recently identified by the macroeconomic literature.

Before formally testing for structural change, the issue of how to model the long-run trend in relative state/national and regional/national per-capita income must be resolved. Econometricians have long debated the trend that best fits the log of U.S. GDP. A linear trend is simple but incapable of extracting the permanent components in the data. One school of thought, based on Nelson and Plosser (1982), argues that the trend is a stochastic process. This conclusion is appealing because various theories have suggested that productivity shocks are the cause of long run economic growth and these shocks tend to have persistent effects. The other school of thought, based on Perron (1989), offers an alternative: the permanent component in the U.S. GDP can be extracted simply by imposing a deterministic trend with a structural break in 1946. This assumption is used by CM. We follow a similar strategy in detrending the data, but we update CM's analysis by using the Bai and Perron (2003) procedure to search for the structural breaks. Because the sample has also been extended 12 years to 2002, there should be more data to identify whether there was a structural break around 1980 as suggested above.

Our procedure sequentially searches for break points using the generalized model from equation (4).

Rather than estimating the structural-change model for the 8 BEA regions, we could instead determine the structural breaks using the club-model shown in equation (7) using all 49 states. However, such an approach would not allow comparison to CM's benchmark results and would be technically more complex. Yet, assuming common-breaks in all eight regions does not strike us as very constraining because if regions undergo a structural change, then their member states should as well.

Given the assumption of *l* structural changes, there are *l*+1 segments of different dynamics in the data to be captured by α_{rk} and β_{rk}. We do not set any cross-equation restrictions across the regions except that we assume any structural change simultaneously affects all regions. Finally, the cross-region covariances of the error terms are assumed to be zero.

We begin with the assumption of *l*=1 and find the first optimal break point by minimizing the log of the determinant of the residual variance-covariance matrix: $\ln[\det(\hat{\Omega})]$. Practically, there are 72 observations when the order of autoregression is equal to 2. We set the minimal number of observations for any segment to 10% of this sample, which equals 7. Once the first optimal point is found, we take this structural change as given, and proceed to find the second break point using the same criteria. This procedure is repeated until we find four potential breaks.

Panels (a)-(d) in Figure 3 illustrate the significance level graphically and Table 1 reports the likelihood statistics. The point estimate of the first break is 1944, which is only two years from what was imposed by CM. In addition, there is a statistically-significant second break point in 1982. On one hand, this is a few years after the 1970s oil shocks and the subsequent increase in the variation in state-level per-capita income. On the other hand, a 1982 break point is consistent with the pattern identified above for increasing within-region income variation. This break point also coincides with the period identified by many recent macroeconomic studies for an aggregate structural break in various real, monetary, and financial indicators (e.g., Stock and Watson, 2002). Hence, the global changes taking place in the macroeconomy may have also altered *intra-national* growth dynamics. By contrast, the third and fourth break points are both insignificant. As a result, we will impose 1944 and 1982 break points in our model.

4.4 Econometric Restrictions in the Past Literature.

Table 2 presents various models that allow us to compare our results to the past literature and to illustrate how the various restrictions that have been imposed affect the econometric estimates.

Essentially, the models reported in Tables 2-4 begin with the most restrictive forms used in the past, eventually relaxing restrictions until the more general forms shown in equation (7) are estimated. However, all of the models reported in Table 2 restrict the regional convergence rate to the nation (approximately $1-\delta$) to be the same across all states/regions so as to be more comparable to the vast majority of the literature. While this greatly simplifies the presentation, this restriction does slightly reduce heterogeneity and may decrease the estimated speed of convergence (Lee, et al. 1997) (although in practice, this restriction had very little impact on average).

Some basic-pooled AR(1) regression models of regional and state relative income are respectively reported in Panels A and B of Table 2. The restricted-autoregressive coefficients (i.e., δ) are reported first with the negative of the approximate convergence rates shown in parentheses (i.e., $1-\delta$).[10] Panel A is the form estimated by CM (1993, 1996b) and others, which follows equations (3)-(4). It is more restrictive because it only considers regions, essentially assuming states within a region all possess the same dynamics. Panel B follows from generally more restricted versions of equation (7) by estimating the model for all 49 states. Panel B's results allow for more heterogeneity because it places less restrictions on the states within a given region. Differing results in Panels A and B then reflect whether examining states versus regions affect the estimated rates of convergence to *nation*. We are asking whether numerous studies have missed key details by only examining regions rather than states. Note these results do not assess the role of *within-region* heterogeneity and regional clubs, which are evaluated below. In other words, the state-to-nation convergence process is assumed to be linear in Panel B as in previous studies.

Before describing the specific results, one general finding is Panel B's results indicate faster convergence rates than in Panel A. The consistency with expectations is reassuring given the greater heterogeneity using the state models, although the difference in results between the two panels is generally not too consequential. Turning to the specific results, Row 1 of Panels A and B report the most restricted model's results with no state or regional fixed effects, no trend variables, and not allowing for structural breaks. In both cases, the results suggest a convergence rate of about 3 percent, which is quite consistent with Sala-i-Martin's (1996) "mnemonic" 2 percent rule for regions.

Row 2's model allows for more heterogeneity by adding region or state fixed effects, but no trend

[10] The approximate convergence rate is $100*(1-\delta_h)$ in which allowances need to be made for our autoregressive specification. See Barro and Sala-i-Martin (1991) and Dobson et al. (2003) for more details.

variables or structural change.[11] As expected, the increased heterogeneity increases convergence rates, which approximately double in both cases. The Wald test reported in the table shows that the null hypothesis that the state fixed effects are all equal to zero can easily be rejected at the 1% level, but this is not the case for the region fixed effects in Panel A. Row 3 introduces a common trend that allows for structural breaks in 1944 and 1982. In both panels, the convergence rates are approximately triple those reported in Rows 2. Likewise, the null hypothesis regarding the joint significance of the structural breaks and (period-specific) fixed effects can easily be rejected in both cases. At least in the regional model in Panel A, allowing for structural breaks clearly alters the interpretation from Row 2, in which the Wald test suggested that fixed regional-compensating differentials in income level were inconsequential.

Row 4 introduces region- or state-specific trends that allow for the two structural breaks. Convergence rates now more than double those in Row 3, illustrating a clear gain to our less-restrictive model.[12] This sea-change shows that allowing only for fixed effects has a modest effect, but allowing for structural change and different region/state trends radically alters the interpretation. Given the past literature has stressed the role of fixed effects or differential convergence rates, this finding regarding heterogeneous trends has clear implications for future research. Specifically, state growth processes are not just differentiated by a simple fixed (level) effect or a speed of adjustment term, but even more consequentially, they experience *multiple* structural breaks and their *trend* growth rates also differ. In fact, the importance of differential trends suggests that simple conditional convergence is quite inadequate in explaining U.S. state growth dynamics, which would likely be even more the case across countries.

Rather than the traditional 2 percent rate, convergence rates of 40 or 50 percent in row 4 are suggestive that states and regions are much closer to their long-run equilibrium growth path than believed in the prior literature. Illustrating how the interpretation of the growth process would change, rather than neoclassical convergence factors related to diminishing marginal returns, short-term deviations from the

[11]One concern with convergence estimates in general is they are affected by a dynamic panel-model bias because the estimating equation has a lagged dependent variable as an explanatory variable (Forbes, 2000). This creates a well-known negative bias in fixed-effect equations that in effect increases the speed of convergence. The bias is very problematic in cases with only a handful observations per unit (i.e., the bias is on order of 1/T where T is the number of observations per unit, Greene, 1997). Yet, because there are over 70 observations per region/state, this bias should be relatively inconsequential in our case.

[12]Dobson et al.'s (2003) meta analysis finds that one of the only factors that systematically affect regional convergence rates in the literature is the length of the sample period, which is negatively related to reported convergence rates. These results suggest that not accounting for heterogeneous trends and structural change could be a key reason for this discrepancy because these factors likely become more problematic in longer samples.

long-term growth path likely result from cyclical/structural shocks or shocks to a region's terms-of-trade.

4.5 Efficiency and Coefficient Estimates Using FGLS

One possible concern with the models in Table 2 is there could be heterogeneity in the cross-regional rates of convergence to the nation as well as cross-sectional correlation of the state residuals. To assess the possible influence of these factors, Tables 3 and 4 report estimates based on equations (4) and (7) using states as the unit of observation. A key difference between the results reported in Table 2 and those in Table 3 is the regional convergence rate to the nation $1-\delta$ is allowed to vary across the eight regions. Model 1 in Table 3 contains the results when estimating the models "equation-by-equation" one region at a time as done by CM and others (equation 4). The columns headed by Model 2 contain the results of pooling all of the states and regions into one model and utilizing FGLS by correcting for any within-region correlation of the residuals (equation 7). The results for δ_h with $J = K = 1$ are reported in Table 3. The bolded numbers in Table 3 represent the approximate convergence rate derived by taking one minus the autoregressive coefficient ($1-\delta_h$). Table 4 reports the corresponding estimates of the state-specific autoregressive terms. Again, the state rate of convergence to the regional average is approximately equal to one minus the reported coefficient (i.e., $1-\gamma_{ij}$).

In Model 1, the average coefficient on the lagged regional income term is about 0.563, which closely corresponds to the 0.5707 value reported in row 4 of Panel A in Table 2. Hence, pooling the regions as done in Table 2 does not appear to produce a misleading estimate of the *average* convergence rate. Yet, the average conceals a wide disparity across regions in which the convergence rates range from about 27.5% in the Southwest to about 69% in the Plains. Again, such a pattern clearly illustrates how in what appears to be very homogeneous groups of American states, there can still exist great disparities in convergence and growth dynamics. This diversity affirms Durlauf's (2001) point about the need to place more weight on heterogeneity in empirical modeling.

Compared to Model 1, the FGLS estimates in Model 2 imply a higher level of persistence in 5 out of the 8 regions. However, the average coefficient on the lagged income term is roughly the same (0.588 in Model 2 versus 0.563 in Model 1) and the only cases that the autoregressive coefficients changed by more than the 0.10 in magnitude are the Plains and Rocky Mountain regions. In addition, the estimates in the two models for all regions except the Plains are not significantly different (see Figure 4). The most notable contribution of the FGLS model is the efficiency improvement. With the exception of the Far West, the estimated standard error shrinks about 10% or more. In particular, the estimates for the Great Lakes, Mid East, New England, Plains, Southeast and Southwest regions all enjoy a significant efficiency improvement. Figure 4 offers a graphical illustration of this gain.

Further analysis also supported using FGLS. First, the LR test implies the estimated covariances across states are significantly different than zero.[13] Likewise, as expected, most of the covariances are positive, although there are a few anomalies that are expected when using a finite sample (the regional variance-convariance matrices are available on request). In sum, using FGLS greatly improves the precision of the results even if it does not dramatically alter any findings.

4.6 Individual State Convergence to the Regional Trend

Corresponding to the region estimates reported for Model 2 in Table 3, Table 4 shows the individual-state FGLS coefficients regarding *intra-region* convergence to the regional average. The results support the notion of individual-region growth clubs with their own dynamics. The joint null hypothesis that the 49 individual state coefficients (γ_{ij}) are equal to each other can be rejected at the 0.0001% level, while the reported Wald tests also suggest the state coefficients generally differ in each region. Thus, the results indicate that convergence cannot simply be described as individual regions conditionally converging to their equilibrium growth path. Indeed, within most regions, there are very diverse growth dynamics.

Many of the state coefficients are quite large in magnitude, suggesting more sluggish convergence to the regional average. For example, the average state coefficient in the Far West, Mideast, Southwest, and New England is all over 0.50. Yet, even within these regions there can be considerable heterogeneity, e.g., Nevada in the Far West. Conversely, there appears to be very rapid convergence in the Plains states with the average autoregressive coefficient equaling 0.29. Yet, the Southeast region really stands out. For instance, Georgia and Mississippi have statistically significant *negative* coefficients, which is consistent with those states diverging from the regional trend. Indeed, the overall average in the Southeast is -0.04, suggesting that the typical Southeast state is not converging to the overall regional trend. Thus unlike

---

[13]The LR statistic is computed from $T\left(\sum_{i=1}^{n}\ln\hat{\sigma}_i^2 - \ln|\hat{\Omega}|\right)$ where $\hat{\sigma}_i^2$ is the estimate variance for each equation from OLS and $\hat{\Omega}$ □ is the estimated variance-covariance matrix from FGLS. n is the number of equations/states in each system. The distribution of the statistics is χ^2. The p-values for all 8 LR statistics are close to zero (not shown).

other regions, the Southeast region does not appear to be a growth club despite the close geographical proximity of its member states. It may be the large number (12) of states in the Southeast is too many to represent a homogeneous grouping. Yet, the evidence suggests the other 7 regions form coherent growth clubs, although even in these regions, there are states that are decidedly following their own growth paths.

4.7 Trends in Convergence and Divergence

The predicted time paths for each state and region relative to the national average are projected in Figure 5. Note these reflect "trend" convergence patterns using the state/region time trends and they are distinct from the state/region conditional convergence terms described above (i.e., the γ and δ from equation (7)). The two break points in 1944 and 1982 separate the time line into three distinct periods. As described in Section 3, we could use the pooled FGLS approach shown in equation (8) to derive the regional paths, but we conservatively use the weighted-average estimates from equation (4).

Figure 5 shows that the 1929-1943 period is a remarkable period of trend convergence in state per-capita income towards the nation. The main exceptions are some Far West states. While trend convergence generally continued between 1944-1981, it was at a greatly diminished rate. In some regions, such as the Mideast, New England, Plains, Rocky Mountains and Southwest, there was only miniscule convergence, which is consistent with CM's (1996a) contention that most states and regions achieved their conditional steady-state by the end of WW II.

The 1982-2002 patterns are quite diverse. First, the initial shock of the 1982 structural change was to widen the per-capita growth paths across most regions, consistent with a divergence shock. After which, some states and regions continue their pre-1982 trend of slow convergence. However, some states continue to diverge from the national level. Indeed, the trends for Montana and Colorado of the Rocky Mountain region in Figure 5f are striking examples of trend divergence. While the vast majority of the literature has contended that states and regions continue to converge, this finding is consistent with the overall theoretical dynamics described in Lee et al. (1997) for mature regions. Likewise, Bernard and Jones (1996) found that productivity rates for many sectors have diverged across U.S. regions.

To examine if states are trend converging or trend diverging within their regions, Figure 6 reports the projected state paths relative to the regional average (i.e., the regional average is subtracted from the state path). Akin to the case reported in Figure 5, there is general within-region trend convergence prior to

1944. Likewise, within-region convergence slowed after 1944. In fact the Plains and the Rocky Mountain regions experienced almost no within-region convergence. Unlike the 1944 common shock, the common 1982 shock increased within-region dispersion, followed by diverse patterns of convergence and divergence within regions. There is even evidence of within-region trend divergence in the Mideast, New England, Plains, Rocky Mountains, and Southwest. To be sure, if we had followed most of the literature and (1) not allowed for (sufficient) heterogeneity and (2) only examined the conditional-convergence coefficient, we would have concluded from Table 2 that there is an on-going pattern of convergence throughout the period. Yet, by considering the entire cross-sectional distribution over time *ala* Quah (1993), Figures 5 and 6 reveal rich patterns of both convergence and divergence.

To assess whether our method of using the equation-by-equation approach from equation (4) is robust in identifying the average regional trends, Figure 7 shows the difference between the trend captured by the equation-by-equation estimate and the trend captured by the pooled FGLS technique. In seven of the eight regions, both methods essentially identify the same trend. The only exception is the Plains region for which the pooled FGLS approach produces a regional trend that is below all of its component states. These regional results clearly display a mixed convergence pattern after 1982. In fact, New England and the Mideast are diverging from the national average from above, which is consistent with these being technologically-leading regions as in HMF (2002).

5. Conclusion

There is a growing recognition in the empirical growth literature that dynamics across economies can be characterized as (1) being heterogeneous with the further possibility of multiple growth clubs; (2) possibly having multiple structural breaks; and (3) the existence of regional spillovers. Yet, most studies have either entirely ignored these complications or have only tackled these one at a time. To varying extents, such omissions may produce inaccurate portrayals of the growth process. Therefore, this study extends the previous literature by *simultaneously* considering whether 1929-2002 U.S. state and region growth dynamics are influenced by these factors. To examine these issues, we derived multiple empirical models to isolate how these issues alter the estimated growth process. One key novelty of our modeling approach is that we explicitly (1) allow regions to (conditionally) converge to the national trend, (2) allow states to conditionally converge to their regional average, and (3) allow independent state-growth trends.

The results point to several novel conclusions. First, consistent with the previous literature beginning with CM (1993), we find a structural break in 1944 which is near the conclusion of WW II. Yet, we also find another structural break in 1982, which is consistent with macroeconomic studies that suggest a large decline in aggregate-cyclical volatility beginning in the first-half of the 1980s. This correspondence suggests a similar mechanism at work, although we leave that possibility for future research. One key feature of the 1982 structural break is that it widened regional inequities. In fact, the subsequent growth path after 1982 in many regions reversed a decades-long trend towards convergence, suggesting the early 1980s structural change was striking in many dimensions, not just macroeconomic in scope.

The role of various empirical restrictions used in the past literature was also assessed. When restricting the amount of state/regional heterogeneity, we find very slow rates of convergence consistent with the past literature regardless of using state or major-region data (i.e., close to the famous 2 percent rule). While allowing for state/region fixed effects marked a modest difference, we uncover very rapid conditional-convergence rates when also allowed for both state and regional heterogeneity in growth trends and for structural breaks in 1944 and 1982. Indeed, our modeling illustrates that standard growth empirics could produce misleading conclusions. One feature of the structural breaks is most of the convergence took place prior to 1944, while convergence was sluggish between 1945 and 1981. As noted before, since 1982, there has been a sea change in the convergence process in many regions.

We also find evidence of regional growth clubs. That is, besides regions converging to the national average, individual states were also converging to the regional average, at least until 1982 in most cases. There is also evidence of within-region spillovers in the covariance of the state error terms. Yet, using FGLS did not dramatically alter the results even as it did markedly improve efficiency.

In sum, our general conclusion is Quah's (1993) contention that one should examine the whole cross section of growth paths to understand the underlying growth dynamics is correct. Only examining rates of conditional convergence would have given the mistaken impression of a general convergence pattern, when in fact there is a much richer mosaic of growth clubs, convergence, and divergence. Indeed, one conclusion is that if issues of heterogeneity, structural change, and growth clubs are so paramount with state data, they must certainly be prevalent in international data. Hence, future research should ascertain these factors with international data, possibly employing some of the empirical novelties used here.

References

Acemoglu, D. and J. Ventura, “The World Income Distribution,” *The Quarterly Journal of Economics.* 117 (2002), 659-694.

Aghion, P., P. Howitt, D. Mayer-Foulkes, “The Effect of Financial Development on Convergence: Theory and Evidence,” Working Paper #10358, National Bureau of Economic Research, 2004.

AlAzzawi, S., “Foreign Direct Investment and Knowledge Flows: Evidence from Patent Citation,” Working Paper, University California, Davis, 2004.

Andrés, J., J.E. Boscá, and R. Doménech, “Convergence in the OECD: Transitional Dynamics or Narrowing Steady-State Differentials,” *Economic Inquiry* 42 (2004), 141-149.

Azariadis, C. and A. Drazen, “Threshold Externalities in Economic Development,” *Quarterly Journal of Economics* 105 (1990), 501-526.

Bai, J. and P. Perron, “Computation and Analysis of Multiple Structural Change Models,” *Journal of Applied Econometrics* 18 (2003), 1-22.

Barro, R.J. and X. Sala-i-Martin, “Convergence Across States and Regions,” *Brookings Papers on Economic Activity* (1991), 107-182.

Barro, R.J. and X. Sala-i-Martin, “Convergence.” *Journal of Political Economy* 100 (1992), 223-251.

Bernard, A.B. and S.N. Durlauf, “Interpreting Tests of the Convergence Hypothesis” *Journal of Econometrics* 71 (1996), 161-173.

Bernard, A.B. and C.I. Jones, “Productivity and Convergence Across U.S. States and Industries.” *Empirical Economics* 21 (1996), 113-135.

Bernat, A.B., “Convergence in State Per Capita Income, 1950-1999,” *Survey of Current Business* 81 (2001), 36-48.

Berthelemy, J.C. and A. Varoudakis, “Economic Growth, Convergence Clubs, and the Role of Financial Development,” *Oxford Economic Papers* 48 (1996), 300-328.

Blanchard, O. and L. F. Katz, “Regional Evolutions,” *Brookings Papers on Economic Activity* (1992), 1-61.

Bottazzi, L. and G. Peri, “Innovation and Spillovers in Regions: Evidence from European Patent Data,” Working Paper, Innocenzo Gasparini Institute for Economic Research, 2002.

Bourguignon, F. and C. Morrisson, “Inequality Among World Citizens: 1820-1992,” *American Economic Review* 92 (2002), 727-744.

Canova, F., “Testing for Convergence Clubs in Income Per Capita: A Predictive Density Approach,” *International Economic Review* 45 (2004), 49-77.

Carlino, G.A. and L. Mills, “Are U.S. Regional Incomes Converging?” *Journal of Monetary Economics* 32 (1993), 335-346.

Carlino, G.A. and L. Mills, “Convergence and the U.S. States: A Time-Series Analysis,” *Journal of Regional Science* 36 (1996a), 597-616.

Carlino, G.A. and L. Mills, “Testing Neoclassical Convergence in Regional Incomes and Earnings,” *Regional Science and Urban Economics* 26 (1996b), 565-590.

Carvalho, V. and A. Harvey, “Convergence and Cycles in the Euro Zone,” Working Paper, Cambridge University, 2003.

Caselli, F. and W.J. Coleman II, “The U.S. Structural Transformation and Regional Convergence: A Reinterpretation,” *Journal of Political Economy* (2001), *584-616.*

Dobson, S., C. Ramlogan, and E. Strobl, “Why Do Rates of Convergence Differ? A Meta-Regression Analysis,” Working Paper, University Otago, 2003.

Durlauf, S.N., “Manifesto for a growth econometrics,” *Journal of Econometrics* 100 (2001), 65-69.

Durlauf, S.N. and P.A. Johnson, “Multiple-Regimes and Cross-Country Growth Behavior,” *Journal of Applied Econometrics* 10 (1995), 365-384.

Durlauf, S.N. and D.T. Quah, “The New Empirics of Economic Growth,” in J.B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics,* Vol. 1 (New York: Elsevier Science, 1999), 235-308.

Evans, P., “How Fast Do Economies Converge?” *Review of Economics and Statistics* 79 (1997), 219-225.

Evans, P. and G. Karras, “Convergence Revisited,” *Journal of Monetary Economics* 37 (1996), 249-265.

Forbes, K.J., “A Reassessment of the Relationship Between Inequality and Growth,” *American Economic Review* 90 (2000), 869-887.

Galor, O., “Convergence? Inferences From Theoretical Models,” *Economic Journal* 106 (1996), 1056-1069.

Greene, W.H., *Econometric Analysis*, 3rd Edition (Upper Saddle River, NJ: Prentice Hall, 1997).

Howitt, P. and D. Mayer-Foulkes, “R&D, Implementation and Stagnation: A Schumpeterian Theory of Convergence Clubs,” Working Paper #9104, National Bureau of Economic Research, 2002.

Jaffe, A., M. Trajtenberg, and R. Henderson, “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citation,” *Quarterly Journal of Economics* 108 (1993), 577-98.

Johnson, P.A. and L.N. Takeyama, “Initial Conditions and Economic Growth in US States,” *European Economic Review* 45 (2001), 919-927.

Kim, C.J., C.R. Nelson, and J. Piger, “The Less Volatile U.S. Economy: A Bayesian Investigation of Timing, Breadth, and Potential Explanations,” Working Paper 2001-016C, Federal Reserve Bank of St. Louis, 2001.

Lee, K., M.H. Pesaran, and R. Smith, “Growth and Convergence in a Multi-Country Empirical Stochastic Solow Model,” *Journal of Applied Econometrics* 12 (1997), 357-392.

Loewy, M. and D.H. Papell, “Are U.S. regional incomes converging? Some further evidence,” *Journal of Monetary Economics* 38 (1996), 587-598.

López-Bazo, E., E. Vayá, and M. Artís, “Regional Externalities and Growth: Evidence From European Regions,” *Journal of Regional Science* 44 (2004), 43-73.

Mankiw, G.N., D. Romer, and D.N. Weil, “A Contribution to the Empirics of Economic Growth,” *Quarterly Journal of Economics* 107 (1992), 407-434.

Mayer-Foulkes, D., “Divergence Today,” Working Paper, Centro de Investigación y Docencia Econónicas, 2002.

Nelson, C.R. and C.I. Plosser, "Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications," *Journal of Monetary Economics* 10 (1982), 139-162.

Peri, G., "Knowledge Flows and Knowledge Externalities." Working Paper #765, CESIFO, 2002.

Perron, P., "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis," *Econometrica* 57 (1989), 1361-1401.

Phillips, P.C.B. and D. Sul, "The Elusive Empirical Shadow of Growth Convergence," Discussion Paper #1398, Cowles Foundation, Yale University, 2003.

Prichett, L., "Divergence, Big-Time," *Journal of Economic Perspectives* 11 (1997), 3-17.

Rey, S. and B. Montouri, "US regional income convergence: A spatial econometric perspective." *Regional Studies* 33 (1999), 143-156.

Quah, D., "Galton's Fallacy and Tests of the Convergence Hypothesis," *Scandinavian Journal of Economics* 95 (1993), 427-443.

Sala-i-Martin, X., "Regional Cohesion: Evidence and theories of regional growth and convergence," *European Economic Review* 40 (1996), 1325-1352.

Sala-i-Martin, X., "15 Years of New Growth Econometrics: What Have We Learnt?" Working Paper, Universitat Pompeu Fabra, 2002.

Slaughter, M., "Per Capita Income Convergence and the Role of International Trade," *American Economic Review* 87 (1997), 194-199.

Stock, J.H. and M.W. Watson, "Has the Business Cycle Changed and Why?" Working Paper #9127, National Bureau of Economics Research, 2002.

Strazicich, M.C. and J. Lee, "Are Regional Incomes Converging in the U.S.? Evidence from Panel Unit Root Tests with Heterogeneous Structural Breaks," Working Paper, University of Alabama, 2002.

Table 1: Likelihood Ratio Statistics for the Structural Change Models

No. of Breaks (l)	$\ln[\det(\hat{\Omega})]_l$	Likelihood Ratio Statistics $T\left(\ln[\det(\hat{\Omega})]_{l-1} - \ln[\det(\hat{\Omega})]_l\right)$
0	-33.6391	--
1 {1944}	-35.1744	129.9775 (0.000)
2 {1944, 1982}	-36.1364	69.2688 (0.0083)
3 {1944, 1982, 1970}	-36.8001	47.8291 (0.2583)
4 {1944, 1982, 1970, 1989}	-37.4398	46.0116 (0.3428)

Note:

1. Empirical p-values are reported in the parenthesis.
2. The empirical p-values are based on Monte Carlo simulations. In our study, a model with *l* breaks is one with restriction and a model with *l+1* is one without. To obtain each p-value, we simulate data 10,000 times under the model with *l* breaks, apply both models on each simulated series and derive a LR statistics, and compare the actual LR statistics with the empirical LR distribution.

Table 2: Results from Pooled Panel Regression

Model	Autoregressive Coefficient Estimate
Panel A: Relative Regional Income to the National Average	
1. With a common constant term but no trend	0.9724 (0.0276)
$x_{rt} = \alpha + \delta x_{r,t-1} + \varepsilon_{rt} \quad \forall r$	
2. With fixed effects but no trend	0.9514 (0.0486)
$x_{rt} = \alpha_r + \delta x_{r,t-1} + \varepsilon_{rt} \quad \forall r$ (Wald: 7.1212; p-value: 0.4164)	
3. With fixed effects and a common trend (& structural breaks)	0.8610 (0.1390)
$x_{rt} = \sum_{k=1}^{2}(\alpha_{rk} + \beta_k t)D_{kt} + \delta x_{r,t-1} + \varepsilon_{rt} \ \forall r$ (Wald: 37.0848; p-value: 0.0077)	
4. With fixed effects and individual trend for each region (& structural breaks)	0.5707 (0.4293)
$x_{rt} = \sum_{k=1}^{2}(\alpha_{rk} + \beta_{rk} t)D_{kt} + \delta x_{r,t-1} + \varepsilon_{rt} \ \forall r$ (Wald: 174.0185; p-value: 0.0000)	
Panel B: Relative State Income to the National Average	
1. With a common constant term but no trend	0.9684 (0.0316)
$x_{it} = \alpha + \delta x_{i,t-1} + \varepsilon_{it} \quad \forall i$	
2. With fixed effects but no trend	0.9245 (0.0755)
$x_{it} = \sum_{k=1}^{2}(\alpha_{ik} + \beta_k t)D_{kt} + \delta x_{i,t-1} + \varepsilon_{it} \quad \forall i$ (Wald: 87.9517; p-value: 0.0003)	
3. With fixed effects and a common trend (& structural breaks)	0.7520 (0.2480)
$x_{it} = \sum_{k=1}^{2}(\alpha_{ik} + \beta_k t)D_{kt} + \delta x_{i,t-1} + \varepsilon_{it} \quad \forall i$ (Wald: 247.3929; p-value: 0.0000)	
4. With fixed effects and individual trend for each state (& structural breaks)	0.4745 (0.5255)
$x_{it} = \sum_{k=1}^{2}(\alpha_{ik} + \beta_{ik} t)D_{kt} + \delta x_{r,t-1} + \varepsilon_{rt} \ \forall i$ (Wald: 1019.7620; p-value: 0.0000)	

Note:

1. In all trend regressions, 1944 and 1982 break points are imposed.
2. We also obtain the results when the regressions are arranged in the error correction form. The results, in terms of their absolute value, are reported in the parentheses.
3. Each of Rows 2-4 respectively contains Wald statistics testing the restriction in the immediate preceding row.

Table 3: Coefficient Estimates for the Relative Income Convergence Regression

	Coefficient Estimates				**Difference in %**
	Model 1 *Eq. by Eq. Estimates for (4)*		Model 2 *FGLS Estimates for (7)*		
	δ_1	$1-\delta_1$	δ_1	$1-\delta_1$	
Far West	0.4755 (0.0867)	**0.5245**	0.5010 (0.0799)	**0.4990**	+5.35 (-7.76)
Great Lakes	0.5203 (0.0899)	**0.4797**	0.5534 (0.0641)	**0.4466**	+6.37 (-28.63)
Mid East	0.6234 (0.0940)	**0.3766**	0.5835 (0.0662)	**0.4165**	-6.41 (-29.55)
New England	0.6879 (0.0662)	**0.3121**	0.6886 (0.0530)	**0.3114**	+0.10 (-20.02)
Plains	0.3088 (0.1134)	**0.6912**	0.4728 (0.0540)	**0.5272**	+53.09 (-52.34)
Rocky Mountains	0.6234 (0.0940)	**0.3766**	0.7340 (0.0848)	**0.2660**	+17.73 (-9.78)
South East	0.5435 (0.1051)	**0.4565**	0.4562 (0.0701)	**0.5438**	-16.07 (-33.30)
South West	0.7248 (0.0860)	**0.2752**	0.7148 (0.0691)	**0.2852**	-1.39 (-19.62)

Note: The bolded numbers are the coefficients when the regressions are in the error correction form.

Table 4: State Convergence to Regional Trend

	Coefficient	Std. Dev.
Far West		
California	0.6816	0.2218
Nevada	0.2463	0.1231
Oregon	0.7025	0.0735
Washington	0.7225	0.0754
(Wald: 11.7735; p-value: 0.0082)		
Great Lakes		
Illinois	0.6519	0.0913
Indiana	0.3072	0.108
Michigan	0.403	0.1046
Ohio	0.3459	0.0954
Wisconsin	0.4933	0.0983
(Wald: 6.9876; p-value: 0.1365)		
Mid East		
D.C.	0.691	0.0628
Delaware	0.5998	0.0991
Maryland	0.5654	0.0679
New Jersey	0.7588	0.087
New York	0.9031	0.1236
Pennsylvania	0.587	0.0738
(Wald: 11.2528; p-value: 0.0466)		
New England		
Connecticut	0.7871	0.0909
Maine	0.4967	0.0782
Massachusetts	0.3756	0.1678
New Hampshire	0.5843	0.0829
Rhode Island	0.5272	0.1119
Vermont	0.6271	0.0687
(Wald: 7.2779; p-value: 0.2008)		
Plains		
Iowa	0.1156	0.0955
Kansas	0.4361	0.0962
Minnesota	0.5743	0.0716
Missouri	0.4263	0.0589
Nebraska	0.1621	0.1021
North Dakota	0.1847	0.088
South Dakota	0.1569	0.0705
(Wald: 26.3091; p-value: 0.0001)		
Rocky Mountains		
Colorado	0.3249	0.1066
Idaho	0.0857	0.1257
Montana	0.0213	0.1159
Utah	0.7797	0.092
Wyoming	0.6804	0.0747
(Wald: 46.5780; p-value: 0.0000)		
South East		
Alabama	-0.0518	0.0753
Arkansas	0.0314	0.0762
Florida	0.1764	0.0596
Georgia	-0.455	0.1505
Kentucky	0.1584	0.072
Louisiana	-0.1652	0.0491
Mississippi	-0.2935	0.0569
North Carolina	0.1854	0.1094
South Carolina	-0.1007	0.0787
Tennessee	-0.0395	0.1211
Virginia	-0.197	0.0604
West Virginia	0.2332	0.071
(Wald: 84.4314; p-value: 0.0000		
South West		
Arizona	0.584	0.0986
Oklahoma	0.6587	0.0681
New Mexico	0.2544	0.1277
Texas	0.8465	0.2561
(Wald: 8.9929; p-value: 0.0294)		

Note: For each region, the joint null hypothesis that the individual state coefficients are equal is tested with the reported Wald test.

NOT TO BE PUBLISHED

Table 5: Covariance-Correlation Matrix of the Residuals from the FGLS Estimation

(Correlation estimates in shaded areas.)

Far West				
	CA	NV	OR	WA
CA	0.000206	0.300333	0.114652	0.155352
NV	0.000193	0.002018	0.108104	0.073579
OR	3.76E-05	0.000111	0.000523	0.567432
WA	4.25E-05	6.30E-05	0.000247	0.000364
LR = 46.6477				

Great Lakes					
	IL	IN	MI	OH	WI
IL	0.000234	0.417214	0.343771	0.389385	0.075152
IN	0.000131	0.000419	0.691859	0.811005	0.255994
MI	0.000145	0.000391	0.000763	0.666751	0.192438
OH	8.84E-05	0.000246	0.000274	0.000221	0.180491
WI	1.75E-05	7.99E-05	8.11E-05	4.09E-05	0.000233
LR = 146.0698					

Mid East						
	DC	DE	MD	NJ	NY	PA
DC	0.001212	0.285019	0.384299	0.382204	0.322754	-0.00241
DE	0.000335	0.001141	0.083777	0.231908	0.188833	0.376198
MD	0.000205	4.34E-05	0.000235	0.360611	0.015935	0.068408
NJ	0.000193	0.000113	8.00E-05	0.000209	0.50646	0.258065
NY	0.000178	0.000101	3.87E-06	0.000116	0.000251	0.047492
PA	-8.87E-07	0.000135	1.11E-05	3.96E-05	7.97E-06	0.000112
LR = 82.0096						

New England						
	CT	ME	MA	NH	RI	VT
CT	0.000403	-0.23738	0.553828	0.390971	0.605849	0.164673
ME	-0.00011	0.000524	-0.03887	0.062081	-0.11188	0.252063
MA	0.000193	-1.54E-05	0.0003	0.444209	0.48949	0.346567
NH	0.000139	2.51E-05	0.000136	0.000313	0.378486	0.480187
RI	0.000284	-5.97E-05	0.000198	0.000156	0.000543	0.244471
VT	5.91E-05	0.000103	0.000107	0.000152	0.000102	0.00032
LR = 101.0218						

Plains							
	IA	KS	MN	MO	NE	ND	SD
IA	0.002988	0.333434	0.793822	0.480072	0.72973	0.490305	0.714495
KS	0.000685	0.001412	0.148723	0.101099	0.647537	0.362814	0.44972
MN	0.001079	0.000139	0.000619	0.362361	0.505638	0.537789	0.760616
MO	0.00032	4.62E-05	0.00011	0.000148	0.293956	0.04816	0.215125
NE	0.002092	0.001276	0.00066	0.000188	0.002752	0.531904	0.69454
ND	0.002598	0.001321	0.001297	5.68E-05	0.002705	0.009396	0.744565
SD	0.00354	0.001531	0.001715	0.000237	0.003302	0.006542	0.008215
LR = 350.6537							

Rocky Mountains					
	CO	ID	MT	UT	WY
CO	0.000752	0.106119	0.312287	0.776173	0.343424
ID	0.000167	0.003285	0.349577	0.187099	-0.00966
MT	0.000373	0.000872	0.001895	0.425034	0.53383
UT	0.000793	0.000399	0.000689	0.001386	0.263366
WY	0.000287	-1.69E-05	0.000708	0.000299	0.000929
LR = 92.8967					

South West				
	AZ	OK	NM	TX
AZ	0.00065	0.35722	0.267819	0.160712
OK	0.000198	0.000472	0.525607	0.361323
NM	0.000197	0.00033	0.000835	0.616352
TX	8.75E-05	0.000168	0.00038	0.000456
LR = 66.1264				

South East

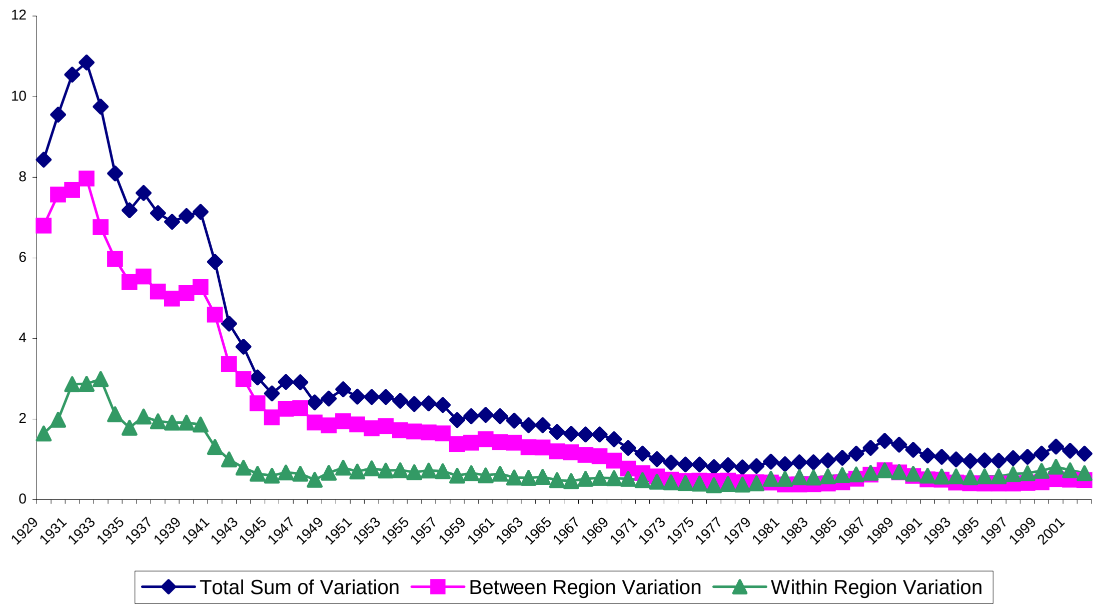
	AL	AK	FL	GA	KY	LA
AL	0.000821	-0.05523	-0.04988	-0.19124	-0.31417	0.395745
AK	-4.66E-05	0.000868	0.484257	-0.07385	0.557273	0.269019
FL	-4.02E-05	0.000401	0.000791	0.032665	0.385929	0.3
GA	-0.00016	-6.27E-05	2.65E-05	0.000829	0.143433	-0.45785
KY	-0.00021	0.000386	0.000255	9.71E-05	0.000553	0.021173
LA	0.000242	0.000169	0.00018	-0.00028	1.06E-05	0.000457
MS	0.000926	8.41E-05	0.000154	-0.00027	-0.00023	0.000425
NC	0.000153	0.000712	0.000913	0.000109	0.000442	0.000202
SC	-0.00021	0.000257	0.000363	-3.49E-07	0.000484	1.80E-06
TN	-0.00011	0.000258	0.000391	6.33E-05	0.000514	-8.41E-06
VA	-7.68E-05	0.000441	0.000356	0.000258	0.0003	2.34E-05
WV	-0.00012	6.15E-05	0.000105	-4.32E-05	0.000248	2.10E-05

South East (Continued)

	MS	NC	SC	TN	VA	WV
AL	0.812752	0.126926	-0.24246	-0.11531	-0.11451	-0.14568
AK	0.071728	0.574105	0.29029	0.26358	0.640039	0.074523
FL	0.137947	0.771076	0.430661	0.418431	0.540664	0.132935
GA	-0.23107	0.090086	-0.0004	0.066247	0.383236	-0.0536
KY	-0.2424	0.44641	0.685665	0.659008	0.544459	0.376256
LA	0.500164	0.22446	0.002802	-0.01185	0.04673	0.035077
MS	0.001583	0.239637	-0.2609	-0.16905	0.054916	-0.3036
NC	0.000401	0.001773	0.445585	0.470664	0.617944	-0.06676
SC	-0.00031	0.000563	0.0009	0.745095	0.419193	0.425773
TN	-0.00022	0.000658	0.000742	0.001102	0.462797	0.502665
VA	5.11E-05	0.000609	0.000294	0.00036	0.000548	0.022598
WA	-0.00034	-7.88E-05	0.000358	0.000467	1.48E-05	0.000785

LR = 520.9090

Figure 1: Variance Decomposition
Panel A: 1929-2002



Panel B: 1965-2002

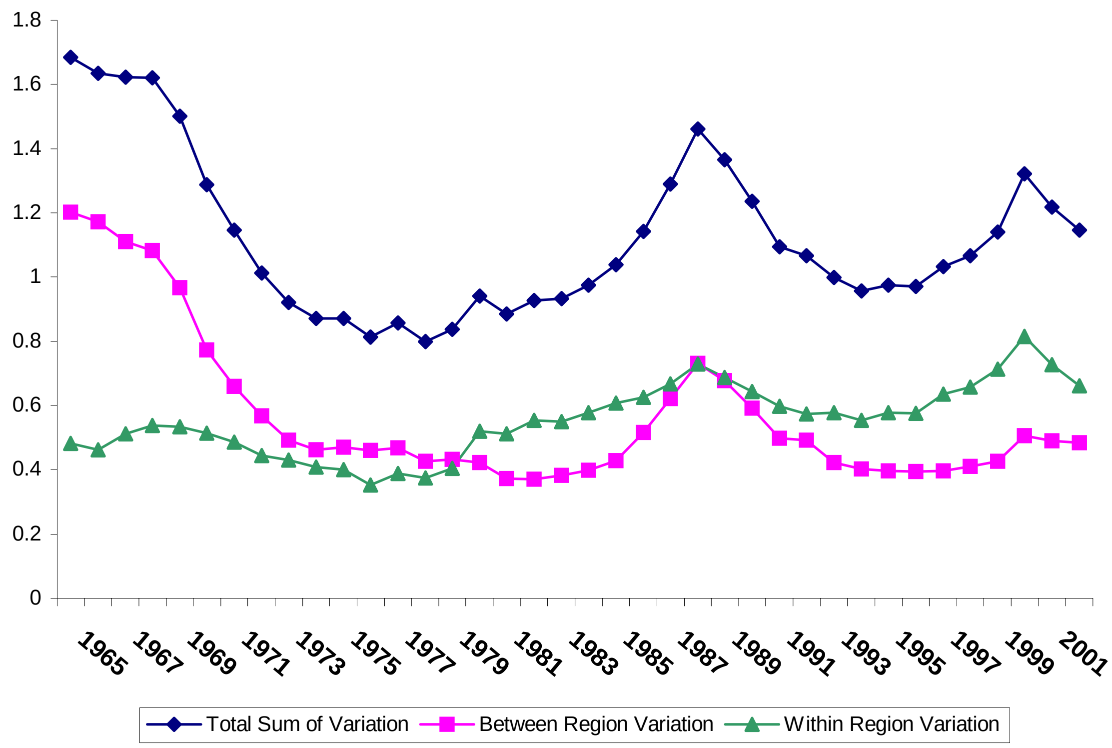
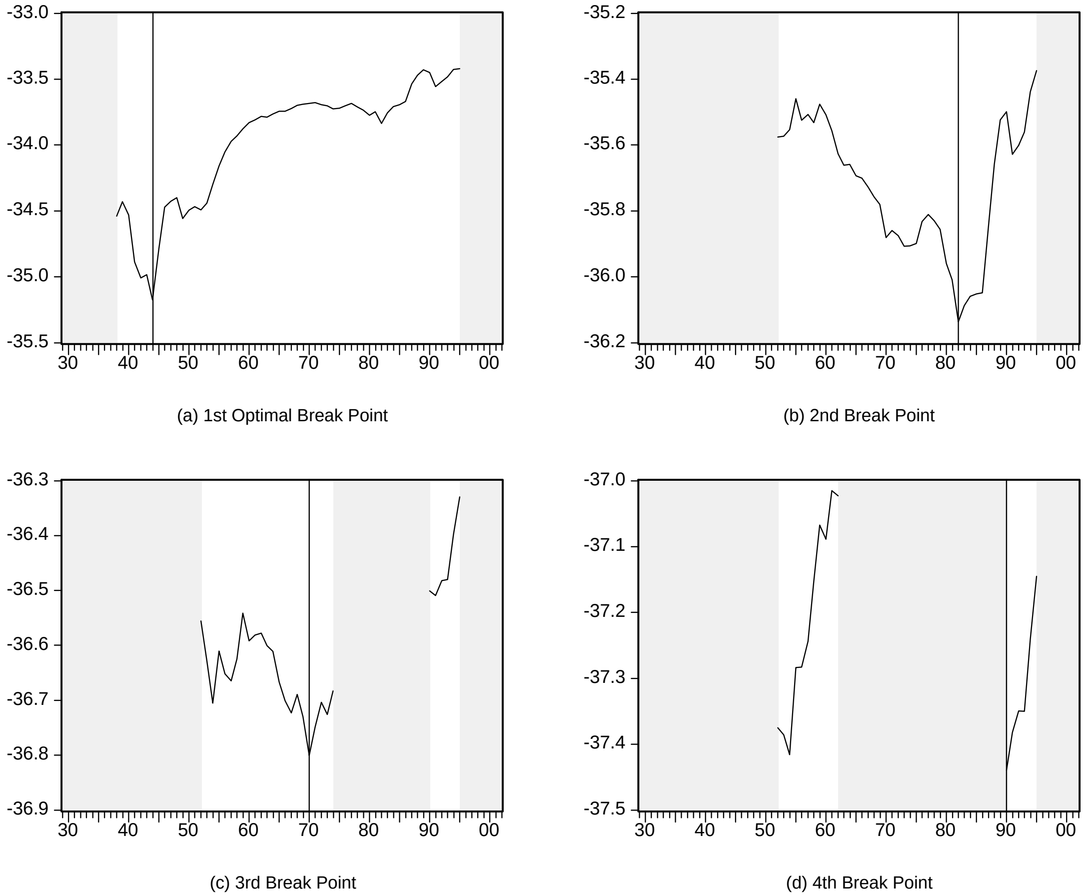


Figure 2:
Share of Overall Variation that is Within and Between Regions

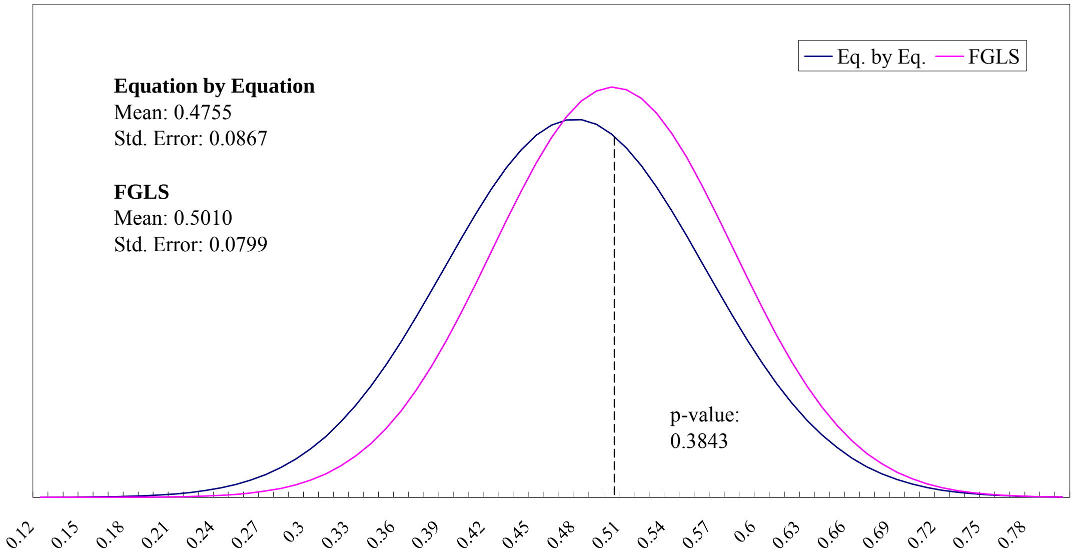
Figure 3: Sequential Search for Structural Breaks in Per-Capita Relative Income



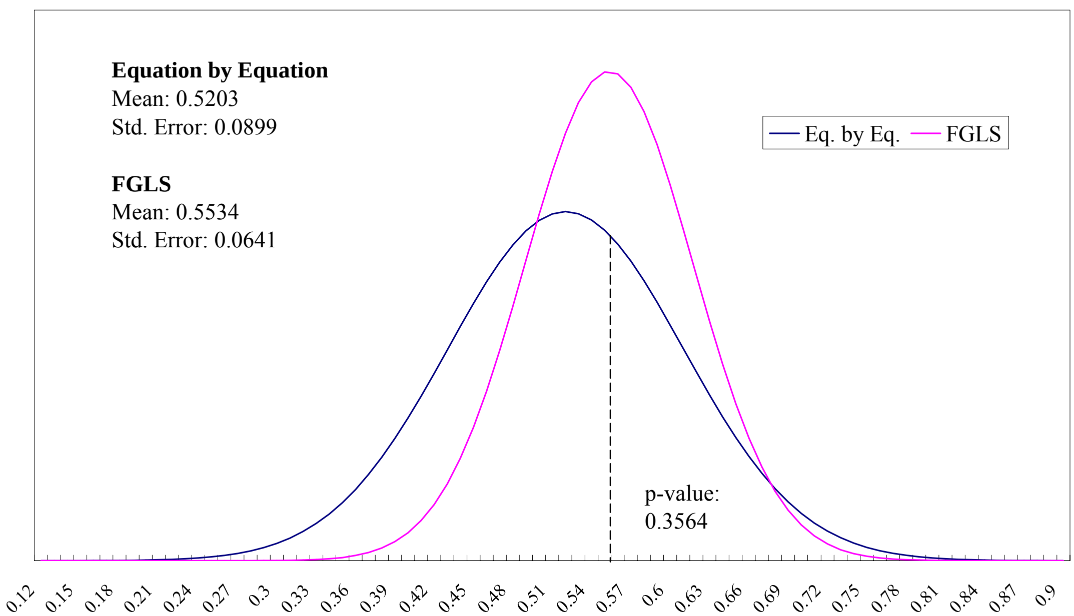
Note: These series are the estimates of $\ln[\det(\hat{\Omega})]_t$ for any given break point at time *t*.

Figure 4: A Graphical Illustration of the Efficiency Gain from the Panel Model (7)

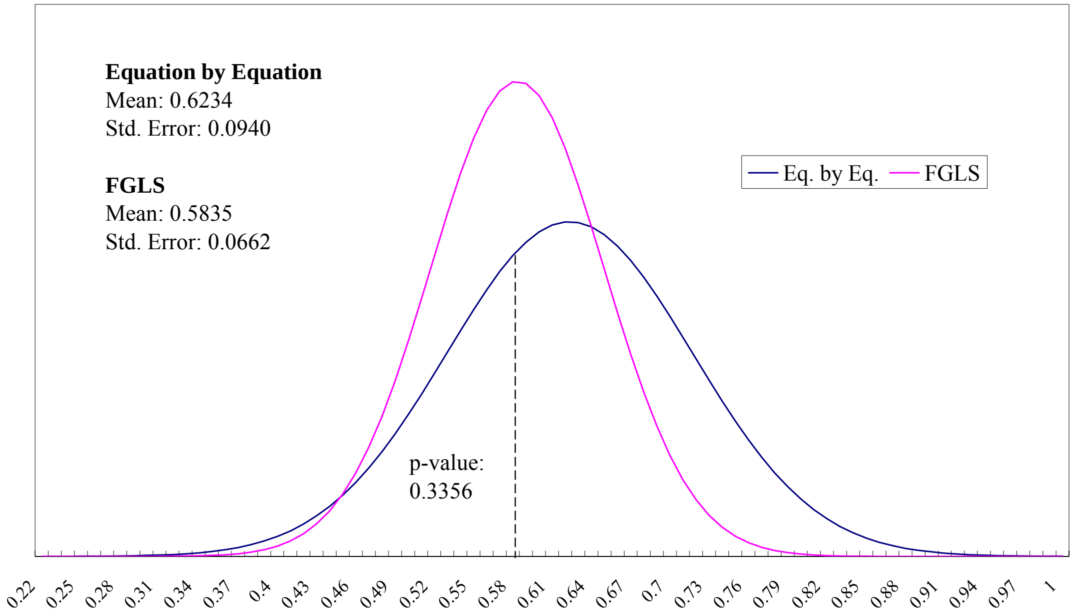
(a) Far West



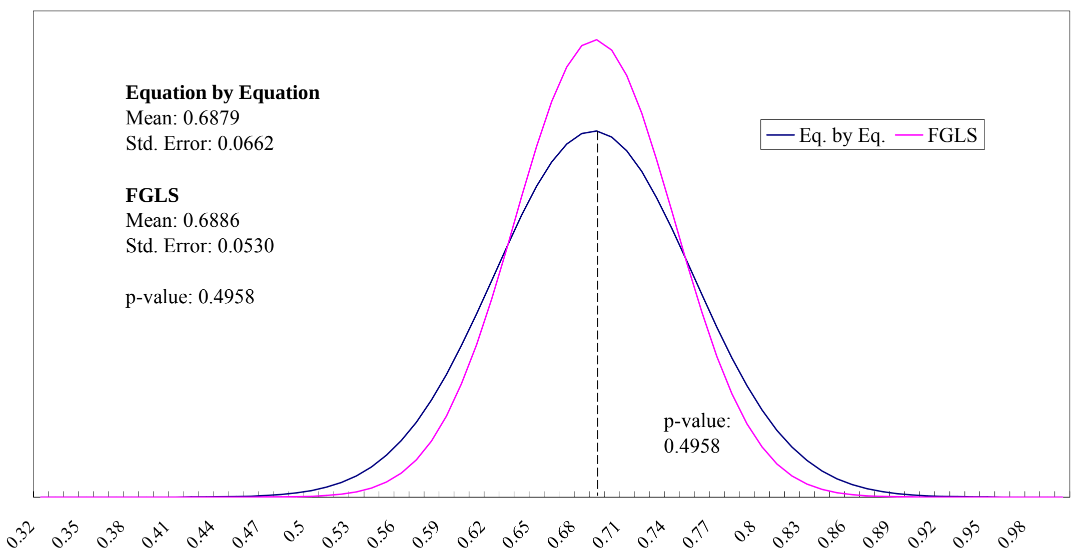
(b) Great Lakes



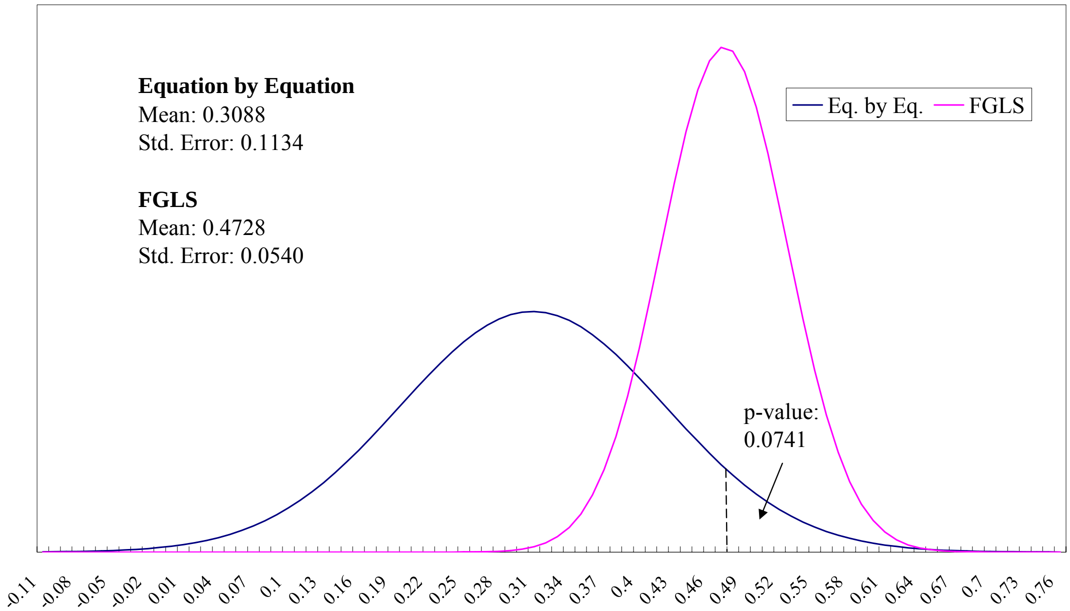
(c) Mid East



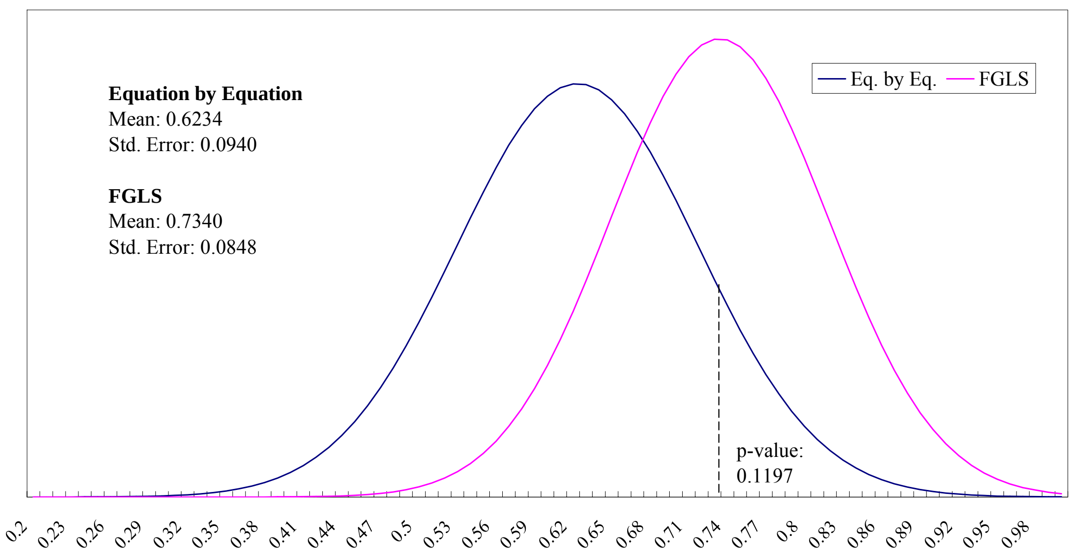
(d) New England



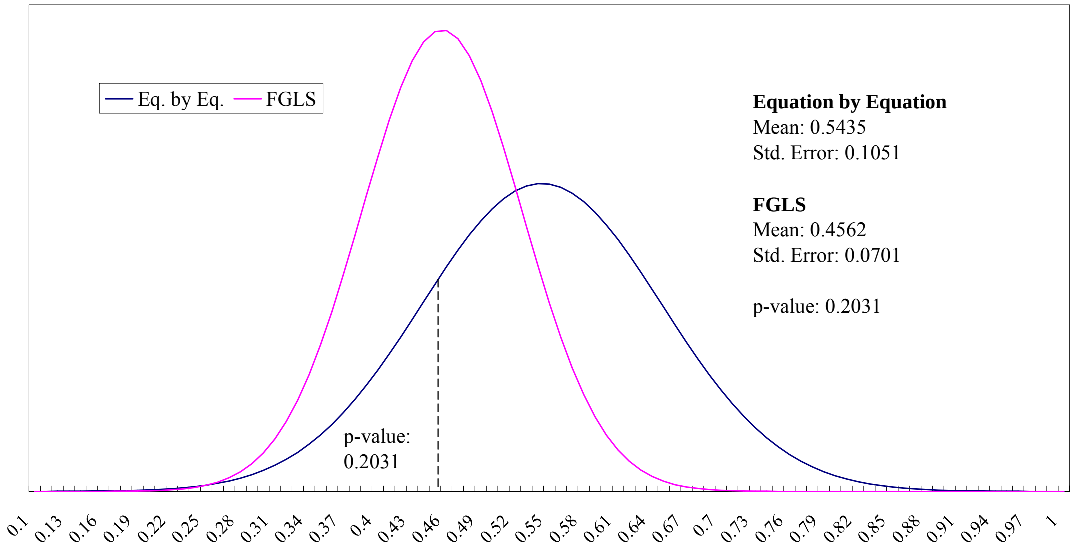
(e) Plains



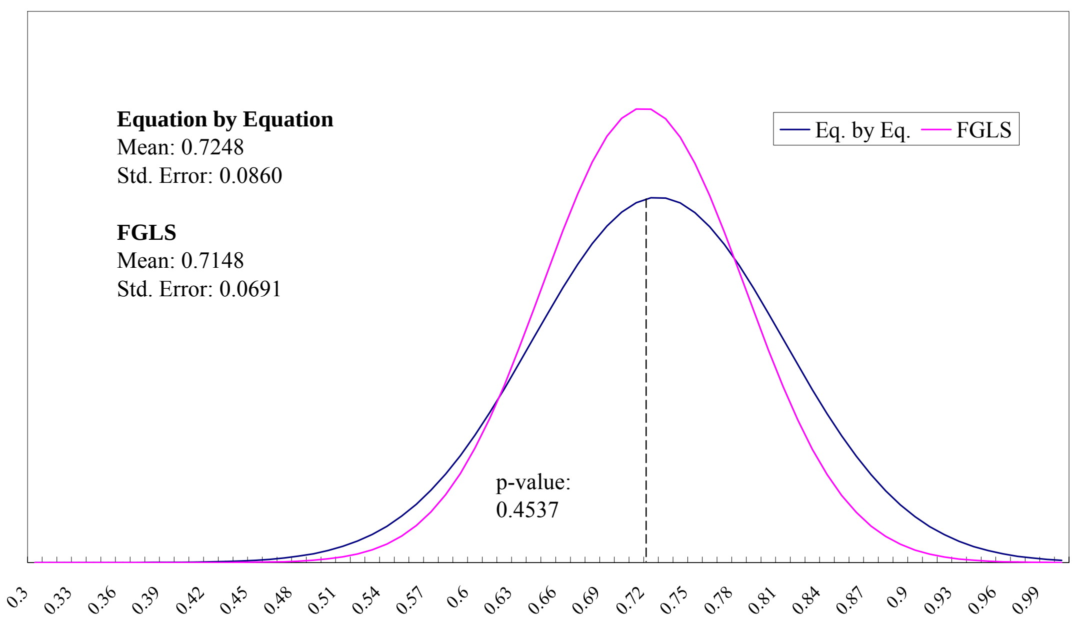
(f) Rocky Mountains



(g) South East

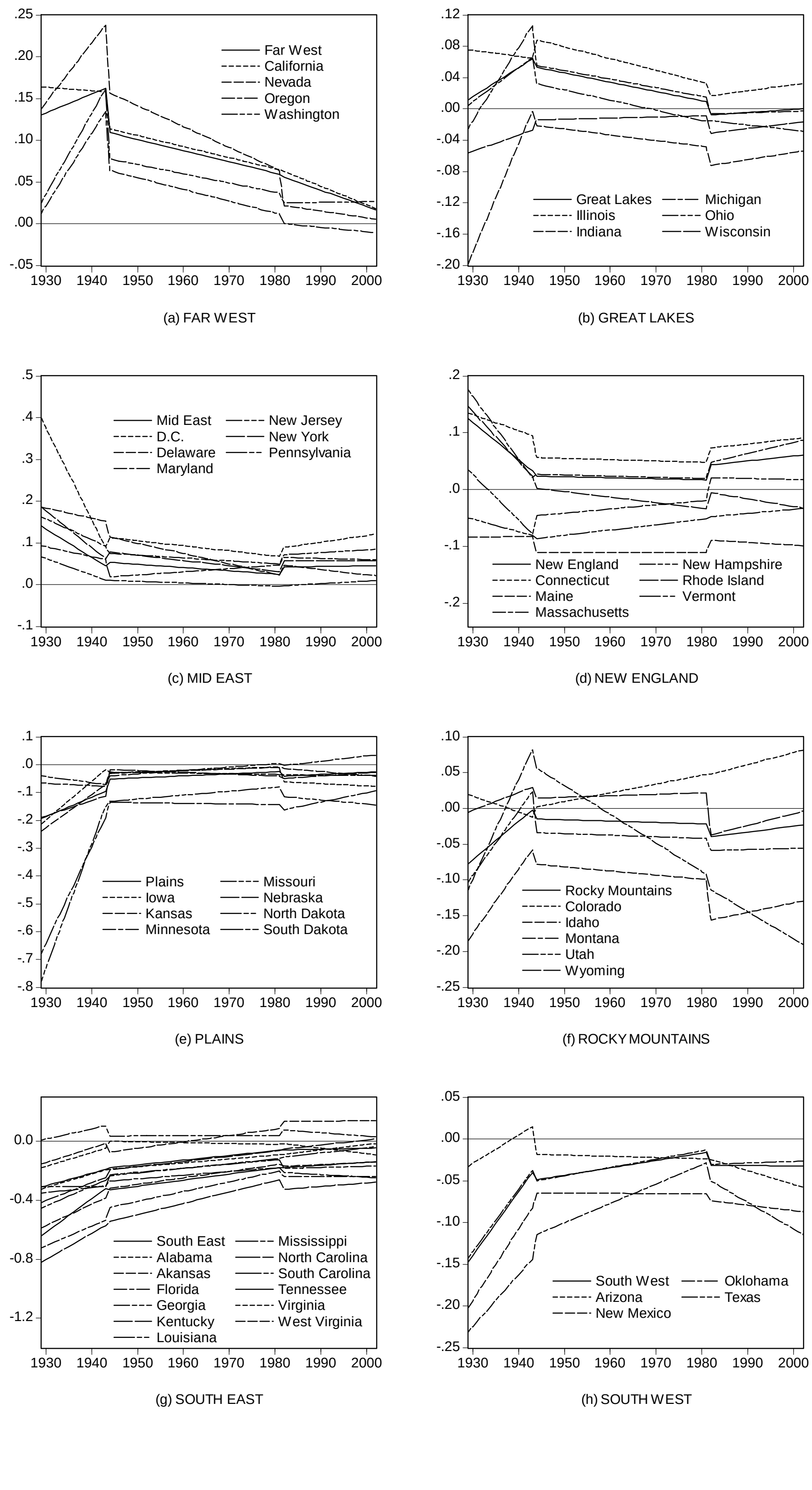


(h) South West



Note: The mean estimate of δ_i and its standard error for equations (4) and (6) are reported in each panel. The p-value of a test when the estimate of δ_i from (4) is set as the true value under the null hypothesis against an alternative value that is equal to the estimate from (6).

Figure 5: Trend of Convergence and Divergence to the National Level



(a) FAR WEST

(b) GREAT LAKES

(c) MID EAST

(d) NEW ENGLAND

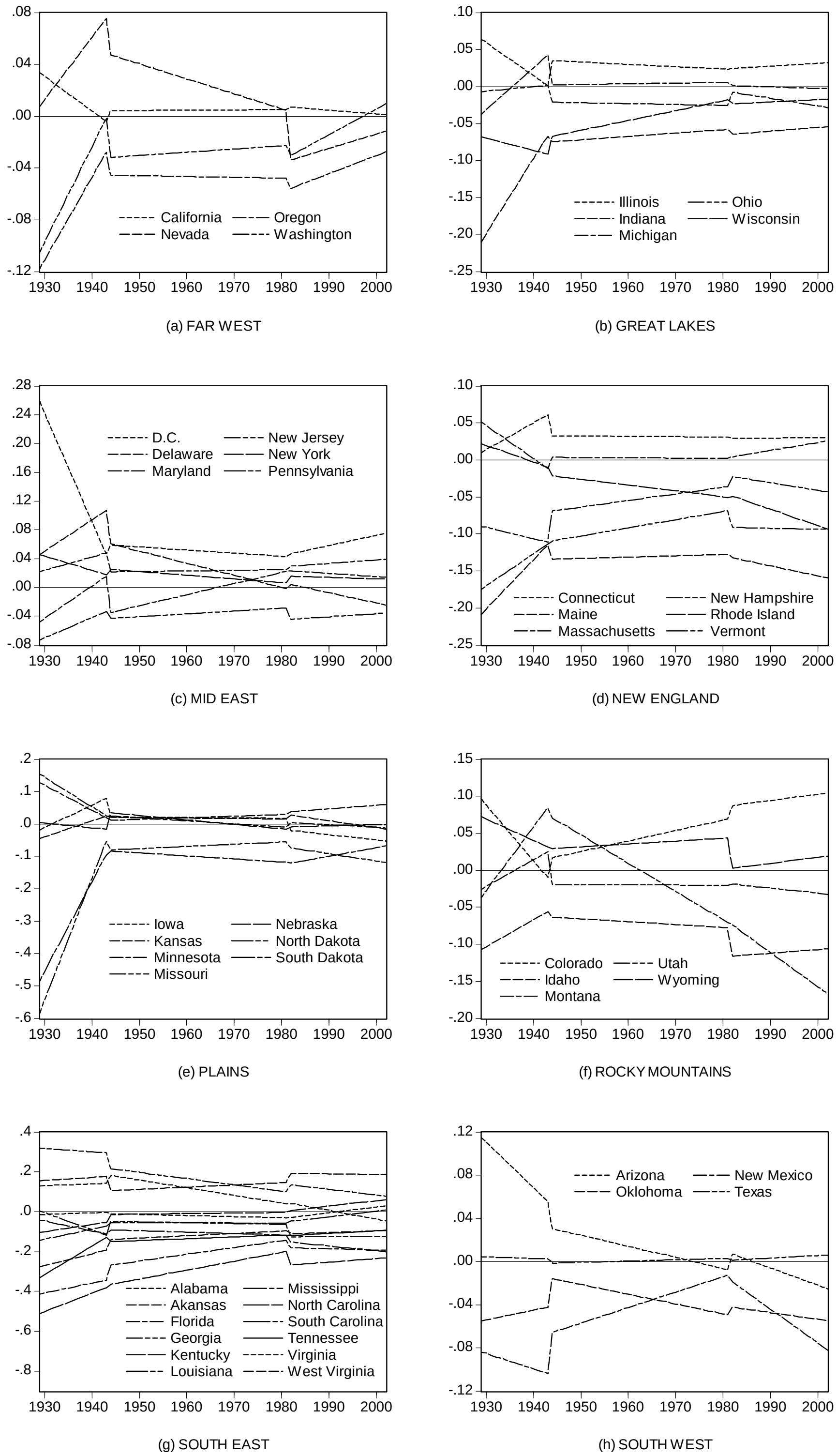
(e) PLAINS

(f) ROCKY MOUNTAINS

(g) SOUTH EAST

(h) SOUTH WEST

Figure 6: Trend of Convergence and Divergence to the Regional Level



(a) FAR WEST (b) GREAT LAKES (c) MID EAST (d) NEW ENGLAND (e) PLAINS (f) ROCKY MOUNTAINS (g) SOUTH EAST (h) SOUTH WEST

Figure 7: Results from Detrending