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

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(This copy contains appendix tables and figures not recommended for publication.)

**Abstract:** This paper examines 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, while at the same time allowing for 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.

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## 1. Introduction

Economic concepts such as purchasing power parity and income convergence are heavily studied in the empirical literature. With our discipline's emphasis on the paradigm of equilibrium, it is easy to understand the enduring effort in searching for evidence of equilibrium adjustment. To specify when an equilibrium is identified, however, is not easy. For example, transaction costs forbid equalization of prices even for tradable goods. As a result, a number of nonlinear time-series models have been developed to re-specify the type of price adjustment we should expect. More recently, Imbs et al (2005) find that the issue is complicated by not only possible nonlinear dynamics but also bias due to the aggregation of data. Income convergence is another clear area where these two concerns co-exist.

Despite the problems of estimating the convergence relationship, 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 at a rate of about 2 percent per year after adjusting for factors that affect the steady-state (i.e., β-convergence) (e.g., Mankiw et al., 1992).[1] 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).

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 (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 diverge 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).

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

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, 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, broader regions in the U.S. may even represent growth clubs with their own unique dynamics. Regions may be 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.

This paper offers a new panel approach based on the assumption of growth clubs. We apply the model on the U.S. data because potential regional growth clubs are more clearly defined. We extend the model of Carlino and Mills (1993, hereafter, CM,) which imposes structural breaks in the time trends of relative U.S. regional income per capita. To conform to their model, we update the timing and the number of break points and impose them in our model. Our results suggest that, in addition to a break date of 1944 in regional income per capita that is very close to CM's 1946, a second break date of 1982 is significant. This is an important finding by itself as studies on the U.S. aggregate variables have unveiled similar patterns (e.g. Kim et al., 2004.)

The contribution of our paper is twofold. First, we establish stylized facts in contrast to those based on a simpler assumption of a single national equilibrium. For example, suppose the club growth model is correct but we use a mis-specified model of a single and uniform equilibrium level, the estimated rate of convergence may appear slow. Figure 1 illustrates two possible ways this could occur—one where convergence is estimated to be too slow and one where it incorrectly suggests long-run divergence. Our findings can be summarized as follows. When focusing on state trend convergence to the national level, the post-1943 dynamics is not as strong as that in the preceding period. This is discouraging in the context of a single equilibrium model. But when we focus on state-trend convergence to the regional-club level, the patterns are in fact stronger after 1943 and the strongest after 1981. This is consistent with our argument that the club-growth pattern may affect the estimation of simplistic linear models. Second, with disaggregated data and a greater number of observations, our new approach increases the efficiency of the estimates, which underlies a foundation for a more powerful testing method.

The organization of this paper is as follows. Section 2 reviews the literature regarding club growth and patterns of income convergence and divergence in the United States. Section 3 presents the model. We present and interpret the results in Section 4 and offer our concluding remarks in Section 5.

## 2. Literature Review on Growth and the 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. 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. (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 model), and positively related to the depreciation and population-growth rates. Another form of convergence is stochastic convergence (Bernard and Durlauf, 1996), which 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). Our use of deterministic trends that vary by state/region essentially rules out this type of convergence, while our allowing for structural change further complicates its use. [2]

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. The β term provides an estimate of the speed of *absolute* convergence. However, assuming all economies are approaching a common equilibrium is 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. Evans and Karras (1996) caution that steady-state income differentials across major U.S. regions can still affect 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.[3] In equation (1), this implies $\beta_0 + \beta \ln y_i^*$ varies across economies, which is accounted for by including control variables that affect the steady state including country/region fixed effects. (See Durlauf and Quah 1999 for examples of conditioning variables). Aside from these concerns, 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 (Barro and Sala-i-Martin 1991). Caselli and Coleman (2001) contend that a majority of the convergence among U.S. regions since the late 1800s is simple convergence of 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 effects.

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[2]Variants of equation (1) have been estimated by many approaches including non-linear least squares, cross-sectional techniques, pooled-OLS, panel techniques, and GMM, each with their advantages and disadvantages. There are well-known problems with the interpretation of the results from equation (1). One is that 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., Quah, 1993; Durlauf and Johnson, 1995; Bernard and Jones, 1996; Sala-i-Martin, 2002).

[3] 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. 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 that will be uncovered in this study, we utilize the more common cross-section approaches.

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) and Corrado et al. (2005) discover multiple 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.[4] Besides their close proximity that helps propagate common regional shocks, states within a region usually have similar industry mixes and are thus exposed to common industry shocks (Choi, 2004). 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 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).

Regional convergence/divergence patterns may change over time. For instance, Lee et al. (1997) show 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. Howitt and Mayer-Foulkes (2002) (hereafter, HMF) develop a Schumpeterian model with three regional groups that resembles core-periphery models in the new economic geography (Fujita et al., 1999). First are technologically-leading countries/regions with a high R&D and intellectual

[4]The eight regions used here are defined by the U.S. Bureau of Economic Analysis (BEA). Choi (2004) finds evidence that states in BEA regions are somewhat synchronized. Namely, 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), whereas Corrado et al. (2005) also find that geographic location is central in the formation of EU clubs. Along with major BEA regions, Phillips and Sul (2003) develop more complex algorithms to identify other regional groupings (also see Canova, 2004; Corrado et al., 2005), but we prefer regions as their contingency better allows for economic spillovers. Note that to the extent that there might be more perfect regional/club groupings than BEA regions, that would imply even stronger club results than what we uncover in section 4 below, which would strengthen our conclusions.

capacity. Possible examples could include growth centers such as Silicon Valley, the Puget Sound area around Seattle, and East-Coast financial-centers. 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 absorptive capacity to eventually implement best-practice technology. Examples may include the manufacturing belt. Finally, there are laggard regions without the capacity to implement the latest innovations. The 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. [5] 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.[6] Growth rates between the three groups may eventually converge, but the follower and especially the laggard find 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 region *i's* steady-state level of income. The error term $\varepsilon_{it}$ reflects regional deviations from the steady state, which

[5]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.

[6]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.

can be rather large if the initial conditions are far from the steady state, or if there is structural change.

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 stochastic-convergence hypothesis implies that regions may be diverging from the national average. CM only rejected the unit-root null when they imposed a structural break of 1946, but only for three regions. 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.[7]

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 log 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. Like CM, we assume there is a trend component in $x_{it}$ that shares the same break dates of the region, which differs from

[7]However, using panel unit-root tests, Choi (2004) finds that states were generally not stochastically converging to the national average, but finds more evidence that they were converging to their BEA regional average.

Lowey and Papell (1996) and Strazicich and Lee (2002), who allowed the breaks to differ by region.[8]

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

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

for $i = 1,\dots,N$ where $y_{it} \equiv x_{it} + x_{rt}$, the logarithmic difference between the state and national per-capita income, whereas $TB_{i,t} \equiv \sum_{k=1}^{l+1} (\alpha_{ik} + \beta_{ik} t) D_{kt}$ and $TB_{r,t} \equiv \sum_{k=1}^{l+1} (\alpha_{rk} + \beta_{rk} t) D_{kt}$ . 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., $\gamma_{ij}$ and $\delta_{rh}$). 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 the pairs $TB_{i,t}$ and $TB_{r,t}$, and $\varepsilon_{it}$ and $v_{rt}$ cannot be estimated simultaneously. Thus, in practice, we first estimate the system pooled across all states and regions:

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

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

To identify $TB_{i,t}$, one may estimate the restricted model:

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

in which it is assumed that $\alpha_{ik} = \beta_{ik} = 0$ for all *i.* Then one would compute the estimates of $\alpha_{ik}$ and $\beta_{ik}$ by taking the difference between $TB_{ir,t}$ and $TB_{r,t}$. However, the restrictions imposed in equation (8) defy our assumption that each state converges to the regional trend at different speeds. An alternative method to identify $TB_{r,t}$ is to use the equation-by-equation approach (or region by region approach) shown in (4).

[8]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. 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 related to WW II would be common across the nation, any ensuing regional structural changes would likely coincide with the nation. Another practical advantage of assuming a common structural change is that pooling the regions increases the efficiency of the break estimate.

While there are efficiency gains from pooling as in equation (8), the equation-by-equation approach ensures region-specific estimates for $TB_{r,t}$. In practice, both methods yield similar results.

While most convergence studies assume that there are no spatial spillovers between regions, this model allows for non-zero cross-equation correlation in the residuals along with the cross-equation restriction on the set of coefficients $\alpha_r$, $\beta_r$ and $\delta_{rh}$. 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 do not affect states in other regions. Thus, with $\varepsilon_{it}$ 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 $\eta_{irt}$ and $\eta_{jrt}$ $\forall i \neq j$ 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.[9]

## 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 Preliminary Analysis*

To demonstrate how our model extends the past literature, we conduct the following preliminary analyses.

#### *4.2.1 Variance Decomposition*

[9] 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 is:

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

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

We first examine trends in per-capita income variation across states, which is akin to σ-convergence. Panels A and B of Figure 2 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. Both panels 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 3 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, which 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.

#### *4.2.2 Updating Structural Changes in the Time Trends*

Before conducting the regression analysis, we first update the break dates from CM (1993) with an additional 12 years of data. The within- and between-region results reported in Section 4.2.1 suggest a structural change near the end of WWII as hypothesized by others. Yet, this evidence suggests another structural break 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. The trend that best fits the log of U.S. GDP has long been debated. 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 also utilize the Bai and Perron (2003) procedure to search for the structural breaks.

Our procedure sequentially searches for break points using the generalized model from equation (4) by pooling the eight BEA regions. Instead, we could determine the structural breaks using the club-model shown in equation (7) using all 49 states. However, this approach would not allow comparison to CM's benchmark results and it is more complex. Yet, assuming common-breaks in all eight regions does not strike us as constraining because if regions undergo structural change, so should their member states.

Given the assumption of $l$ structural changes, there are $l$+1 segments of different dynamics in the data to be captured by $\alpha_{rk}$ and $\beta_{rk}$. 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: $\ln[\det(\hat{\Omega})]$. There are 72 observations when the order of autoregression equals 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.

Table 1 reports the likelihood statistics and panels (a)-(d) in Appendix Figure A1 graph the significance level (the appendix is available upon request.) The point estimate of the first break is 1944, which is only two years from what was imposed by CM. There is also a statistically-significant second break point in 1982. A 1982 break is consistent with the pattern identified above for increasing within-region income variation and 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. The third and fourth break points are both insignificant. As a result, we will impose 1944 and 1982 break points in our model.

***4.2.3 Econometric Restrictions Compared to 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 modestly reduces 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., $\delta$ ) 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

[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.

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 variables or structural change.[11] As expected, allowing for more 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 Row 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 clear differences in our less-restrictive model. This large 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. Since the past literature has stressed the role of fixed effects or differential convergence rates, this finding regarding

[11] A general concern with convergence estimates is they are affected by a dynamic panel-model bias because the estimating equation has a lagged dependent variable (Forbes, 2000). This creates a well-known negative bias in fixed-effect equations that in effect increases the estimated convergence speed. The bias is severe in cases with only a few 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, with over 70 observations per region/state, this bias should be relatively inconsequential in our case.

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

### *4.3 Results from the Panel Model*

#### *4.3.1 Comparing Regional Autoregressive Estimates from Pooled and Equation-by-Equation Models*

The models in Table 2 could have both heterogeneity in the cross-regional rates of convergence to the nation as well as cross-sectional correlation of the state residuals. To assess these possible 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 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 states and regions into one model and utilizing FGLS by correcting for any within-region correlation of the residuals (equation 7). The results for $\delta_h$ 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 roughly equal to one minus the reported coefficient ($1-\gamma_{ij}$).

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 6 out of the 8 regions. However, the average coefficient on the lagged income term is roughly the same (0.601 in Model 2 versus 0.563 in Model 1) and the only cases that the autoregressive coefficients changed by more than 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. 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, with declines being much larger in most cases. This finding is encouraging from an econometric perspective, even though we note that it is preliminary. Various tests have long been suffering from lack of power to reject the null of unit root. So by using disaggregated data (e.g. state per capita income in a region) that are used to create the aggregate data (e.g. the regional per capita income) in a panel model, we are able to raise the number of observations and improve the efficiency of the autoregressive coefficient estimates.[12]

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 (not shown), suggesting BEA regions perform as clear functional economic regions.

***4.3.2 Individual State Autoregressive Coefficient Estimates***

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 ($\gamma_{ij}$) are equal to each other can be rejected at the 0.0001% level, while

[12] We stress that this model is not the same as a panel unit root model which has different specification and cross-equation restrictions. However, the possibility of applying a more powerful panel test to study income convergence and purchasing-power parity deserves more research attention. Whether a unit root test is viable and whether it may suffer from a size problem is an important issue.

[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 $\chi^2$. The p-values for all 8 LR statistics are close to zero (not shown).

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, Southeast, Southwest, and New England are 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. Thus, the evidence suggests the 8 regions form coherent growth clubs, although even in these regions, there are states that are decidedly following their own growth paths.

#### *4.3.3 State Trend Convergence to Region and Regional Trend Convergence to the Nation*

In this section, we summarize our results regarding the direction of time trends for each region and each state and interpret them in relations to income convergence and growth club. The predicted time paths for each state and region relative to the national average are projected in Figure 4 and 5. Their computation is based on the constant and the slope estimate for $TB_{r,t}$ (from CM's regression) and $TB_{ir,t}$ (from the panel,) which are reported in the Appendix Table A1. Note these reflect "trend" convergence patterns using the state/region time trends (i.e., the $\alpha$ and $\beta$ terms) and they are distinct from the state/region conditional convergence terms described above (i.e., not $\gamma$ and $\delta$ 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 equation-by-equation estimates from equation (4).

The pattern in Figure 4 agrees with that in CM (1993), that convergence speed appears to be faster in 1929-1943 and it slows down after that. 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 WWII.

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, our richer findings are 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.

In addition to presenting the results graphically, we also derive statistics based on the coefficient estimates. Two approaches are used. Trend convergence is evident when the constant term ($\alpha_r$ and $\alpha_i$) and the slope coefficient ($\beta_r$ and $\beta_i$) takes opposite sign. Thus, we first report the percentage of regions and percentage of states that are converging to the national level in Table 5. The results agree with our eye-balling analysis from Figure 4 and 5. The percentage of converging regions is roughly the same: 75% of the regions in 1929-1943 and 87% in 1944-2002. It is astonishing to find that a different pattern is observed for state trend convergence: the percentage falls from 86% in 1929-1943, to 80% in 1944-1981 and to 78% in 1982-2002 (see the second row.)

Our second approach makes use of the estimated end-point of the trend at the conclusion of each of the three periods—1943, 1981 and 2002. The closer the estimates are to zero, the closer a region/club is to the long-run equilibrium, while a declining standard deviation indicates *ongoing* convergence. Appendix Table A2 reports the estimates for each region and the mean and the standard deviations for these group estimates. We report only the latter two in Table 6. These results strengthen our earlier findings: a clear regional convergence pattern between 1943-1981, but there is slight divergence between 1981 and 2002. Table 6 also includes similar estimates for state time trend (to the national average.) Again, the estimates suggest a strong converging pattern by 1981, but they suggest divergence for the 1981-2002 period.

To examine if states are trend converging or trend diverging within their regions, Figure 6 shows the projected state paths relative to the regional average (i.e., the regional average is subtracted from the state path). The underlying statistics are summarized at the bottom of Table 6. Akin to the case in Figure 5, there is general within-region trend convergence prior to 1944. Likewise, within-region convergence slowed after 1944. In fact, as shown by the rising trend-standard deviations in Table 6, the Rocky Mountain region did not experience within-region convergence after 1944. Unlike the 1944 common shock, the common 1982 shock increased within-region dispersion. Relative to 1981, a general pattern for each region was greater divergence in 2002, except for the Far West. To be sure, if we had followed most of the literature and (1) not allowed for (sufficient) cross-regional 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-section distribution over time *ala* Quah (1993), Figures 4-6 reveal rich patterns of both convergence and divergence.

Using our "counting" approach, we find a strong-weak-strongest pattern of growth clubs in the three periods. The results are reported at the bottom of Table 5. The average percentage of converging time trend found in 1929-1943 is 58%. The average percentage for 1944-1981 is not much weaker. But the club pattern is the strongest after 1981. The only region that shows a weakening pattern over all three periods is the Plains. Thus, the pattern of club divergence between 1981 and 2002 shown in Figure 6 and Table 6 is more a result of the aggregate shock in 1982 than a long-run movement toward divergence after the 1982 shock. That is, after the 1982 shock, within-region convergence resumed. This rich pattern would not have been identified if we had not jointly considered structural breaks in a club environment.

## 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. The key novelties of our modeling approach are 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, we find a structural break in 1944 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, there was wider variation across regions and states throughout the 1982-2002 period than in 1981, suggesting the early 1980s structural change was striking in many dimensions, not just macroeconomic in scope. Yet, in terms of regional growth clubs, though the 1982 shock increased within-region club variation, the underlying fundamentals suggested that within-club patterns of convergence had reasserted themselves after the shock.

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 when clubs are not considered in the context of structural breaks. 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, the 1982 shock greatly altered the convergence process. Finally, there is evidence of within-region spillovers in the covariance of the state error terms. Yet, using FGLS did not greatly alter the results even as it did markedly improve efficiency.

In sum, our findings support Quah's (1993) contention that one should examine the whole cross section of growth paths to understand the underlying dynamics. 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 U.S. state data, they must certainly be prevalent in other settings, which warrants further research.

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**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.
4. In parentheses are the approximate conditional convergence rates (1-δ).

**Table 3: Region Autoregressive Coefficient Estimates—A Comparison**

| | Coefficient Estimates | | | | Difference in % |
|---|---|---|---|---|---|
| | Model 1 *Eq. by Eq. Estimates for (4)* | | Model 2 *FGLS Estimates for (7)* | | |
| | $\delta_1$ | $1-\delta_1$ | $\delta_1$ | $1-\delta_1$ | |
| 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** | 0.5567 (0.0551) | **0.4433** | +2.43 (-47.57) |
| South West | 0.7248 (0.0860) | **0.2752** | 0.7148 (0.0691) | **0.2852** | -1.39 (-19.62) |

Note: 1. The bolded numbers are the coefficients when specified in error correction form and represent the approximate region-to-nation conditional convergence rates. 2. Plains is the only region with the difference between the two estimates being significant at a 10% level.

**Table 4: State Autoregressive Coefficient Estimates**

| | Coefficient | Std. Dev. | | Coefficient | Std. Dev. | | Coefficient | Std. Dev. | | Coefficient | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Far West* | | | *Mid East* | | | *Plains* | | | *South East* | | |
| California | 0.6816 | 0.2218 | D.C. | 0.691 | 0.0628 | Iowa | 0.1156 | 0.0955 | Alabama | 0.8335 | 0.0632 |
| Nevada | 0.2463 | 0.1231 | Delaware | 0.5998 | 0.0991 | Kansas | 0.4361 | 0.0962 | Arkansas | 0.2309 | 0.0713 |
| Oregon | 0.7025 | 0.0735 | Maryland | 0.5654 | 0.0679 | Minnesota | 0.5743 | 0.0716 | Florida | 0.6171 | 0.0668 |
| Washington | 0.7225 | 0.0754 | New Jersey | 0.7588 | 0.087 | Missouri | 0.4263 | 0.0589 | Georgia | 0.6993 | 0.0733 |
| (*Wald: 11.7735; p-value: 0.0082*) | | | New York | 0.9031 | 0.1236 | Nebraska | 0.1621 | 0.1021 | Kentucky | 0.1584 | 0.072 |
| | | | Pennsylvania | 0.587 | 0.0738 | North Dakota | 0.1847 | 0.088 | Louisiana | 0.7353 | 0.0681 |
| *Great Lakes* | | | (*Wald: 11.2528; p-value: 0.0466*) | | | South Dakota | 0.1569 | 0.0705 | Mississippi | 0.3687 | 0.0652 |
| Illinois | 0.6519 | 0.0913 | | | | (*Wald: 26.3091; p-value: 0.0001*) | | | North Carolina | 0.5677 | 0.0817 |
| Indiana | 0.3072 | 0.108 | *New England* | | | | | | South Carolina | 0.6953 | 0.0700 |
| Michigan | 0.4030 | 0.1046 | Connecticut | 0.7871 | 0.0909 | *Rocky Mountains* | | | Tennessee | 0.4934 | 0.4934 |
| Ohio | 0.3459 | 0.0954 | Maine | 0.4967 | 0.0782 | Colorado | 0.3249 | 0.1066 | Virginia | 0.6270 | 0.0694 |
| Wisconsin | 0.4933 | 0.0983 | Massachusetts | 0.3756 | 0.1678 | Idaho | 0.0857 | 0.1257 | West Virginia | 0.7001 | 0.0624 |
| (*Wald: 6.9876; p-value: 0.1365*) | | | New Hampshire | 0.5843 | 0.0829 | Montana | 0.0213 | 0.1159 | (*Wald: 69.7796; p-value: 0.0000*) | | |
| | | | Rhode Island | 0.5272 | 0.1119 | Utah | 0.7797 | 0.092 | | | |
| | | | Vermont | 0.6271 | 0.0687 | Wyoming | 0.6804 | 0.0747 | *South West* | | |
| | | | (*Wald: 7.2779; p-value: 0.2008*) | | | (*Wald: 46.5780; p-value: 0.0000*) | | | 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. One minus the coefficient $\gamma_{ij}$ approximately equals the state to region club-convergence rate from equation (7).

**Table 5: Counts of Converging Time Trends**

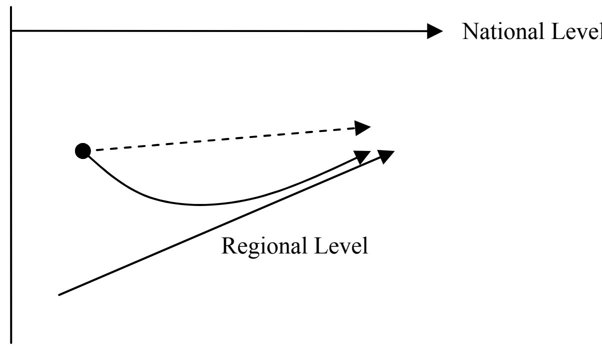
| | *1929-1943* | *1944-1981* | *1982-2002* |
|---|---|---|---|
| | % | % | % |
| Regions to National Average | *75* | *87* | *87* |
| States to National Average | *86* | *80* | *78* |
| States to Regional Average (within each club) | | | |
| Far West | 75 | 50 | 100 |
| Great Lakes | 20 | 100 | 80 |
| Mideast | 67 | 50 | 50 |
| New England | 50 | 50 | 50 |
| Plains | 71 | 57 | 43 |
| Rocky Mountains | 80 | 80 | 80 |
| Southeast | 50 | 8 | 83 |
| Southwest | 50 | 25 | 75 |
| ***Average*** | ***58*** | ***53*** | ***70*** |

**Table 6: Mean and Standard Deviation for End-Period Estimates of Time Trends**

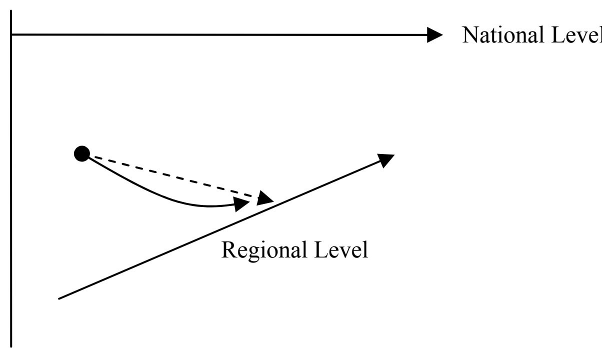
| | | *1943* | *1981* | *2002* |
|---|---|---|---|---|
| ***To National Average*** | | | | |
| Regional Trends | Mean | -0.0032 | -0.0016 | -0.0004 |
| (CM Approach) | Std. Dev. | 0.1073 | 0.0367 | 0.0384 |
| ***To National Average*** | | | | |
| State Trends | Mean | -0.0432 | -0.0278 | -0.0305 |
| | Std. Dev. | 0.1346 | 0.0590 | 0.0717 |
| ***To Regional Average*** | | | | |
| State Trends | | | | |
| Far West | Mean | 0.0103 | -0.0153 | -0.0072 |
| | Std. Dev. | 0.0451 | 0.0254 | 0.0162 |
| Great Lakes | Mean | -0.0227 | -0.0145 | -0.0140 |
| | Std. Dev. | 0.0549 | 0.0311 | 0.0320 |
| Mideast | Mean | 0.0278 | 0.0061 | -0.0082 |
| | Std. Dev. | 0.0509 | 0.0283 | 0.0669 |
| New England | Mean | -0.0519 | -0.0455 | -0.0630 |
| | Std. Dev. | 0.0730 | 0.0570 | 0.0807 |
| Plains | Mean | -0.0288 | -0.0333 | -0.0720 |
| | Std. Dev. | 0.0947 | 0.0625 | 0.1136 |
| Rocky Mountains | Mean | 0.0036 | -0.0234 | -0.0683 |
| | Std. Dev. | 0.0536 | 0.0588 | 0.1089 |
| Southeast | Mean | -0.0392 | -0.0308 | -0.0420 |
| | Std. Dev. | 0.1232 | 0.0603 | 0.0831 |
| Southwest | Mean | -0.0223 | -0.0167 | -0.0391 |
| | Std. Dev. | 0.0675 | 0.0228 | 0.0379 |

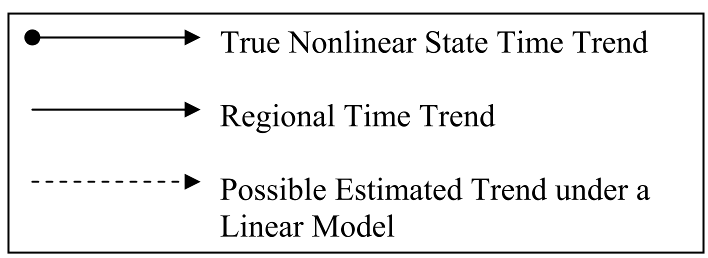
**Figure 1: Linear and Nonlinear State Time Trend**

**(a) Case of Slower Convergence Estimate**



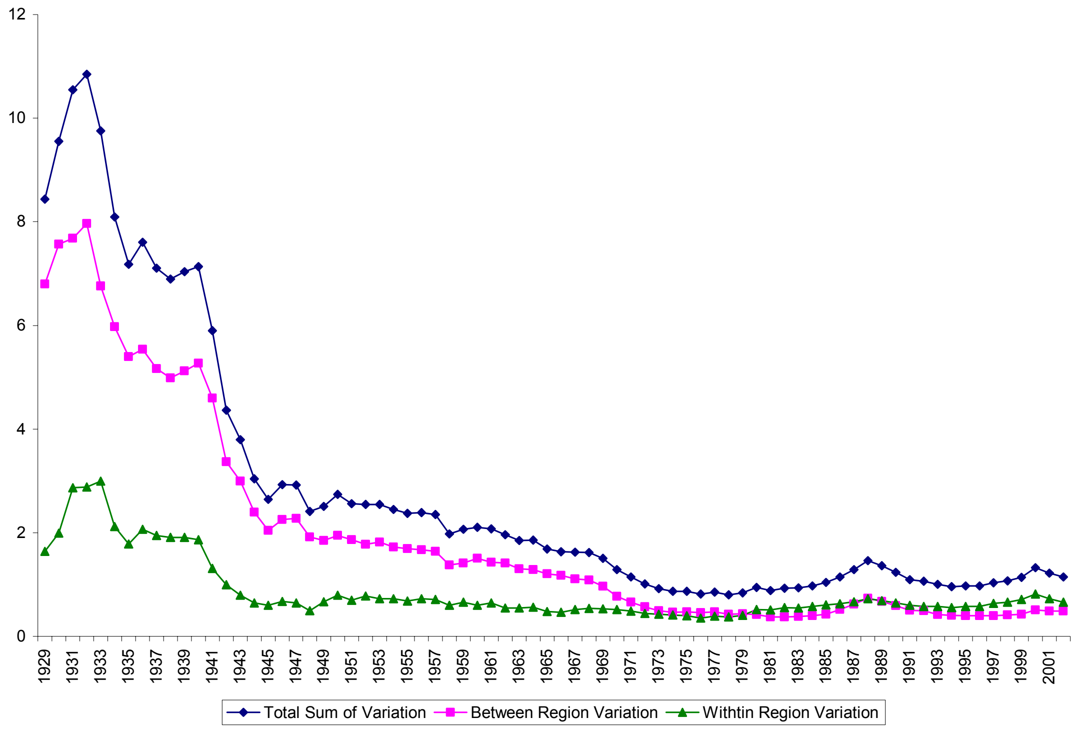

**(b) Case of Divergence Estimate**



# Figure 2: Variance Decomposition

## Panel A: 1929-2002




## Panel B: 1965-2002

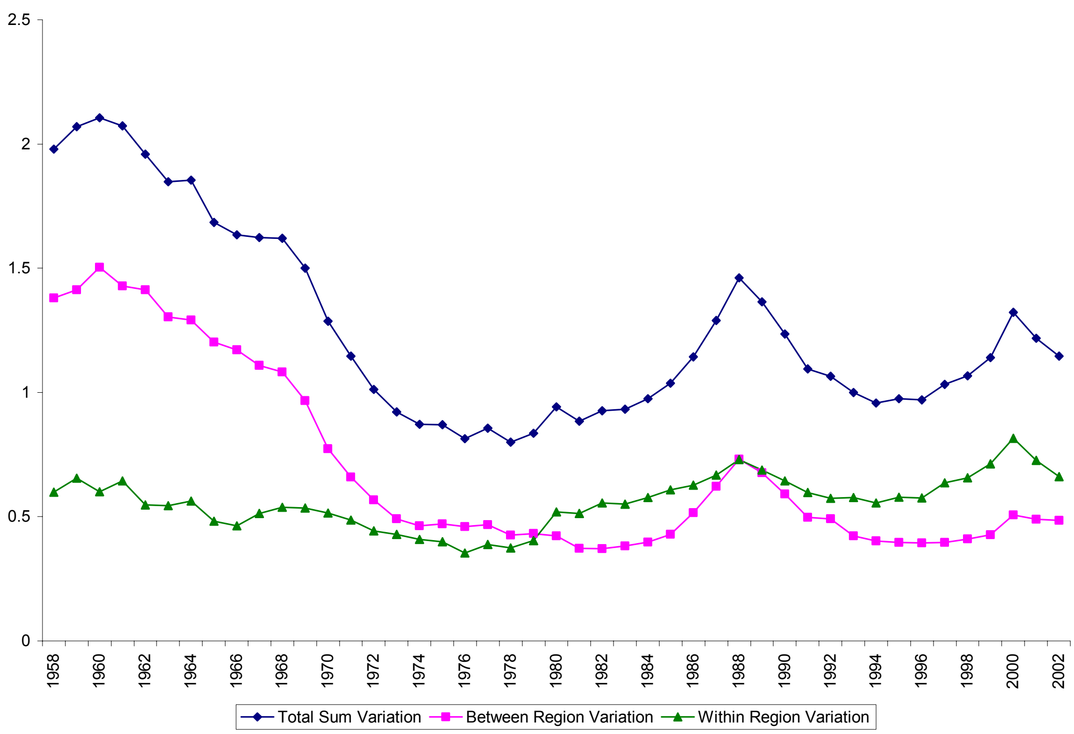


**Figure 3:**
**Share of Overall Variation that is Within and Between Regions**

**Figure 4: Regional Trend to the National Average**

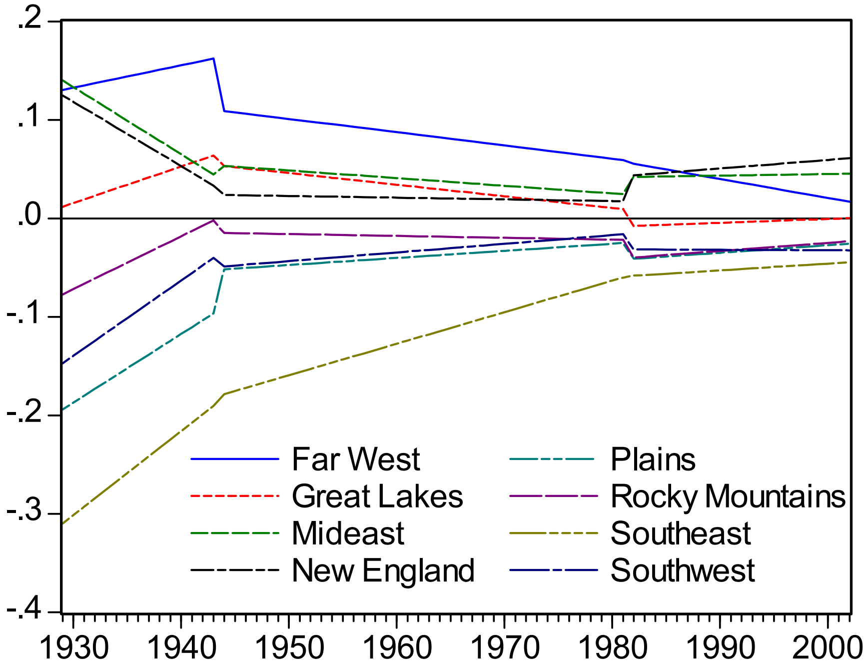
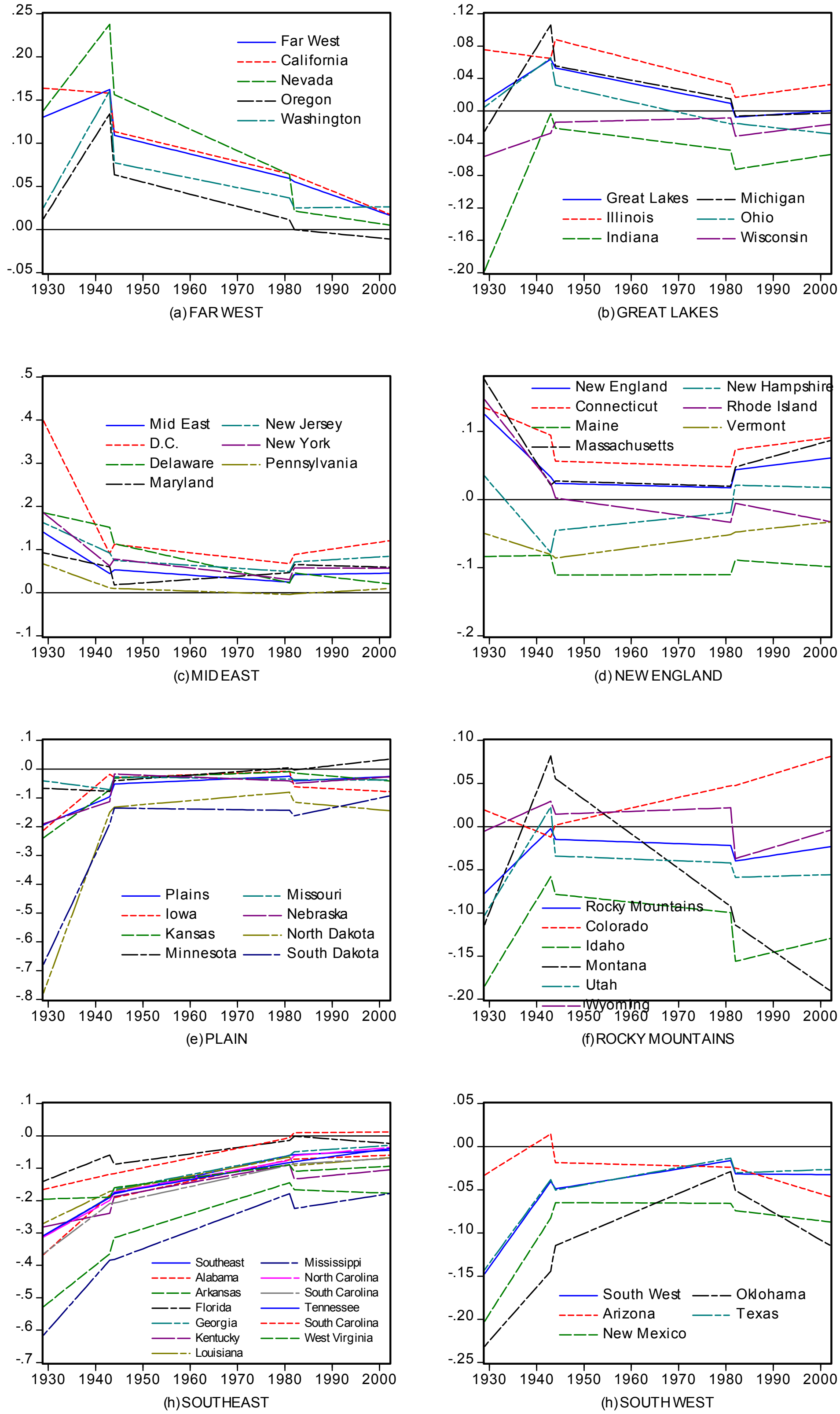
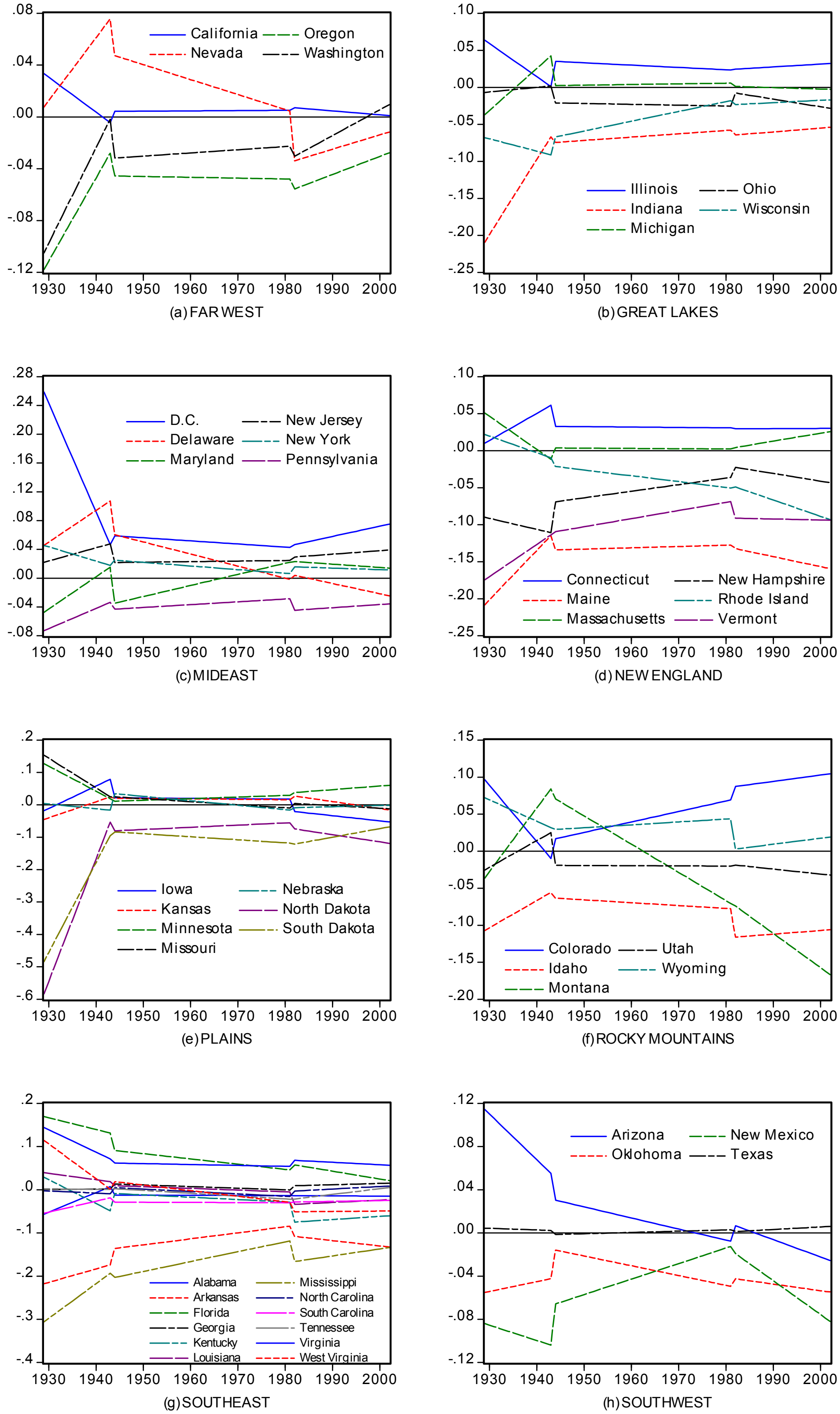


**Figure 5: State Trend to the National Average**



# Figure 6: State Trend Convergence to the Corresponding Region



**Appendix Table A1: Estimates for the State Trend Convergence to the National Average**

**(Not to be published)**

| | *1929-1943* | | *1944-1981* | | *1982-2002* | |
|---|---|---|---|---|---|---|
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Far West* | 0.1304 | 0.0023 | 0.1292 | -0.0013 | 0.1574 | -0.0019 |
| | (0.0229) | (0.0009) | (0.0256) | (0.0004) | (0.0432) | (0.0006) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| California | 0.1637 | -0.0004 | 0.1332 | -0.0013 | 0.1801 | -0.0022 |
| | (0.0336) | (0.0013) | (0.0254) | (0.0003) | (0.0507) | (0.0007) |
| Nevada | 0.1380 | 0.0071 | 0.1937 | -0.0025 | 0.0645 | -0.0008 |
| | (0.0326) | (0.0034) | (0.0340) | (0.0007) | (0.1077) | (0.0017) |
| Oregon | 0.0126 | 0.0087 | 0.0845 | -0.0014 | 0.0278 | -0.0005 |
| | (0.0347) | (0.0017) | (0.0271) | (0.0004) | (0.0686) | (0.0010) |
| Washington | 0.0255 | 0.0096 | 0.0937 | -0.0011 | 0.0213 | 0.0001 |
| | (0.0315) | (0.0015) | (0.0258) | (0.0004) | (0.0618) | (0.0009) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Great Lakes* | 0.0118 | 0.0037 | 0.0707 | -0.0012 | -0.0286 | 0.0004 |
| | (0.0098) | (0.0010) | (0.0151) | (0.0003) | (0.0332) | (0.0005) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| Illinois | 0.0753 | -0.0008 | 0.1104 | -0.0015 | -0.0248 | 0.0008 |
| | (0.0198) | (0.0013) | (0.0153) | (0.0003) | (0.0351) | (0.0006) |
| Indiana | -0.1976 | 0.0139 | -0.0106 | -0.0007 | -0.1208 | 0.0009 |
| | (0.0346) | (0.0020) | (0.0178) | (0.0003) | (0.0488) | (0.0007) |
| Michigan | -0.0252 | 0.0094 | 0.0717 | -0.0011 | -0.0168 | 0.0002 |
| | (0.0166) | (0.0020) | (0.0175) | (0.0004) | (0.0631) | (0.0010) |
| Ohio | 0.0048 | 0.0043 | 0.0512 | -0.0013 | 0.0187 | -0.0006 |
| | (0.0093) | (0.0010) | (0.0120) | (0.0003) | (0.0343) | (0.0005) |
| Wisconsin | -0.0563 | 0.0021 | -0.0162 | 0.0001 | -0.0690 | 0.0007 |
| | (0.0160) | (0.0010) | (0.0194) | (0.0003) | (0.0350) | (0.0006) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Mideast* | 0.1399 | -0.0068 | 0.0648 | -0.0008 | 0.0332 | 0.0002 |
| | (0.0303) | (0.0011) | (0.0166) | (0.0002) | (0.0244) | (0.0004) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| D.C. | 0.3982 | -0.0219 | 0.1300 | -0.0012 | 0.0045 | 0.0016 |
| | (0.0440) | (0.0025) | (0.0248) | (0.0005) | (0.0795) | (0.0013) |
| Delaware | 0.1855 | -0.0024 | 0.1502 | -0.0025 | 0.1124 | -0.0013 |
| | (0.0319) | (0.0030) | (0.0281) | (0.0006) | (0.0786) | (0.0013) |
| Maryland | 0.0925 | -0.0023 | 0.0069 | 0.0008 | 0.0805 | -0.0003 |
| | (0.0301) | (0.0015) | (0.0182) | (0.0003) | (0.0359) | (0.0006) |
| New Jersey | 0.1618 | -0.0050 | 0.0853 | -0.0007 | 0.0369 | 0.0006 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0271) | (0.0013) | (0.0161) | (0.0003) | (0.0331) | (0.0005) |
| New York | 0.1853 | -0.0088 | 0.0973 | -0.0013 | 0.0602 | 0.0000 |
| | (0.0316) | (0.0015) | (0.0186) | (0.0003) | (0.0361) | (0.0006) |
| Pennsylvania | 0.0668 | -0.0040 | 0.0158 | -0.0004 | -0.0347 | 0.0006 |
| | (0.0239) | (0.0009) | (0.0141) | (0.0002) | (0.0246) | (0.0004) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *New England* | 0.1247 | -0.0065 | 0.0263 | -0.0002 | -0.0022 | 0.0009 |
| | (0.0220) | (0.0011) | (0.0109) | (0.0002) | (0.0355) | (0.0006) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| Connecticut | 0.1348 | -0.0029 | 0.0597 | -0.0002 | 0.0258 | 0.0009 |
| | (0.0222) | (0.0016) | (0.0227) | (0.0003) | (0.0479) | (0.0008) |
| Maine | -0.0836 | 0.0001 | -0.1106 | 0.0000 | -0.0631 | -0.0005 |
| | (0.0338) | (0.0016) | (0.0220) | (0.0003) | (0.0535) | (0.0009) |
| Massachusetts | 0.1755 | -0.0110 | 0.0303 | -0.0002 | -0.0547 | 0.0019 |
| | (0.0216) | (0.0015) | (0.0109) | (0.0003) | (0.0433) | (0.0007) |
| Maine | 0.0346 | -0.0080 | -0.0562 | 0.0007 | 0.0302 | -0.0002 |
| | (0.0268) | (0.0012) | (0.0223) | (0.0004) | (0.0417) | (0.0007) |
| Rhode Island | 0.1465 | -0.0088 | 0.0166 | -0.0010 | 0.0658 | -0.0013 |
| | (0.0209) | (0.0016) | (0.0138) | (0.0004) | (0.0569) | (0.0010) |
| Vermont | -0.0498 | -0.0022 | -0.0997 | 0.0009 | -0.0864 | 0.0007 |
| | (0.0313) | (0.0012) | (0.0262) | (0.0003) | (0.0427) | (0.0007) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Plains* | -0.1940 | 0.0070 | -0.0626 | 0.0007 | -0.0815 | 0.0008 |
| | (0.0332) | (0.0020) | (0.0189) | (0.0004) | (0.0659) | (0.0010) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| Iowa | -0.2123 | 0.0139 | -0.0392 | 0.0006 | -0.0181 | -0.0008 |
| | (0.0348) | (0.0037) | (0.0290) | (0.0008) | (0.1251) | (0.0020) |
| Kansas | -0.2390 | 0.0119 | -0.0404 | 0.0006 | 0.0584 | -0.0014 |
| | (0.0277) | (0.0025) | (0.0205) | (0.0006) | (0.0885) | (0.0014) |
| Minnesota | -0.0668 | -0.0008 | -0.0587 | 0.0012 | -0.1025 | 0.0019 |
| | (0.0201) | (0.0017) | (0.0148) | (0.0004) | (0.0576) | (0.0009) |
| Missouri | -0.0410 | -0.0022 | -0.0238 | -0.0002 | -0.0333 | -0.0001 |
| | (0.0124) | (0.0009) | (0.0079) | (0.0002) | (0.0281) | (0.0004) |
| Nebraska | -0.1900 | 0.0055 | -0.0078 | -0.0006 | -0.1092 | 0.0011 |
| | (0.0327) | (0.0036) | (0.0283) | (0.0008) | (0.1198) | (0.0019) |
| North Dakota | -0.7776 | 0.0448 | -0.1531 | 0.0014 | -0.0386 | -0.0015 |
| | (0.0830) | (0.0070) | (0.0519) | (0.0014) | (0.2214) | (0.0035) |
| South Dakota | -0.6781 | 0.0347 | -0.1323 | -0.0002 | -0.3441 | 0.0034 |
| | (0.0683) | (0.0063) | (0.0484) | (0.0013) | (0.2083) | (0.0033) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Rocky Mountains* | -0.0772 | 0.0054 | -0.0119 | -0.0002 | -0.0836 | 0.0008 |
| | (0.0236) | (0.0019) | (0.0131) | (0.0004) | (0.0572) | (0.0009) |

| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
|---|---|---|---|---|---|---|
| Colorado | 0.0192 | -0.0022 | -0.0164 | 0.0012 | -0.0416 | 0.0017 |
| | (0.0251) | (0.0021) | (0.0146) | (0.0005) | (0.0629) | (0.0010) |
| Idaho | -0.1844 | 0.0090 | -0.0698 | -0.0006 | -0.2259 | 0.0013 |
| | (0.0410) | (0.0039) | (0.0311) | (0.0009) | (0.1331) | (0.0021) |
| Montana | -0.1135 | 0.0140 | 0.1156 | -0.0040 | 0.0873 | -0.0038 |
| | (0.0305) | (0.0032) | (0.0274) | (0.0008) | (0.1024) | (0.0017) |
| Utah | -0.1026 | 0.0090 | -0.0308 | -0.0002 | -0.0670 | 0.0002 |
| | (0.0285) | (0.0026) | (0.0196) | (0.0006) | (0.0856) | (0.0013) |
| Wyoming | -0.0052 | 0.0025 | 0.0114 | 0.0002 | -0.1236 | 0.0016 |
| | (0.0270) | (0.0022) | (0.0171) | (0.0005) | (0.0745) | (0.0012) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Southeast* | -0.3098 | 0.0085 | -0.2266 | 0.0032 | -0.0946 | 0.0007 |
| | (0.0720) | (0.0018) | (0.0552) | (0.0008) | (0.0440) | (0.0006) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| Alabama | -0.3665 | 0.0131 | -0.2385 | 0.0032 | -0.1049 | 0.0006 |
| | (0.0422) | (0.0018) | (0.0326) | (0.0005) | (0.0599) | (0.0009) |
| Arkansas | -0.5274 | 0.0116 | -0.3835 | 0.0046 | -0.1383 | -0.0005 |
| | (0.0465) | (0.0021) | (0.0377) | (0.0006) | (0.0684) | (0.0011) |
| Florida | -0.1402 | 0.0058 | -0.1177 | 0.0020 | 0.0586 | -0.0011 |
| | (0.0437) | (0.0016) | (0.0349) | (0.0005) | (0.0554) | (0.0008) |
| Georgia | -0.3092 | 0.0086 | -0.2078 | 0.0028 | -0.1009 | 0.0010 |
| | (0.0390) | (0.0015) | (0.0303) | (0.0005) | (0.0464) | (0.0007) |
| Kentucky | -0.2810 | 0.0030 | -0.2271 | 0.0027 | -0.2083 | 0.0014 |
| | (0.0380) | (0.0017) | (0.0309) | (0.0005) | (0.0488) | (0.0007) |
| Louisiana | -0.2703 | 0.0070 | -0.2114 | 0.0028 | -0.1566 | 0.0012 |
| | (0.0407) | (0.0019) | (0.0319) | (0.0006) | (0.0625) | (0.0010) |
| Mississippi | -0.6158 | 0.0166 | -0.4640 | 0.0055 | -0.3466 | 0.0023 |
| | (0.0534) | (0.0028) | (0.0455) | (0.0008) | (0.0975) | (0.0015) |
| North Carolina | -0.3123 | 0.0080 | -0.2136 | 0.0026 | -0.1285 | 0.0013 |
| | (0.0411) | (0.0019) | (0.0315) | (0.0005) | (0.0614) | (0.0009) |
| South Carolina | -0.3642 | 0.0111 | -0.2549 | 0.0032 | -0.1324 | 0.0009 |
| | (0.0468) | (0.0022) | (0.0333) | (0.0006) | (0.0614) | (0.0009) |
| Tennessee | -0.3077 | 0.0084 | -0.2143 | 0.0025 | -0.1865 | 0.0020 |
| | (0.0395) | (0.0017) | (0.0308) | (0.0005) | (0.0569) | (0.0009) |
| Virginia | -0.1657 | 0.0033 | -0.1617 | 0.0030 | 0.0037 | 0.0001 |
| | (0.0386) | (0.0017) | (0.0300) | (0.0005) | (0.0528) | (0.0008) |
| West Virginia | -0.1956 | 0.0005 | -0.1887 | 0.0019 | -0.1509 | 0.0008 |
| | (0.0417) | (0.0018) | (0.0311) | (0.0006) | (0.0550) | (0.0009) |
| | $\alpha_{r1}$ | $\beta_{r1}$ | $\alpha_{r2}$ | $\beta_{r2}$ | $\alpha_{r3}$ | $\beta_{r3}$ |
| *Southwest* | -0.1471 | 0.0076 | -0.0620 | 0.0009 | -0.0291 | 0.0000 |
| | (0.0413) | (0.0017) | (0.0217) | (0.0004) | (0.0491) | (0.0008) |
| | $\alpha_{ir1}$ | $\beta_{ir1}$ | $\alpha_{ir2}$ | $\beta_{ir2}$ | $\alpha_{ir3}$ | $\beta_{ir3}$ |
| Arizona | -0.0328 | 0.0034 | -0.0163 | -0.0001 | 0.0628 | -0.0017 |
| | (0.0397) | (0.0019) | (0.0221) | (0.0005) | (0.0603) | (0.0010) |
| New Mexico | -0.2023 | 0.0085 | -0.0644 | 0.0000 | -0.0390 | -0.0007 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.0377) | (0.0017) | (0.0198) | (0.0004) | (0.0507) | (0.0008) |
| Oklahoma | -0.2312 | 0.0062 | -0.1493 | (0.0023 | 0.1179 | -0.0032 |
| | (0.0380) | (0.0021) | (0.0276) | (0.0005) | (0.0733) | (0.0012) |
| Texas | -0.1427 | 0.0075 | -0.0652 | 0.0010 | -0.0405 | 0.0002 |
| | (0.0357) | (0.0016) | (0.0209) | (0.0004) | (0.0519) | (0.0009) |

**Appendix Table A2: End-Period Estimates for Relative Regional Time Trends**

**(Not to be published)**

| | $\hat{TB}_{r,1943}$ | $\hat{TB}_{r,1981}$ | $\hat{TB}_{r,2002}$ |
|---|---|---|---|
| Far West | 0.1622 | 0.0592 | 0.0169 |
| Great Lakes | 0.0637 | 0.0092 | 0.0001 |
| Mideast | 0.0445 | 0.0245 | 0.0453 |
| New England | 0.0332 | 0.0174 | 0.0610 |
| Plains | -0.0965 | -0.0251 | -0.0258 |
| Rocky Mountains | -0.0021 | -0.0218 | -0.0233 |
| Southeast | -0.1904 | -0.0601 | -0.0447 |
| Southwest | -0.0403 | -0.0162 | -0.0325 |
| Mean | -0.0032 | -0.0016 | -0.0004 |
| Standard Deviation | 0.1073 | 0.0367 | 0.0384 |

**Appendix Table A3: End-Period Estimates for Relative State-to-Nation Time Trends**

**(Not to be published)**

| | $\hat{TB}_{ir,1943}$ | $\hat{TB}_{ir,1981}$ | $\hat{TB}_{ir,2002}$ |
|---|---|---|---|
| *Far West* | | | |
| California | 0.1578 | 0.0643 | 0.0179 |
| Nevada | 0.2377 | 0.0637 | 0.0053 |
| Oregon | 0.1341 | 0.0112 | -0.0108 |
| Washington | 0.1604 | 0.0365 | 0.0264 |
| | | | |
| *Great Lakes* | | | |
| Illinois | 0.0647 | 0.0326 | 0.0323 |
| Indiana | -0.0034 | -0.0487 | -0.0540 |
| Michigan | 0.1062 | 0.0149 | -0.0027 |
| Ohio | 0.0654 | -0.0162 | -0.0284 |
| Wisconsin | -0.0275 | -0.0088 | -0.0169 |
| | | | |
| *Mideast* | | | |
| D.C. | 0.0911 | 0.0671 | 0.1203 |
| Delaware | 0.1517 | 0.0226 | 0.0207 |
| Maryland | 0.0597 | 0.0465 | 0.0591 |
| New Jersey | 0.0920 | 0.0490 | 0.0843 |
| New York | 0.0621 | 0.0306 | 0.0566 |
| Pennsylvania | 0.0108 | -0.0042 | 0.0095 |
| | | | |
| *New England* | | | |
| Connecticut | 0.0943 | 0.0481 | 0.0909 |
| Maine | -0.0818 | -0.1103 | -0.0986 |
| Massachusetts | 0.0214 | 0.0196 | 0.0866 |
| Maine | -0.0778 | -0.0189 | 0.0176 |
| Rhode Island | 0.0234 | -0.0333 | -0.0323 |
| Vermont | -0.0806 | -0.0515 | -0.0330 |
| | | | |
| *Plains* | | | |
| Iowa | -0.0177 | -0.0075 | -0.0784 |
| Kansas | -0.0722 | -0.0095 | -0.0415 |
| Minnesota | -0.0776 | 0.0042 | 0.0344 |
| Missouri | -0.0715 | -0.0352 | -0.0381 |
| Nebraska | -0.1129 | -0.0414 | -0.0273 |
| South Dakota | -0.1503 | -0.0803 | -0.1447 |
| North Dakota | -0.1918 | -0.1435 | -0.0938 |
| | | | |
| *Rocky Mountains* | | | |
| Colorado | -0.0121 | 0.0473 | 0.0812 |
| Idaho | -0.0580 | -0.0996 | -0.1296 |
| Montana | 0.0820 | -0.0926 | -0.1901 |
| Utah | 0.0229 | -0.0420 | -0.0556 |
| Wyoming | 0.0294 | 0.0218 | -0.0043 |

| | | | |
|---|---|---|---|
| *Southeast* | | | |
| Alabama | -0.1831 | -0.0736 | -0.0596 |
| Arkansas | -0.3646 | -0.1447 | -0.1773 |
| Florida | -0.0592 | -0.0143 | -0.0237 |
| Georgia | -0.1886 | -0.0607 | -0.0296 |
| Kentucky | -0.2391 | -0.0889 | -0.1051 |
| Louisiana | -0.1717 | -0.0652 | -0.0678 |
| Mississippi | -0.3839 | -0.1785 | -0.1786 |
| North Carolina | -0.1997 | -0.0758 | -0.0361 |
| South Carolina | -0.2093 | -0.0901 | -0.0695 |
| Tennessee | -0.1900 | -0.0821 | -0.0396 |
| Virginia | -0.1190 | -0.0061 | 0.0120 |
| West Virginia | -0.1892 | -0.0895 | -0.0939 |
| *Southwest* | | | |
| Arizona | 0.0148 | -0.0239 | -0.0580 |
| New Mexico | -0.0826 | -0.0657 | -0.0873 |
| Oklahoma | -0.1442 | -0.0288 | -0.1144 |
| Texas | -0.0380 | -0.0133 | -0.0265 |
| Mean | -0.0432 | -0.0278 | -0.0305 |
| Standard Deviation | 0.1346 | 0.0590 | 0.0717 |

**Appendix Table A4: Estimates for the State Trend Convergence to the Regional Average**

**(Not to be published)**

| | $\alpha_{r1}-\alpha_{ir1}$ | $\beta_{r1}-\beta_{ir1}$ | $\alpha_{r2}-\alpha_{ir2}$ | $\beta_{r2}-\beta_{ir2}$ | $\alpha_{r3}-\alpha_{ir3}$ | $\beta_{r3}-\beta_{ir3}$ |
|---|---|---|---|---|---|---|
| *Far West* | | | | | | |
| California | 0.0333 | -0.0027 | 0.0040 | 0.0000 | 0.0228 | -0.0003 |
| Nevada | 0.0076 | 0.0049 | 0.0645 | -0.0012 | -0.0929 | 0.0011 |
| Oregon | -0.1178 | 0.0064 | -0.0446 | -0.0001 | -0.1296 | 0.0014 |
| Washington | -0.1050 | 0.0074 | -0.0355 | 0.0002 | -0.1361 | 0.0020 |
| *Great Lakes* | | | | | | |
| Illinois | 0.0636 | -0.0045 | 0.0397 | -0.0003 | 0.0038 | 0.0004 |
| Indiana | -0.2093 | 0.0102 | -0.0813 | 0.0004 | -0.0922 | 0.0005 |
| Michigan | -0.0370 | 0.0057 | 0.0010 | 0.0001 | 0.0118 | -0.0002 |
| Ohio | -0.0069 | 0.0006 | -0.0194 | -0.0001 | 0.0473 | -0.0010 |
| Wisconsin | -0.0680 | -0.0017 | -0.0869 | 0.0013 | -0.0405 | 0.0003 |
| *Mid East* | | | | | | |
| D.C. | 0.2583 | -0.0151 | 0.0652 | -0.0004 | -0.0287 | 0.0014 |
| Delaware | 0.0456 | 0.0044 | 0.0853 | -0.0017 | 0.0791 | -0.0014 |
| Maryland | -0.0474 | 0.0045 | -0.0580 | 0.0015 | 0.0472 | -0.0005 |
| New Jersey | 0.0219 | 0.0018 | 0.0205 | 0.0001 | 0.0037 | 0.0005 |
| New York | 0.1412 | -0.0113 | 0.0726 | -0.0018 | -0.0193 | -0.0013 |
| Pennsylvania | -0.0731 | 0.0028 | -0.0490 | 0.0004 | -0.0680 | 0.0004 |
| *New England* | | | | | | |
| Connecticut | 0.0101 | 0.0036 | 0.0334 | -0.0001 | 0.0280 | 0.0000 |
| Maine | -0.2083 | 0.0067 | -0.1368 | 0.0002 | -0.0609 | -0.0014 |
| Massachusetts | 0.0508 | -0.0045 | 0.0040 | 0.0000 | -0.0525 | 0.0011 |
| Maine | -0.0901 | -0.0015 | -0.0825 | 0.0009 | 0.0324 | -0.0010 |
| Rhode Island | 0.1243 | -0.0104 | -0.0060 | -0.0013 | 0.0178 | -0.0021 |
| Vermont | -0.1745 | 0.0043 | -0.1260 | 0.0011 | -0.0842 | -0.0001 |
| *Plains* | | | | | | |
| Iowa | -0.0183 | 0.0069 | 0.0235 | -0.0001 | 0.0634 | -0.0016 |
| Kansas | -0.0450 | 0.0050 | 0.0222 | -0.0001 | 0.1400 | -0.0021 |
| Minnesota | 0.1271 | -0.0077 | 0.0040 | 0.0005 | -0.0209 | 0.0011 |
| Missouri | 0.1530 | -0.0091 | 0.0388 | -0.0009 | 0.0482 | -0.0008 |
| Nebraska | -0.2248 | 0.0018 | -0.0368 | -0.0015 | -0.2343 | -0.0009 |
| South Dakota | -0.5837 | 0.0378 | -0.0905 | 0.0007 | 0.0429 | -0.0022 |
| North Dakota | -0.4841 | 0.0278 | -0.0696 | -0.0009 | -0.2626 | 0.0027 |
| *Rocky Mountains* | | | | | | |
| Colorado | 0.0963 | -0.0076 | -0.0045 | 0.0014 | 0.0420 | 0.0009 |
| Idaho | -0.1072 | 0.0037 | -0.0578 | -0.0004 | -0.1423 | 0.0005 |
| Montana | -0.0363 | 0.0086 | 0.1275 | -0.0038 | 0.1709 | -0.0046 |
| Utah | -0.0254 | 0.0036 | -0.0189 | 0.0000 | 0.0166 | -0.0007 |
| Wyoming | -0.0302 | 0.0004 | -0.0032 | -0.0003 | -0.1865 | 0.0006 |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Southeast* | | | | | | |
| Alabama | -0.0567 | 0.0046 | -0.0120 | 0.0000 | -0.0103 | -0.0001 |
| Arkansas | -0.2176 | 0.0031 | -0.1569 | 0.0014 | -0.0437 | -0.0012 |
| Florida | 0.1696 | -0.0027 | 0.1089 | -0.0012 | 0.1532 | -0.0018 |
| Georgia | 0.0007 | 0.0001 | 0.0188 | -0.0004 | -0.0063 | 0.0003 |
| Kentucky | -0.3232 | 0.0011 | -0.2598 | 0.0021 | -0.2682 | 0.0005 |
| Louisiana | 0.0395 | -0.0015 | 0.0152 | -0.0004 | -0.0620 | 0.0005 |
| Mississippi | -0.3060 | 0.0080 | -0.2374 | 0.0023 | -0.2520 | 0.0016 |
| North Carolina | -0.0025 | -0.0005 | 0.0130 | -0.0006 | -0.0339 | 0.0006 |
| South Carolina | -0.0544 | 0.0025 | -0.0283 | 0.0000 | -0.0378 | 0.0002 |
| Tennessee | 0.0021 | -0.0001 | 0.0123 | -0.0007 | -0.0918 | 0.0013 |
| Virginia | 0.1441 | -0.0052 | 0.0649 | -0.0002 | 0.0983 | -0.0006 |
| West Virginia | 0.1142 | -0.0081 | 0.0379 | -0.0013 | -0.0563 | 0.0001 |
| | | | | | | |
| *Southwest* | | | | | | |
| Arizona | 0.1144 | -0.0042 | 0.0457 | -0.0010 | 0.0919 | -0.0016 |
| New Mexico | -0.0551 | 0.0009 | -0.0023 | -0.0009 | -0.0099 | -0.0006 |
| Oklahoma | -0.0841 | -0.0014 | -0.0873 | 0.0014 | 0.1471 | -0.0031 |
| Texas | 0.0044 | -0.0002 | -0.0032 | 0.0001 | -0.0114 | 0.0002 |

**Appendix Table A5: End-Period Estimates for Relative State-to-Region Time Trends**

| | $\hat{TB}_{r,1943} - \hat{TB}_{ir,1943}$ | $\hat{TB}_{r,1981} - \hat{TB}_{ir,1981}$ | $\hat{TB}_{r,2002} - \hat{TB}_{ir,2002}$ |
|---|---|---|---|
| *Far West* | | | |
| California | -0.0044 | 0.0051 | 0.0010 |
| Nevada | 0.0755 | 0.0045 | -0.0116 |
| Oregon | -0.0281 | -0.0480 | -0.0277 |
| Washington | -0.0018 | -0.0227 | 0.0095 |
| *Mean* | 0.0103 | -0.0153 | -0.0072 |
| *Standard Deviation* | 0.0451 | 0.0254 | 0.0162 |
| | | | |
| *Great Lakes* | | | |
| Illinois | 0.0009 | 0.0234 | 0.0322 |
| Indiana | -0.0671 | -0.0580 | -0.0541 |
| Michigan | 0.0425 | 0.0056 | -0.0028 |
| Ohio | 0.0017 | -0.0255 | -0.0285 |
| Wisconsin | -0.0913 | -0.0180 | -0.0170 |
| *Mean* | *-0.0227* | *-0.0145* | *-0.0140* |
| *Standard Deviation* | *0.0549* | *0.0311* | *0.0320* |
| | | | |
| *Mideast* | | | |
| D.C. | 0.0466 | 0.0426 | 0.0750 |
| Delaware | 0.1072 | -0.0018 | -0.0246 |
| Maryland | 0.0152 | 0.0220 | 0.0138 |
| New Jersey | 0.0475 | 0.0245 | 0.0390 |
| New York | -0.0164 | -0.0223 | -0.1164 |
| Pennsylvania | -0.0336 | -0.0287 | -0.0358 |
| *Mean* | *0.0278* | *0.0061* | *-0.0082* |
| *Standard Deviation* | *0.0509* | *0.0283* | *0.0669* |
| | | | |
| *New England* | | | |
| Connecticut | 0.0611 | 0.0307 | 0.0300 |
| Maine | -0.1150 | -0.1277 | -0.1596 |
| Massachusetts | -0.0118 | 0.0022 | 0.0256 |
| New Hampshire | -0.1110 | -0.0363 | -0.0434 |
| Rhode Island | -0.0207 | -0.0733 | -0.1365 |
| Vermont | -0.1138 | -0.0688 | -0.0940 |
| *Mean* | *-0.0519* | *-0.0455* | *-0.0630* |
| *Standard Deviation* | *0.0730* | *0.0570* | *0.0807* |
| | | | |
| *Plains* | | | |
| Iowa | 0.0789 | 0.0176 | -0.0526 |
| Kansas | 0.0243 | 0.0157 | -0.0156 |
| Minnesota | 0.0189 | 0.0294 | 0.0603 |
| Missouri | 0.0250 | -0.0100 | -0.0123 |
| Nebraska | -0.1996 | -0.1126 | -0.2971 |
| North Dakota | -0.0538 | -0.0552 | -0.1188 |
| South Dakota | -0.0952 | -0.1183 | -0.0680 |
| *Mean* | *-0.0288* | *-0.0333* | *-0.0720* |
| *Standard Deviation* | *0.0947* | *0.0625* | *0.1136* |

| | | | |
|---|---|---|---|
| *Rocky Mountains* | | | |
| Colorado | -0.0099 | 0.0691 | 0.1044 |
| Idaho | -0.0558 | -0.0778 | -0.1063 |
| Montana | 0.0841 | -0.0708 | -0.1668 |
| Utah | 0.0251 | -0.0202 | -0.0323 |
| Wyoming | -0.0253 | -0.0174 | -0.1403 |
| *Mean* | *0.0036* | *-0.0234* | *-0.0683* |
| *Standard Deviation* | *0.0536* | *0.0588* | *0.1089* |
| | | | |
| *Southeast* | | | |
| Alabama | 0.0073 | -0.0135 | -0.0149 |
| Arkansas | -0.1741 | -0.0846 | -0.1326 |
| Florida | 0.1313 | 0.0458 | 0.0211 |
| Georgia | 0.0018 | -0.0006 | 0.0151 |
| Kentucky | -0.3072 | -0.1500 | -0.2319 |
| Louisiana | 0.0187 | -0.0051 | -0.0230 |
| Mississippi | -0.1935 | -0.1184 | -0.1339 |
| North Carolina | -0.0092 | -0.0157 | 0.0086 |
| South Carolina | -0.0189 | -0.0300 | -0.0248 |
| Tennessee | 0.0004 | -0.0220 | 0.0051 |
| Virginia | 0.0715 | 0.0540 | 0.0567 |
| West Virginia | 0.0012 | -0.0294 | -0.0492 |
| *Mean* | *-0.0392* | *-0.0308* | *-0.0420* |
| *Standard Deviation* | *0.1232* | *0.0603* | *0.0831* |
| | | | |
| *Southwest* | | | |
| Arizona | 0.0551 | -0.0077 | -0.0255 |
| Oklahoma | -0.0424 | -0.0495 | -0.0549 |
| New Mexico | -0.1040 | -0.0126 | -0.0820 |
| Texas | 0.0022 | 0.0029 | 0.0060 |
| *Mean* | *-0.0223* | *-0.0167* | *-0.0391* |
| *Standard Deviation* | *0.0675* | *0.0228* | *0.0379* |

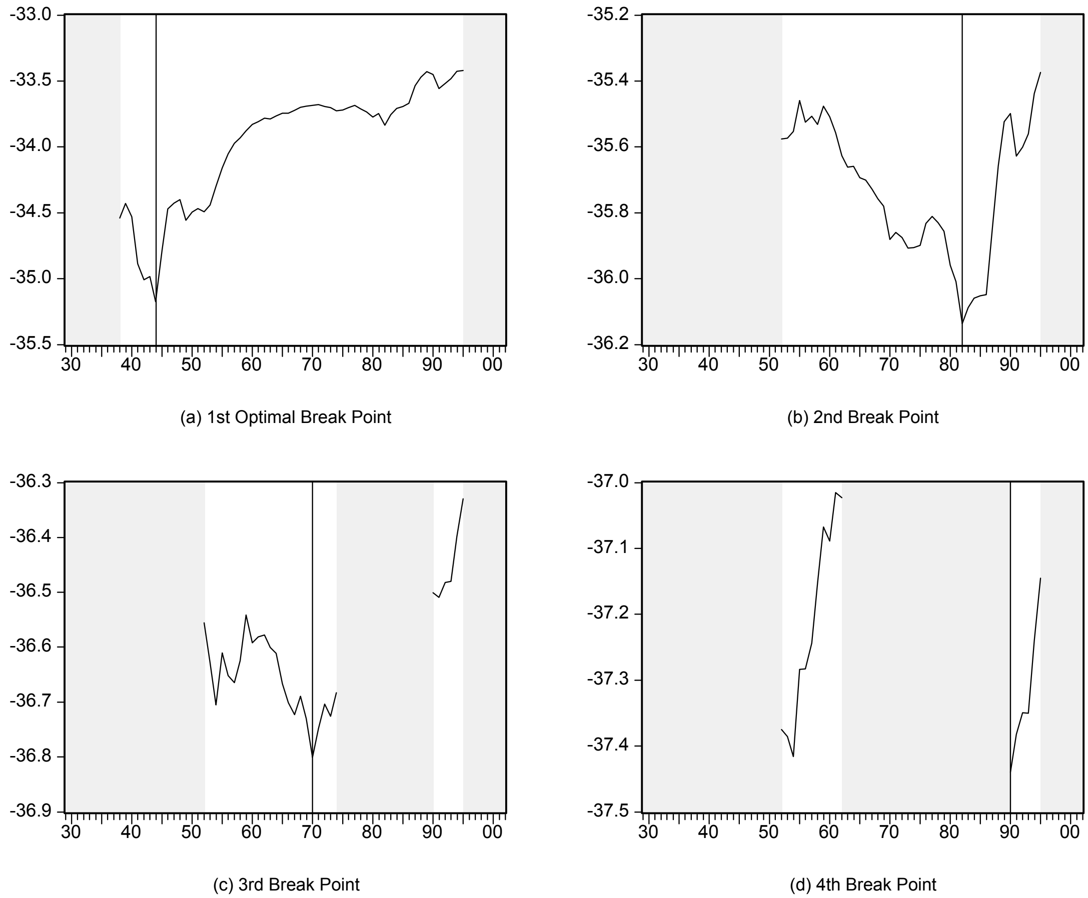
**Appendix Table A6: Time Trend Estimates from a Linear Model (Equation 9)**

**(Not to be published)**

| | *1929-1943* | | *1944-1981* | | *1982-2002* | |
|---|---|---|---|---|---|---|
| | $\alpha_{i1}$ | $\beta_{i1}$ | $\alpha_{i2}$ | $\beta_{i2}$ | $\alpha_{i3}$ | $\beta_{i3}$ |
| California | 0.1899 | -0.0012 | 0.1443 | -0.0014 | 0.2081 | -0.0026 |
| Nevada | 0.2642 | 0.0129 | 0.3741 | -0.0047 | 0.2219 | -0.0028 |
| Oregon | -0.0378 | 0.0081 | 0.0274 | -0.0007 | -0.0446 | 0.0004 |
| Washington | -0.0306 | 0.0094 | 0.0372 | -0.0004 | -0.0599 | 0.0011 |
| Illinois | 0.0809 | -0.0013 | 0.1071 | -0.0014 | -0.0212 | 0.0008 |
| Indiana | -0.1708 | 0.0139 | 0.0233 | -0.0012 | -0.1237 | 0.0010 |
| Michigan | -0.0177 | 0.0091 | 0.0787 | -0.0012 | -0.0186 | 0.0002 |
| Ohio | 0.0143 | 0.0046 | 0.0717 | -0.0016 | 0.0086 | -0.0005 |
| Wisconsin | -0.0447 | 0.0021 | -0.0047 | 0.0000 | -0.0654 | 0.0007 |
| D.C. | 0.3410 | -0.0204 | 0.1015 | -0.0009 | 0.0061 | 0.0013 |
| Delaware | 0.1562 | -0.0027 | 0.1233 | -0.0021 | 0.1025 | -0.0012 |
| Maryland | 0.0982 | -0.0026 | 0.0101 | 0.0007 | 0.0795 | -0.0003 |
| New York | 0.1350 | -0.0036 | 0.0804 | -0.0006 | 0.0397 | 0.0007 |
| New Jersey | 0.1408 | -0.0079 | 0.0751 | -0.0011 | 0.0619 | -0.0004 |
| Pennsylvania | 0.0896 | -0.0049 | 0.0226 | -0.0006 | -0.0462 | 0.0008 |
| Connecticut | 0.1561 | -0.0020 | 0.0895 | -0.0004 | 0.0377 | 0.0011 |
| Maine | -0.0197 | -0.0009 | -0.0797 | -0.0001 | -0.0773 | 0.0003 |
| Massachusetts | 0.1596 | -0.0096 | 0.0325 | -0.0003 | -0.0288 | 0.0015 |
| New Hampshire | 0.0565 | -0.0077 | -0.0284 | 0.0004 | 0.0257 | 0.0000 |
| Rhode Island | 0.1576 | -0.0093 | 0.0238 | -0.0008 | 0.0393 | -0.0006 |
| Vermont | -0.0263 | -0.0023 | -0.0795 | 0.0007 | -0.0814 | 0.0009 |
| Iowa | -0.2959 | 0.0156 | -0.0736 | 0.0010 | -0.0480 | -0.0006 |
| Kansas | -0.1942 | 0.0111 | -0.0329 | 0.0005 | 0.0332 | -0.0009 |
| Minnesota | -0.0655 | -0.0009 | -0.0753 | 0.0017 | -0.1293 | 0.0025 |
| Missouri | -0.0506 | -0.0019 | -0.0269 | -0.0002 | -0.0356 | 0.0000 |
| Nebraska | -0.2405 | 0.0074 | -0.0337 | -0.0002 | -0.1201 | 0.0012 |
| North Dakota | -0.6328 | 0.0379 | -0.1330 | 0.0014 | -0.0736 | -0.0005 |
| South Dakota | -0.6141 | 0.0314 | -0.1272 | 0.0001 | -0.2953 | 0.0029 |
| Colorado | -0.0419 | 0.0012 | -0.0147 | 0.0006 | -0.0611 | 0.0013 |
| Idaho | -0.2799 | 0.0141 | -0.0714 | -0.0011 | -0.2419 | 0.0011 |
| Montana | -0.1433 | 0.0128 | 0.0529 | -0.0025 | -0.0232 | -0.0015 |
| Utah | -0.2362 | 0.0139 | -0.0516 | -0.0015 | -0.1413 | -0.0003 |
| Wyoming | -0.0024 | 0.0011 | -0.0005 | 0.0003 | -0.1757 | 0.0026 |
| Alabama | -0.0910 | 0.0048 | -0.0439 | 0.0002 | 0.0780 | -0.0021 |
| Arkansas | -0.2574 | 0.0100 | -0.0894 | 0.0002 | -0.0298 | -0.0011 |
| Florida | -0.3575 | 0.0103 | -0.1953 | 0.0027 | 0.1217 | -0.0036 |
| Georgia | -0.1038 | 0.0066 | -0.0461 | 0.0008 | -0.0542 | 0.0006 |
| Kentucky | -0.3739 | 0.0123 | -0.2384 | 0.0029 | -0.1230 | 0.0007 |
| Louisiana | -0.8121 | 0.0173 | -0.6030 | 0.0076 | -0.2417 | 0.0002 |
| Mississippi | -0.0589 | 0.0031 | -0.0598 | 0.0011 | 0.0561 | -0.0010 |
| North Carolina | -0.2115 | 0.0066 | -0.1333 | 0.0018 | -0.0638 | 0.0007 |
| South Carolina | -0.4501 | 0.0066 | -0.3557 | 0.0045 | -0.2713 | 0.0020 |
| Tennessee | -0.1651 | 0.0047 | -0.1315 | 0.0017 | -0.1121 | 0.0007 |
| Virginia | -0.7665 | 0.0196 | -0.5806 | 0.0071 | -0.4071 | 0.0028 |
| West Virginia | -0.2667 | 0.0069 | -0.1814 | 0.0022 | -0.1024 | 0.0010 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Arizona | -0.2880 | 0.0096 | -0.1948 | 0.0023 | -0.1046 | 0.0006 |
| Oklahoma | -0.2755 | 0.0080 | -0.1900 | 0.0023 | -0.1481 | 0.0015 |
| New Mexico | -0.1958 | 0.0056 | -0.1880 | 0.0037 | 0.0185 | 0.0001 |
| Texas | -0.0930 | -0.0016 | -0.1089 | 0.0008 | -0.1112 | 0.0005 |

**Appendix Figure A1: 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*.