University of Pretoria
Department of Economics Working Paper Series

Convergence in Income Inequality: Further Evidence from the Club Clustering Methodology across the U.S. States

Nicholas Apergis
Northumbria University
Christina Christou
University of Piraeus
Rangan Gupta
University of Pretoria
Stephen M. Miller
University of Nevada, Las Vegas
Working Paper: 2015-39
June 2015

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Convergence in Income Inequality: Further Evidence from the Club Clustering Methodology across the U.S. States

Nicholas Apergis
Northumbria University, Newcastle upon Tune, U.K.
nicholas.apergis@northumbria.ac.uk

Christina Christou
University of Piraeus, Piraeus, Greece
christou@unipi.gr

Rangan Gupta
Department of Economics, University of Pretoria
Pretoria, 0002, South Africa
Rangan.Gupta@up.ac.za

Stephen M. Miller*
Department of Economics, University of Nevada, Las Vega
Las Vegas, NV 89154-6005
stephen.miller@unlv.edu

Abstract:

This paper contributes to the sparse literature on inequality convergence by empirically testing convergence across the U.S. States. This sample period encompasses a series of different periods that are discussed in the existing literature -- the Great Depression (1929-1944), the Great Compression (1945-1979), the Great Divergence (1980-present), the Great Moderation (1982-2007), and the Great Recession (2007-2009). This paper implements the relatively new methodology of panel convergence testing, recommended by Phillips and Sul (2007). This method examines the club convergence hypothesis, which argues that certain countries, states, sectors, or regions belong to a club that moves from disequilibrium positions to their club-specific steady-state positions. We find strong support for convergence through the late 1970s and early 1980s and then evidence of divergence. The divergence, however, moves the dispersion of inequality measures across states only a fraction of the way back to their levels in the early part of the 19th Century.

JEL Codes: C22, D63

Key words: Club convergence, Inequality measures, Panel data, US states

* Corresponding author.

1. Introduction

Dew-Becker and Gordon (2005) show that from 1966-2001, only the top 10 percent of the income distribution gained real income equal to the growth in labour productivity. Gordon (2009) also argues that abundant evidence documents that US income inequality worsened since the 1970s.

Solow (1956) and Swan (1956) first proposed the convergence hypothesis as part of the neoclassical growth models. These models exemplify diminishing returns to factors of production, which predicts that per capita income in poor countries will eventually converge to that in rich countries. The convergence hypothesis sparked enormous interest and led to an extensive literature testing convergence in average incomes both within and across countries. Benabou (1996) noted that neoclassical growth models can yield convergence of the entire distribution of income, not just the mean. Inequality levels will fall in countries with high inequality and will rise in countries with low inequality.

This paper contributes to the sparse literature on inequality convergence by empirically testing convergence across the U.S. States, using annual state-level data from 1916 to 2012 constructed by Frank (2014). This sample period encompasses a series of different periods that are discussed in the existing literature -- the Great Depression (1929-1944), the Great Compression (1945-1979), the Great Divergence (1980-present), the Great Moderation (1982-2007), and the Great Recession (2007-2009). Goldin and Margo (1992) identified the Great Compression as the time after the Great Depression; when income inequality fell dramatically compared to the Great Depression. Krugman (2007) described the period after the Great Compression as the Great Divergence, when income inequality grew. Piketty and Saez (2003) claim that the Great Compression ended in the 1970s and then income inequality worsened in the U.S. Thus, we anticipate that our analysis will document convergence in income inequality through the late 1970s and then divergence in the rest of the sample.

The existing literature uses several alternative approaches to identify whether and when convergence occurs, with most analyses examining the convergence of per capita real GDPs across countries. Initial empirical tests of the convergence hypothesis considered β-convergence (Barro and Sala-i-Martin, 1992; Mankiw et al., 1992; Quah 1996). Without additional control variables, the test considered absolute convergence, whereas with additional control variables, the test examined conditional convergence. Tests of β-convergence generally estimate a log-linearized solution to a non-stochastic model with an additive error term. Alternatively, σ-convergence (Friedman, 1992; Quah, 1993), argues that a group of countries/sectors/regions converge when the cross-section variance of the variable under consideration declines over time. As noted by Bliss (1999; 2000), however, the underlying assumption of an evolving data distribution introduces difficulties in the interpretation of the test distribution under the null. Moreover, the rejection of the σ-convergence hypothesis does not necessarily mean that they do not converge. That is, the presence of transitional dynamics in the data can lead to the rejection of the null hypothesis of σ-convergence.

Critics of β-convergence argue that if countries/sectors/regions converge to a common equilibrium with identical internal structures. Then, the dispersion of the variable under study should disappear in the long-run as all converge to the same long-run path. If, however, they converge to convergence clubs or to their own unique equilibrium, the dispersion of this variable will not approach zero (Miller and Upadhyay, 2002). Moreover, in the latter case of specific equilibrium, the movements of the dispersion will depend on the initial distribution of the variable under investigation relative to their final long-run outcomes. Overall, these two approaches suffer from specific estimation deficiencies associated with the time series used (Caporale *et al.*, 2009).

Other approaches to testing the convergence hypothesis uses cointegration and unit-root tests. These tests also experience a number of serious drawbacks. Lau (1999) theoretically argues that integration and cointegration properties arise intrinsically in stochastic endogenous growth models and produce steady-state growth even in the absence of exogenous growth-generating mechanisms. In the usual I(0)/I(1) approach or the standard cointegration framework, however, researchers infrequently find evidence in favour of convergence or catching-up effects, notably across the developing economies. The literature (Ericsson and Halket, 2002; Cheung and Pascual, 2004) claims that this failure to find convergence reflects spurious regressions. First, these tests fail to detect convergence when more than one equilibria exist and, second, if the countries do converge, but the data available to the econometrician reflect a time period in which transitional dynamics prevail, cointegration and unit-root tests may not "catch" the tendency to converge. Thus, to study the issue of convergence requires that the researcher model both transitional dynamics and long-run behavior together in a consistent framework. Unfortunately, standard existing testing methodologies for convergence fail to account for both regularities and, thus, cannot suitably test economic convergence. Pesaran (2007) extends the cointegration methodology such that it does not require the assumption of similarity in all respects for convergent countries. The main advantage of his extension is that it does not require a benchmark against which we measure convergence. According to this methodology, convergence between two countries can be identified if their output gap is stationary with a constant mean.

Finally, another strand of research claims that the I(0)/I(1) setting does not provide the appropriate framework to test for convergence, since aggregate outputs are suitably modelled by fractionally integrated processes. In other words, such processes account for long-memory characteristics of the series through a differencing parameter d that can take fractional values and not only integer ones (Gil-Alana, 2001; Haudrich and Lo, 2001; Abadir and Talmain, 2002; Halket, 2005; Cunado et al., 2006; Stengos and Yazgan 2014). In particular, Stengos and Yazgan (2014) make use of a long memory framework, which does not require a benchmark country, while it allows for the presence of structural breaks, a feature that exemplifies this approach vis-a-vis all the previous ones. This approach's primary drawback is that it cannot draw inferences on whether a group of countries form a convergence club (Marinucci and Robinson, 2001). Another statistical problem encountered with long-memory processes lies in the estimation of the memory parameter (Bond et al., 2007). Moreover, although fractional unit-root modelling increases the potential of cointegration testing, it gives rise to a new set of problems. Fractional integration tests can support the presence of unit roots, but may also suggest fractional integration of different orders for different variables. The number of possible integration orders makes it difficult to choose the ones giving rise to further problems in modelling the unit-root distribution. This procedure is not robust to any misspecification in the order of integration. Finally, it is not easy to identify fractional unit roots empirically from models with regime switching or general nonlinearities (Bond et al., 2007).

This paper implements the relatively new methodology of panel convergence testing, recommended by Phillips and Sul (2007). This method examines the club convergence hypothesis, which argues that certain countries, states, sectors, or regions belong to a club that moves from disequilibrium positions to their club-specific steady-state positions. This method, which shares a number of similarities with the fractional integrated methodological approaches of convergence, includes several appealing characteristics. First, no specific assumptions concerning the stationarity of the variable of interest and/or the existence of common factors are necessary. Nevertheless, we can interpret this convergence test as an asymptotic cointegration test without suffering from the small sample problems of unit-root and cointegration testing. Second, the method relies on a quite general form of a nonlinear time-varying factor model, where the common stochastic trends employed allow for long-run co-movements in aggregate behaviour without requiring the presence of cointegration. Third, it also permits the estimation of transitional effects. Finally, the most substantial advantage of this method over all the previous convergence approaches is that it avoids the assumption that the convergence process needs further modelling as a time-varying transition path to long-run equilibrium.

2. Literature Review

A number of papers in the literature describe and explain the association between inequality and the level of a country's development. This literature begins with the seminal paper by Kuznets (1955) who provides the first piece of evidence for an inverted-U relationship between the level of a country's development and its degree of income inequality. This nonlinear relationship is primarily explained through "dual economy dynamics," associated with the transition from an agricultural to an industrial economy.

In this strand of the literature, Alesina and Rodrik (1994), Perotti (1996), Persson and Tabellini (1994), and others highlight a negative relationship between these two variables, which reflects either the negative effect of inequality on education or on the presence of capital market imperfections and credit constraints. By contrast, Li and Zou (1998), Barro (2000), and Forbes (2000) document a positive relationship, reflecting either the relative savings propensities of rich versus poor or the presence of investment indivisibilities. Lundberg and Squire (2003) argue that openness and civil liberties affect both variables in the same direction, thereby giving a positive relationship between income inequality and growth.

In a different strand of the literature, a number of studies explore income inequality convergence within the same country rather than across countries. In particular, Marina

(2000) investigates 25 provinces in Argentina and finds evidence of β-convergence. Gomes (2007) reaches the same conclusion for Brazil. Panizza (2001) uncovers evidence to support the convergence hypothesis across the states in the US. Goerlich and Mas (2004) find strong evidence of β-convergence across Spanish provinces. Ezcurra and Pascual (2009) use Quah's (1996) non-parametric approach and find σ-convergence of inequality across states in the US. Lin and Huang (2011, 2012a, 2012b) investigate convergence in the US over 80 years, using data on top income shares in addition to the Gini index. Their findings show strong evidence on convergence.

Finally, other papers investigate convergence across countries, Ravallion (2003) finds that developing countries converge toward medium inequality in the 1990s. Bleaney and Nishiyama (2003) find that compared to developing countries, income distribution among OECD countries converged significantly faster and to a more equal distribution. Lopez (2004) compares convergence in income levels with convergence in inequality and finds that between 1960 and 2000, inequality within countries converged much faster than their average incomes. Rajan (2010) underscores how inequality intensifies the leverage and financial cycle, sowing the seeds for an economic crisis, while Berg and Ostry (2011) document with multi-country evidence that greater equality can help sustain growth. In a recent study, Ostry et al. (2014) provide further evidence that inequality can undermine progress in health and education, cause political and economic instability, and undercut the social consensus required to adjust in the face of major shocks, and thus further trim the intensity and duration of growth.

Hence, based on the literature related to convergence of income inequality, we can see that the analyses primarily consider the full-sample of the data used. Our paper adds to this literature by taking a time-varying approach, which, besides providing full-sample information on convergence, also tracks the convergence path of each of the cross-sectional units (US states) over time. In addition, since the methodology opens the possibility of convergence clubs, important policy implications also emerge. If only one convergence club exists for the entire economy, policy makers can pursue an uniform policy for reduction of inequality across the entire country. If multiple convergence clubs exist, however, club-specific policies need to account for the commonality amongst the states comprising the specific club. Finally, since our data set covers the period of 1916 to 2012, we can also track the convergence path over the most recent abnormal episode of the "Great Recession," over and above other unique episodes spanning 87 years of history on various types of inequality measures of the US economy.

3. Econometric Methodology

This section outlines the methodology proposed by Phillips and Sul (2007) to test for convergence in a panel of countries and to identify convergence clubs, if any. Phillips and Sul (2007) propose a new econometric approach for testing the convergence hypothesis and the identification of convergence clubs. Their method uses a nonlinear time-varying factor model and provides the framework for modeling transitional dynamics as well as long-run behavior.

The new methodology adopts the following time-varying common-factor representation for y_{it} of country i:

$$y_{it} = \delta_{it}\mu_t , \tag{1}$$

where μ_t is a single common component and δ_{it} is a time-varying idiosyncratic element that captures the deviation of country i from the common path defined by μ_t. Within this framework, all N economies will converge, at some point in the future, to the steady state, if $\lim_{k\to\infty}\delta_{it+k} = \delta$ for all i = 1, 2, …, N, irrespective of whether countries are currently near the steady state or in transition. This is an important point given that the paths to the steady state (or states) across countries can differ significantly.

Phillips and Sul (2007) test whether economic variables y_{it}, i = 1, 2, …, N converge to a single steady state as $t \to \infty$. Thus, they adopt a factor representation $y_{it} = \delta_{it}\mu_t$ (equation 1) for each economic variable in the sample. The factor μ_t is assumed common across individuals (economies), while the transition dynamics are captured by the idiosyncratic components δ_{it}, which can vary across cross-section units and time. Convergence is a dynamic process. Since δ_{it} traces the transition paths, we examine convergence through temporal relative evolution of δ_{it}. Phillips and Sul (2007) do not assume any parametric form for μ_t; they just factor it out and concentrate on δ_{it}.

Since we cannot directly estimate δ_{it} from equation (1) because the number of parameters exceeds the number of observations, Phillips and Sul (2007) assume a semiparametric form for δ_{it}, which enables them to construct a formal test for convergence. In particular, they eliminate the common component μ_t through rescaling by the panel average:

$$h_{it} = \frac{y_{it}}{\frac{1}{N}\sum_{i=1}^{N} y_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}}. \tag{2}$$

The relative measure h_{it} captures the transition path with respect to the panel average. Defining a formal econometric test of convergence as well as an empirical algorithm of defining club convergence requires the following assumption for the semi-parametric form of the time-varying coefficients δ_{it}:

$$\delta_{it} = \delta_i + \sigma_{it}\xi_{it}, \tag{3}$$

where $\sigma_{it} = \dfrac{\sigma_i}{L(t)t^{\alpha}}$, $\sigma_i > 0$, $t \geq 0$, and ξ_{it} is weakly dependent over t, but iid(0,1) over i. The function $L(t)$ varies slowly, increasing and diverging at infinity.[1] Under this specific form for δ_{it}, the null hypothesis of convergence for all i takes the form: $H_0: \ \delta_i = \delta, \ \ \alpha \geq 0$, while the alternative hypothesis of non-convergence for some i takes the form: $H_A: \ \delta_i \neq \delta \ \ or \ \ \alpha < 0$. Phillips and Sul (2007) show that we can test for the null of convergence in the framework of the following regression:[2]

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = \hat{c} + \hat{b}\log t + \hat{u}_t, \tag{4}$$

for $t = [rT], [rT]+1, \ .....,\ T$, and $r > 0$.[3] In this regression, $H_t = \dfrac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^2$ and $\hat{b} = 2\hat{\alpha}$, where h_{it} is defined in equation (2) and $\hat{\alpha}$ is the least squares estimate of α. Under the null hypothesis of convergence, the dependent variable diverges whether $\alpha > 0$ or $\alpha = 0$. In this case, we can test the convergence hypothesis by a *t*-test of the inequality, $\alpha \geq 0$. The *t*-test statistic follows the standard normal distribution asymptotically and is constructed using heteroskedastic and autocorrelation consistent standard errors. Phillips and Sul (2007) call the one-sided t-test, which is based on $t_{\hat{b}}$, the $\log t$ test due to the presence of the log *t* regressor in equation (4).[4]

The empirical convergence literature also deals with the possible existence of multiple equilibriums. In that case, rejection of the null hypothesis that all countries in the sample converge does not imply the absence of convergence clubs in the panel. In this study, we

[1] In this paper, we set $L(t) = \log t$.

[2] Appendix B of Phillips and Sul (2007) reports the analytic proof under the convergence hypothesis for this regression equation.

[3] Following the recommendation of Phillips and Sul (2007), we choose *r* values in the interval [0.2, 0.3].

[4] The log *t* test exhibits favorable asymptotic and finite sample properties.

implement the club convergence and clustering procedure proposed by Phillips and Sul (2007). That procedure involves the following steps. (1) Order the N countries with respect to the last-period value of the time series. For example, in the case of GDP per capita, we order the countries in a descending order with the first country having the highest last period income, the second with the next highest income, and so on. (2) Form all possible core (club) groups C_k by selecting the first k highest countries, with $k = 2, 3, ..., N$. Then, test for convergence using the $\log t_k$ test within each subgroup of size k. Finally, define the core club $C*$ of size k^* as the club for which the maximum computed $\log t_{k^*}$ statistic occurs, given that the $\log t_k$ statistic supports the convergence hypothesis. (3) From the remaining *N*-*k** countries, add one country at a time to the core club *C** and test for convergence through the log*t* test. If the test strongly supports the convergence hypothesis ($\log t \geq 0$), then include the country in group $C*$. Find all countries that, according to the $\log t$ test, converge to the same steady state with the core group $C*$. These countries together with the countries of the core group $C*$ form the first convergence club in the panel. (4) Then, for the remaining countries (if any), repeat the procedure described in steps 1-3 to determine the next convergence club, if one exists. Finally, terminate the procedure when the remaining economies fail to converge.

4. Data

This study also makes use of alternative measures of income inequality constructed by Frank (2014). These measures include the share of total income held by the top 1% and top 10% of the income distribution, the Gini coefficient, the Atkinson inequality measure, the relative mean deviation, and the Theil index, covering the annual period of 1916-2012.

The metrics that use different (percentage) shares of total population are simple comparisons across different income groups, ranked according to income ranges. Their advantages include simpleness to compute and easy to interpret and explain. Their drawbacks are only sensitive to changes in the two compared income shares, so they do not depict overall changes in within distribution, while they do not provide an absolute measure of income inequality, because they do not fall into an absolute scale of measurement. Finally, their measure can be skewed due to outliers in the distribution and they do not weight the included observations.

The Gini coefficient can compare different income distributions of different groups of populations (i.e., countries, states, regions) based on the Lorenz curve. Lundberg and Squire (2003) note that the Gini coefficient does not convey any information about the shape of the Lorenz curve. Moreover, this index provides a point estimate of the income distribution and does not capture the lifetime income of a person, which changes over time and can affect its position within the income distribution.

The Atkinson index permits different weighting on different parts of the income distribution, which the Gini coefficient does not permit. The Atkinson index of inequality measures social welfare on a range from zero to one with higher values indicating more inequality. We use the Atkinson index that Frank (2014) calculates with an inequality aversion parameter (**ε**) of 0.5, which provides more sensitivity to changes at the upper-end of the income distribution. In addition, the Atkinson index can calculate the portion of current income needed to achieve the same level of social welfare with an equal distribution of income. For example, an Atkinson index of .25 means that we can achieve the same level of social welfare from 75% of current income by distributing it equally across individuals.

The relative mean deviation compares the income levels of each individual with the mean income of the population, then sums the absolute values of the differences between them and views it as a proportion of the total income. This measure, however, proves insensitive to regressive transfers, that is, to transfers from poorer individuals below the mean income to richer ones that also lie below the mean. As a result, it provides potentially inaccurate measures of income inequality.

The Theil income inequality measure belongs to the entropy measures from information theory, where reallocations of income cause changes in inequality that depend only on the relative distances between individuals. Its main advantage is its decomposability, which permits breaking down the inequality measure into a weighted average of the inequality existing within subgroups of the population and the inequality existing between them. Its main shortcomings include the inability to compare populations with different sizes and computational complexity. Sen (1973) argues that "the fact remains that it is an arbitrary formula, and the average of the logarithms of the reciprocals of income shares weighted by income shares is not a measure that is exactly overflowing with intuitive sense." (p. 35)

5. Empirical Analysis

5.1. Convergence

Table 1 and 2 report results for the shares of income held by the top 1% and 10% of the national population, respectively. The top 1% is the only inequality measure that supports full income inequality convergence, or one club, of the entire 48 states and the District of Columbia (DC). The value of log(t) statistic equals 6.948, against a critical value of -1.67, which supports the null hypothesis of full convergence. For the top 10%, the first row reports the test for full convergence (i.e., convergence among all States and DC), while rows 2 and 3 display the results of the club clustering procedure. The results of the full sample reject the null hypothesis of income inequality convergence, since the log(t) statistic is -5.532 (with critical value of -1.67). The formation of the two different convergence clubs shows that there exist two clubs of 12 and 37 States and DC, respectively.

[Insert Tables 1 and 2 about here]

Table 3 reports the results of the panel convergence methodology for the Gini income inequality index. This time the results seem different. The first row reports the test full convergence (i.e., convergence among all States and DC), while rows 2 and 3 display the results for the club clustering procedure. The full sample rejects the null hypothesis of income inequality convergence, since the log(*t*) statistic is -3.656 (with critical value of -1.67). The formation of the two different convergence clubs leads to two clubs of 30 and 19 members, respectively. Comparing the lists of States and DC in the two clubs in Tables 2 and 3 leads to the following observations. All members of club 1 in Table 2 for the top 10% inequality measure also appear in club 1 in Table 3 for the Gini coefficient, but 18 States moved from club 2 in Table 2 to club 1 in Table 3. Thus, all 19 members in club 2 for the Gini coefficient also appear in club 2 for the top 10% measure.

[Insert Table 3 about here]

Next, we repeat the convergence analysis for the Atkinson inequality index. The new results appear in Table 4. This time the findings link to Table 2. In particular, the first row reports the test with respect to the full sample that rejects the null hypothesis of income inequality convergence, since the log(*t*) statistic is -3.278 (with critical value of -1.67). The formation of the three different convergence clubs occurs with 6, 7, and 36 members, respectively. Now, club 1 for the top 10% matches clubs 1 and 2 for the Atkinson index with the addition of Washington in club 2. Thus, club 2 for the top 10% matches club 3 for the Atkinson index with the loss of Washington in club 3.

[Insert Table 4 about here]

Table 5 reports the convergence results for the relative mean deviation. The findings seem similar to those presented in Table 3 for the Gini index. First, they confirm the absence of full convergence with a log(*t*) statistic of -3.865 (against a critical value of -1.67). The formation of the two different convergence clubs occurs with 28 and 21 members, respectively. Comparing Tables 3 and 5, Alabama and Arkansas move from club 2 for the Gini coefficient to club 1 for the mean deviation measure. Otherwise, the membership in clubs 1 and 2 for the two inequality measures do not differ.

[Insert Table 5 about here]

Finally, Table 6 reports the findings for the Theil index. This time the results illustrate simultaneously a different, but also similar, picture. In particular, after we reject the full convergence hypothesis with the log(t) statistic of -2.636 (against a critical value of -1.67), the analysis generates five different clubs with 8, 5, 4, 23, and 9 members, respectively, indicating an unbalanced income inequality convergence process. At the same time, however, the results for the Theil index do show similarities to the Atkinson index. That is, clubs 1 and 2 match between these two inequality indexes with California and Nevada moving from club 2 for the Atkinson index to club 1 for the Theil index. In addition, club 3 for the Atkinson index matches exactly clubs 3, 4, and 5 for the Theil index.

[Insert Table 6 about here]

5.2. Relative Transition Curves and Their Dispersion

Following Phillips and Sul (2007), we alternatively estimate the relative transition measures, h_{it}, defined in equation (2), which capture the transition paths with respect to the panel average. Figures 1 to 6 display the relative transition curves and the standard deviation of those transition curves at each point in time for the convergence clubs associated with the six income inequality indexes.

Figure 1 illustrates the transition curves and their standard deviation for the Top 1% measure of inequality. As Table 1 reported, only for this measure of inequality do we find one convergence club made up of all 48 states and DC. We observe convergence (Great Compression) before the early 1980s and since then, a divergence (Great Divergence). The dispersion of the top 1% across states in 2012 matches its value at the end of WWII. The outlier state in the transition curves is Delaware, which experienced the highest inequality until the early 1970s.

Figure 2 shows the transition curves and their standard deviation for the top 10% measure of inequality for the two convergence clubs. Club 1 and 2 both experience convergence until the late 1970s and early 1980s, respectively. Both also experience a divergence after their bottom, although the divergence is less dramatic than for the Top 1% in Figure 1. Moreover, the dispersion of the Top 10% falls below the dispersion of the Top 1%.

Figure 3 displays the transition curves and their standard deviation for the Gini coefficient measure of inequality for the two convergence clubs. The transition curves and standard deviations tell similar stories to those for the Top 10% information in Figure 2. We noted above that 18 states moved from club 2 for the Top 10% measure to club 1 for the Gini coefficient.

Figure 4 presents the transition curves and their standard deviation for the Atkinson index of inequality for the three convergence clubs. We noted that Table 4 for the Atkinson index and Table 2 for the Top 10% prove similar. That is, club 2 for the Top 10% and club 3 for the Atkinson index contain the same states except for Washington. That is, the transition curve and standard deviation graphs for club 2 in the Top 10% chart and club 3 in the Atkinson chart provide basically the same information. Then clubs 1 and 2 in the Atkinson chart break out the states and DC included in club 1 for the Top 10% chart.

Figure 5 illustrates the transition curves and their standard deviation for the Median deviation measure of inequality for the two convergence clubs. As noted above, the clubs for the Gini coefficient and the Median deviation prove nearly identical. Thus, w=hen we compare the transition curves and standard deviations for the two clubs in each measure, we find that the graphs tell the same story. Once again, the outlier state in the early part of our complete sample is Delaware.

Figure 6 plots the transition curves and their standard deviation for the Theil index measure of inequality for the five convergence club. These five clubs prove remarkably similar to the three clubs for the Atkinson index. That is, clubs 1 and 2 in both measures contain he same states with two states moving between clubs whereas clubs 3, 4, and 5 for the Theil index ontain all the sates in club 3 for the Atkinson index. Thus, the charts for clubs 1 and 2 appear nearly the same whereas the club 4 charts for the Theil index, which contains most of the states from club 3 of the Atkinson index, matches closely the charts for club 3 for the Atkinson index.

5.3. Robustness Tests

Phillips and Sul (2009) argue that their convergence club methodology tends to find more members of clubs than their true number. To avoid this over-determination, they run the algorithm across the sub-clubs to assess whether any evidence exists to support the merging of smaller clubs into larger clubs. Tables 7 to 11 report the results of the new convergence tests for the five indices for which the method identified clubs. Following Phillips and Sul (2009), we consider adjacent sub-clubs and the column “tests of club-merging” reports the fitted regression coefficient. The empirical findings imply that across all five income inequality indexes and across all sub-clubs, no evidence supports mergers of the original clubs.

[Insert Tables 7 to 11 about here]

6. Conclusions

This paper implements the Phillips and Sul (2007) method of testing for club convergence. The club convergence hypothesis argues that groups of countries, states, sectors, or regions from a club that moves units from disequilibrium positions to their club-specific steady-state equilibrium positions. This paper contributes to the sparse literature on inequality convergence by empirically testing convergence of different inequality measures -- the share of total income held by the top 1% and top 10% of the income distribution, the Gini coefficient, the Atkinson inequality measure, the relative mean deviation, and the Theil index -- across the U.S. States. This sample period from 1916 to 2012 includes a numbers of different episodes that the existing literature discusses -- the Great Depression (1929-1944), the Great Compression (1945-1979), the Great Divergence (1980-present), the Great Moderation (1982-2007), and the Great Recession (2007-2009).

We find strong support for convergence through the late 1970s and early 1980s and then evidence of divergence. The divergence, however, moves the dispersion of inequality measures across states only a fraction of the way back to their levels in the early part of the 19th Century. More specifically, we find a convergence club that encompasses the entire set of 48 states and DC only for the Top 1% measure of inequality. Two convergence clubs exist for the Top 10% as well as for the Gini and the Mean deviation measures. The Atkinson and Theil indexes generate 3 and 5 clubs, respectively. Even though the number of clubs differs across inequality measures, each of the clubs relates to the clubs in the other inequality measures with some modifications in membership. More importantly, our results tend to indicate that policy related to inequality eradication cannot be uniform across the U.S. states, but needs to be designed keeping in mind the commonality of the states that is included in the various convergence clubs, as well as the metric of inequality analyzed.

References

Abadir, K. and Talmain, G. 2002. Aggregation, persistence and volatility in a macro model. *Review of Economic Studies*, 69, 749-779.

Alesina, A. and Rodrik, D. 1994. Distributive politics and economic growth. *Quarterly Journal of Economics*, 109, 465-490.

Autor, D., and Dorn, D. 2008. Inequality and specialization: The growth of low-skill service jobs in the United States. Draft paper.

Autor, D., Katz, L.F., and Kearney, M.S. 2008. Trends in U.S. wage inequality: Revising the revisionists. *Review of Economics and Statistics*, 90, 300-323.

Barro, R.J. 2000. Inequality and growth in a panel of countries. *Journal of Economic Growth*, 5, 5-32.

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

Bénabou, R. 1996. Inequality and growth. In Bernanke B.S. and Rotemberg J.J. (eds), *NBER Macroeconomics Annual*, 11, MIT Press, Cambridge.

Berg, A., and Ostry, J.D. 2011. Inequality and unsustainable growth: Two sides of the same coin? IMF Staff Discussion Note, No. 11/08, Washington: International Monetary Fund.

Bleaney, M. and Nishiyama, A. 2003. Convergence in income inequality: Differences between advanced and developing countries. *Economics Bulletin*, 4, 1-10.

Bliss, C. 2000. Galton's fallacy and economic convergence: A reply to Cannon and Duck. *Oxford Economic Papers*, 52, 420-422.

Bliss, C. 1999. Galton's fallacy and economic convergence. *Oxford Economic Papers*, 51, 4-14.

Bond, D., Harrison, M. and O'Brien, E. 2007. Demand for money: A study in testing time series for long memory and nonlinearity. *Economic and Social Review*, 38, 1-24.

Caporale, G.M., Erdogan, B. and Kuzin, V. 2009. Testing for convergence in stock markets: A nonlinear factor approach. Discussion Paper No. 932, 2009, Deutsches Institut fur Wirtschaftsforschung, Berlin.

Cheung, Y-W., and Pascual, A.G. 2004. Testing for output convergence: A re-examination. *Oxford Economic Papers*, 54, 45-63.

Cunado, J., Gil-Alana, L.A. and Pérez de Gracia, F. 2006. Additional empirical evidence on real convergence: A fractionally integrated approach. *Review of World Economics*, 142, 67-91.

Dew-Becker, I., and Gordon, R.J. 2005. Where did the productivity growth go? Inflation dynamics and the distribution of income. *Brookings Papers on Economic Activity*, 36, 67-127.

Elliott, G., Rothenberg, T.J. and Stock, J.H. 1996. Efficient tests for an autoregressive unit root. *Econometrica*, 64, 813-836.

Ericsson, N.R., and Halket, J.R. 2002. Convergence of output in the G-7 countries. Mimeo, Division of International Finance, Federal Reserve Board.

Ezcurra, R. and Pascual, P. 2009. Convergence in income inequality in the United States: A nonparametric analysis. *Applied Economic Letters*, 16, 1365-1368.

Forbes, K. 2000. A reassessment of the relationship between inequality and growth. *American Economic Review*, 90, 869-887.

Frank, M. W. 2014 A New State-Level Panel of Annual Inequality Measures over the Period 1916-2005. *Journal of Business Strategies*, 31, 241-263.

Friedman, M. 1992. Do old fallacies ever die? *Journal of Economics Literature*, 30, 2129-2132.

Frydman, C., and Saks, R.E. 2008. Executive compensation: A new view from a long-term perspective, 1936-2005. NBER Working Paper, No. 14145.

Gil-Alana, L.A. 2001. Seasonal long memory in the aggregate output. *Economics Letters*, 74, 333-337.

Goerlich, F. and Mas, M. 2004. Three (marginal?) questions regarding convergence. *Journal of Economic Studies*, 31, 25-38.

Goldin, C., and Margo, R., 1992. The Great Compression: The wage structure in the United States at mid-century. *Quarterly Journal of Economics* 107, 1-34.

Gomes, F.A.R. 2007. Convergence in income inequality, the case of Brazilian municipalities. *Economics Bulletin*, 15, 1-9.

Gordon, R.J. 2009. Has the rise in American inequality been exaggerated? Mimeo,

Halket, J.R.L. 2005. Multivariate fractional cointegration and GDP convergence. Mimeo NYU.

Haubrich, J.G. and Lo, A.W.. 2001. The sources and nature of long-term memory in aggregate output. *Economic Review*, QII, 15-30.

Jarque, A. 2009. CEO compensation trends, market changes, and regulation. Federal Reserve Bank of Richmond *Economic Quarterly*, 94, 265-300.

Krugman, P., 2007. *The Conscience of a Liberal*. W.W. Norton & Company, New York, 124-128.

Kuznets, S. 1955. Economic growth and income inequality. *American Economic Review*, 45, 1-28.

Lau, P.S-H. 1999. I(0) in, integration and cointegration out: Time series properties of endogenous growth models. *Journal of Econometrics,* 93, 1-24.

Li, H.Y., and Zou, H.F. 1998. Income inequality is not harmful to growth: Theory and evidence. *Review of Development Economics*, 2, 318-334.

Lin, P.-C. and Huang H.-C., 2011. Inequality convergence in a panel of states. *Journal of Economic Inequality* 9, 195-206.

Lin, P.-C. and Huang H.-C., 2012a. Convergence of income inequality? Evidence from panel unit root tests with structural breaks. *Empirical Economics* 43, 153-174.

Lin, P.-C. and Huang H.-C., 2012b. Inequality convergence revisited: Evidence from stationarity panel tests with breaks and cross correlation. *Economic Modelling* 29, 316-326.

Lopez, H. 2004. Pro-growth, pro-poor: Is there a trade-off? World Bank Policy Research Working Paper, No. 3378, The World Bank.

Lundberg, M., and Squire, L. 2003. The simultaneous evolution of growth and inequality. *Economic Journal*, 113, 326-344.

Mankiw, N. G., Romer, D.H. and Weil, D.N. 1992. A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107, 407-437.

Marina, A. 2000. Economic convergence of the first and second moment in provinces of Argentina. *Estudios de Economía*, 27, 259-277.

Marinucci, D. and Robinson, P.M. 2001. Semiparametric fractional cointegration analysis. *Journal of Econometrics*, 105, 225-247.

Miller, S.M. and Upadhyay, M.P. 2002. Total factor productivity and the convergence hypothesis. *Journal of Macroeconomics*, 24, 267-286.

Ostry, J.D., Berg, A. and Tsangarides, C.G. 2014. Redistribution, inequality, and growth. IMF Short Discussion Note, No. 02-14, Washinghton DC: International Monetary Fund.

Panizza, U. 2001. Convergence in income inequality. *Journal of Income Distribution*, 10, 5-12.

Perotti, R. 1996. Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, 1, 149-187.

Persson, T. and Tabellini, G. 1994. Is inequality harmful for growth? *American Economic Review*, 84, 600-621.

Pesaran M.H. 2007. A pair-wise approach for testing output and growth convergence. *Journal of Econometrics*, 138, 312-355.

Phillips P.C.B. and Sul, D. 2009. Economic transition and growth. *Journal of Applied Econometrics*, 24, 1153-1185.

Phillips, P.C.B. and Sul, D. 2007. Transition modeling and econometric convergence tests. *Econometrica*, 75, 1771-1855.

Quah, D.T. 1996. Empirics for economic growth and convergence. *European Economic Review*, 40, 1353-1375.

Quah, D.T. 1993. Galton's fallacy and the convergence hypothesis. *Scandinavian Journal of Economics*, 95, 427-443.

Rajan, R. 2010. Fault Lines: How Hidden Fractures Still Threaten the World Economy, Princeton: Princeton University Press.

Ravallion, M. 2003. Inequality convergence. *Economics Letters*, 80, 351-356.

Sen, A. 1973. *On Economic Inequality*. New York: Norton.

Stengos, T. and Yazgan, E. 2014. Persistence in convergence. *Macroeconomic Dynamics*, 18, 753-782.

Table 1. Income inequality convergence-top1% share of the population approach

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	6.948

Table 2. Income inequality convergence-top10% share of the population approach

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	-5.532
1st club	California, Connecticut, Delaware, District of Columbia, Florida, Illinois, Massachusetts, Nevada, New Jersey, New York, Texas, Wyoming	3.721
2nd club	Alabama, Arizona, Arkansas, Colorado, Georgia, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Mexico, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin	2.985

Table 3. Income inequality convergence-Gini index

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	-3.656
1st club	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Louisiana, Massachusetts, Michigan, Mississippi, Montana, Nebraska, Nevada, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, South Dakota, Tennessee, Texas, Utah, Washington, Wyoming,	3.211
2nd club	Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Minnesota, Missouri, New Hampshire, North Carolina, North Dakota, Ohio, Oregon, Rhode Island, South Carolina, Vermont, Virginia, West Virginia, Wisconsin	8.445

Table 4. Income inequality convergence-Atkinson index

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	-3.278
1st club	Connecticut, Delaware, District of Columbia, Florida, New York, Wyoming	5.292
2nd club	California, Illinois, Massachusetts, Nevada, New Jersey, Texas, Washington	9.849
3rd club	Alabama, Arizona, Arkansas, Colorado, Georgia, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Mexico, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, Vermont, Virginia, West Virginia, Wisconsin	-1.053

Table 5 Income inequality convergence-relative mean deviation approach

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	-3.865
1st club	Arizona, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Louisiana, Massachusetts, Michigan, Mississippi, Montana, Nebraska, Nevada, New Jersey, New Mexico, New York, Oklahoma, Pennsylvania, South Dakota, Tennessee, Texas, Utah, Washington, Wyoming	-4.214
2nd club	Alabama, Arkansas, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Minnesota, Missouri, New Hampshire, North Carolina, North Dakota, Ohio, Oregon, Rhode Island, South Carolina, Vermont, Virginia, West Virginia, Wisconsin	26.002

Table 6. Income inequality convergence-Theil index

Group	States	t-stat
Full sample	Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming	-2.636
1st club	California, Connecticut, Delaware, District of Columbia, Florida, Nevada, New York, Wyoming	10.243
2nd club	Illinois, Massachusetts, New Jersey, Texas, Washington	13.521
3rd club	Colorado, New Hampshire, Oklahoma, Utah	5.023
4th club	Alabama, Arizona, Arkansas, Georgia, Idaho, Indiana, Kansas, Louisiana, Maryland, Michigan, Minnesota, Missouri, Montana, Nebraska, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, South Dakota, Tennessee, Virginia, Wisconsin	0.220
5th club	Iowa, Kentucky, Maine, Mississippi, New Mexico, North Dakota, South Carolina, Vermont, West Virginia	-1.202

Table 7. Convergence club classification-Income inequality index: Top10% share of the population approach

Club	Tests of club merging
1	Club 1+2 = 1.116* (5.73)

* denotes statistical significant at the 5% level, while it rejects the null hypothesis of merging. Figures in parenthesis denote t-statistics.

Table 8. Convergence club classification-Income inequality index: Gini

Club	Tests of club merging
1	Club 1+2 = 1.458* (6.35)

Similar to Table 7.

Table 9. Convergence club classification-Income inequality index: Atkinson

Club	Tests of club merging
1	Club 1+2 = 0.931* (5.29)
2	Club 2+3 = -1.238* (-3.86)

Similar to Table 7.

Table 10. Convergence club classification-Income inequality index: Mean deviation approach

Club	Tests of club merging
1	Club 1+2 = 1.458* (6.35)

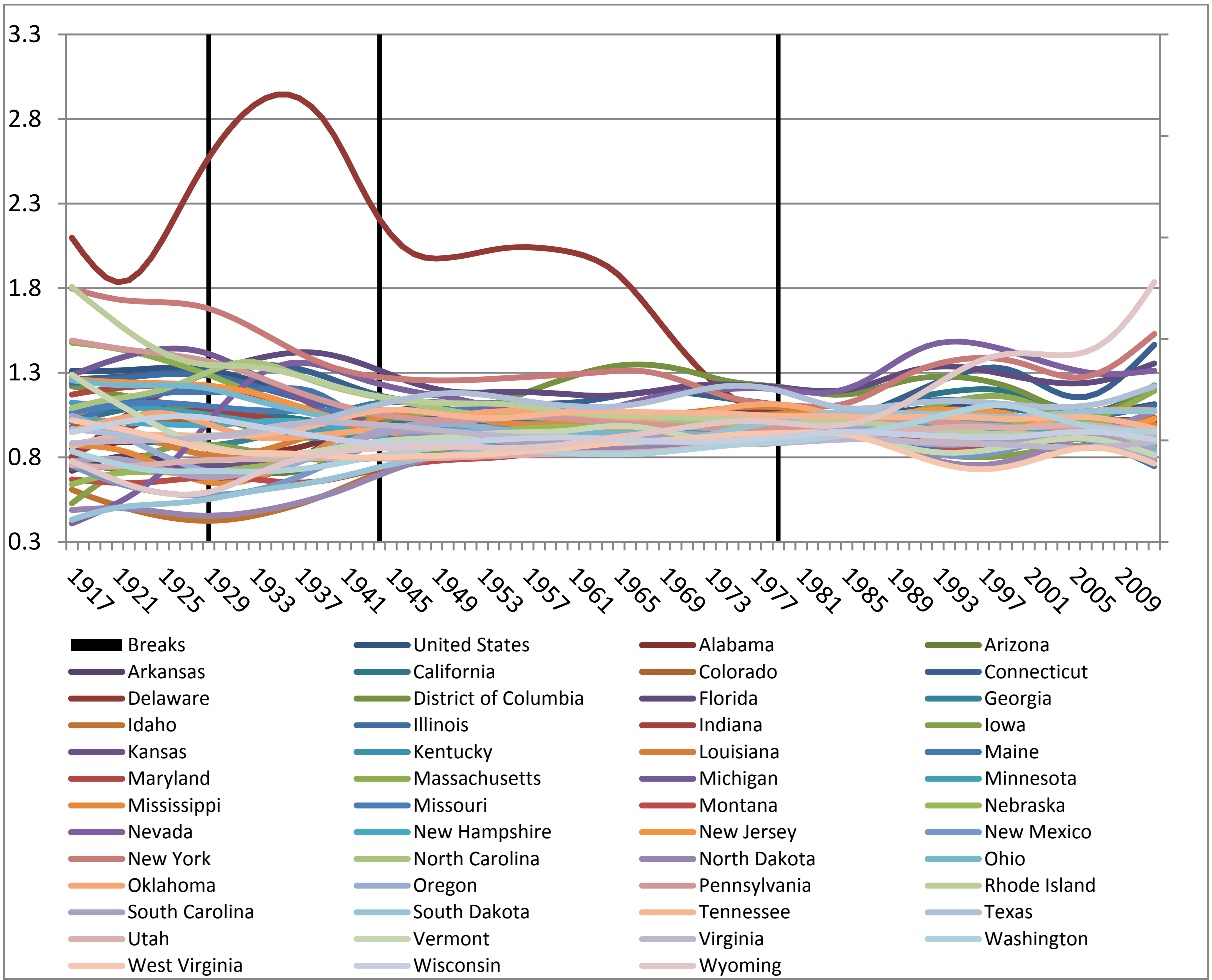
Similar to Table 7.

Table 11. Convergence club classification-Income inequality index: Theil

Club	Tests of club merging
1	Club 1+2 = 1.114* (8.67)
2	Club 2+3 = -0.412* (-4.28)
3	Club 3+4 = 0.117* (5.03)
4	Club 4+5 = -0.509* (-4.42)

Similar to Table 7.

Figure 1. Relative Transition Curve and Standard Deviation: Top1% Inequality Measure



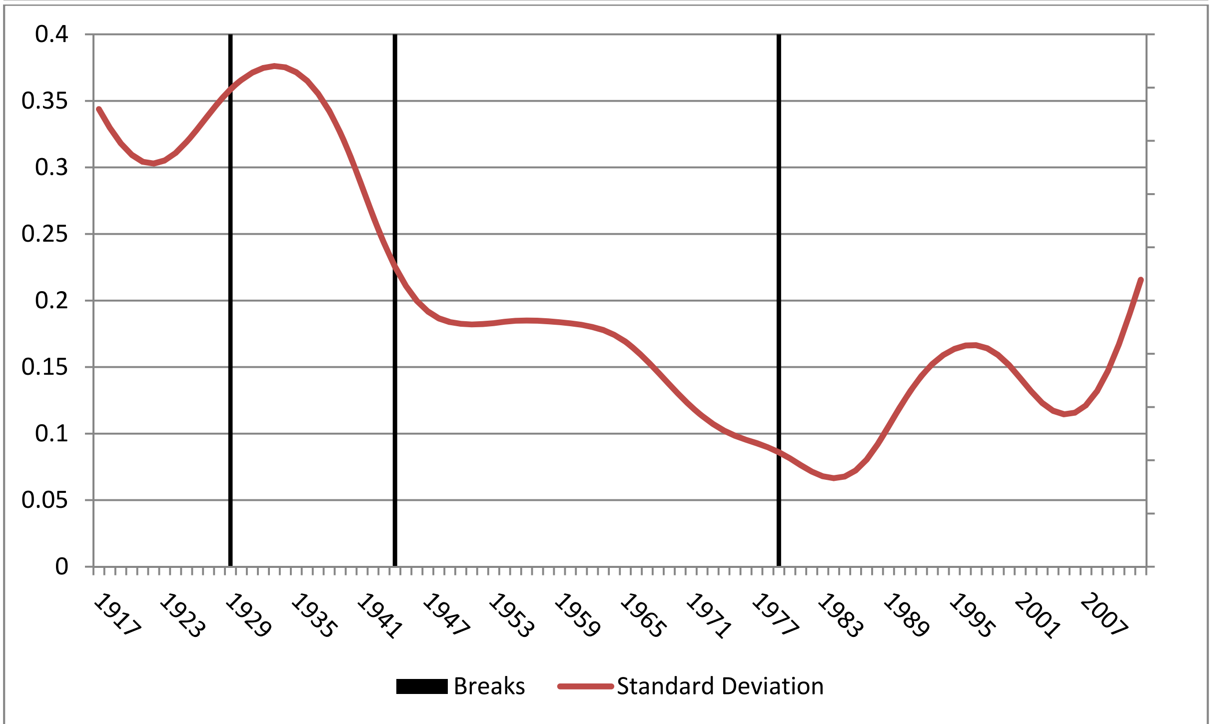


Figure 2. Relative Transition Curves and Standard Deviations: Top10% Inequality Measure

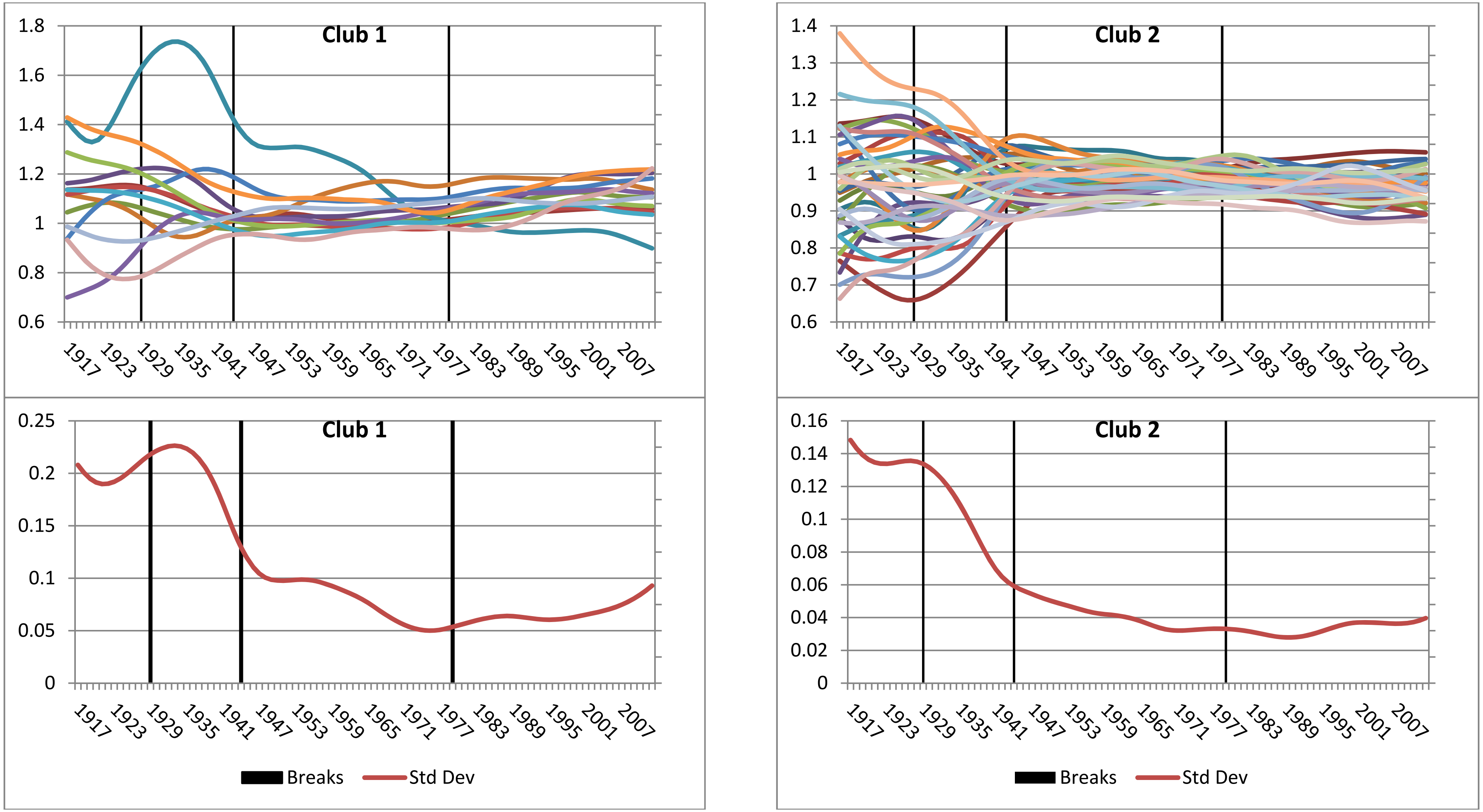


Figure 3. Relative Transition Curves and Standard Deviations: Gini Index

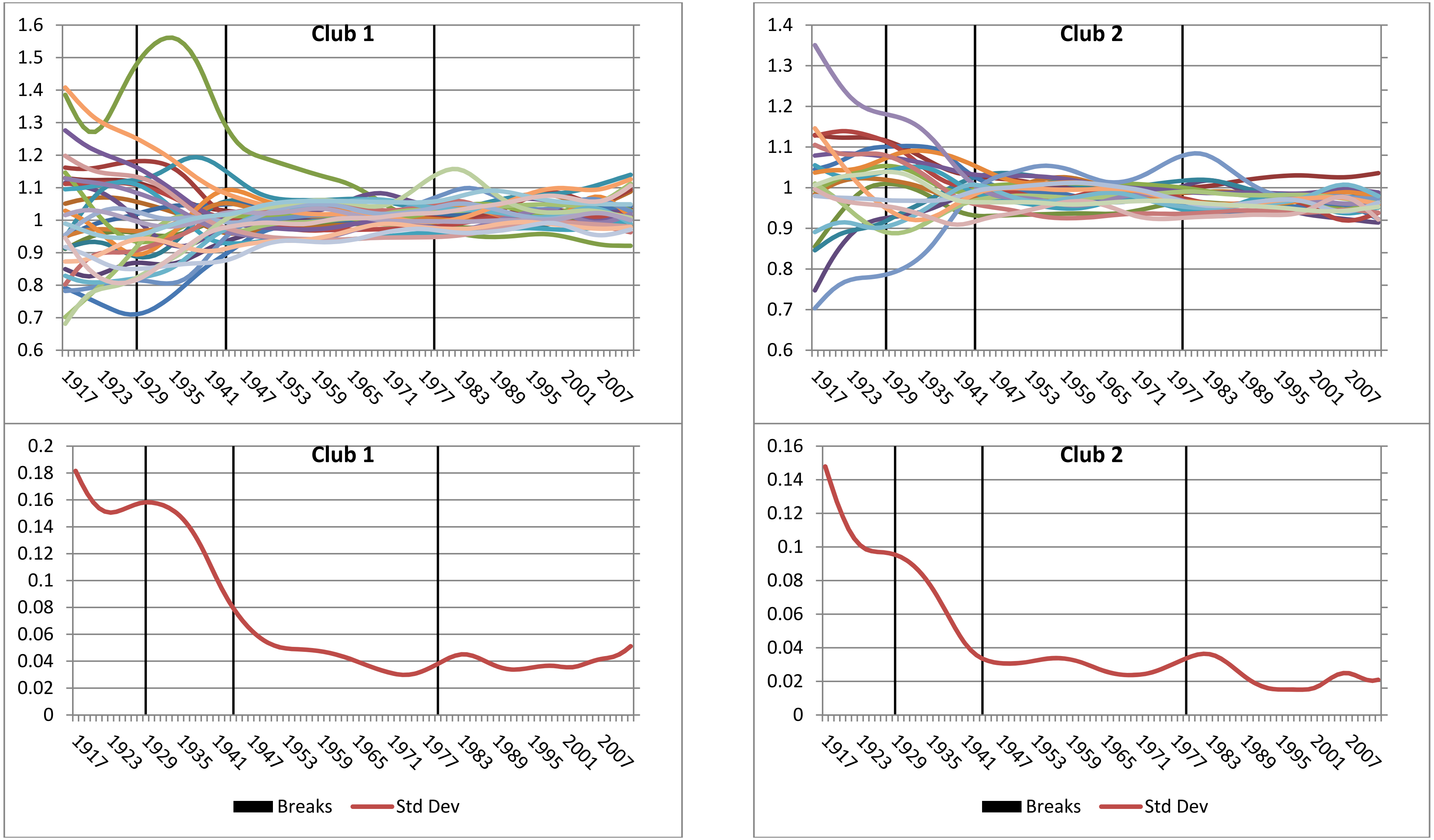


Figure 4. Relative Transition Curves and Standard Deviations: Atkinson Index

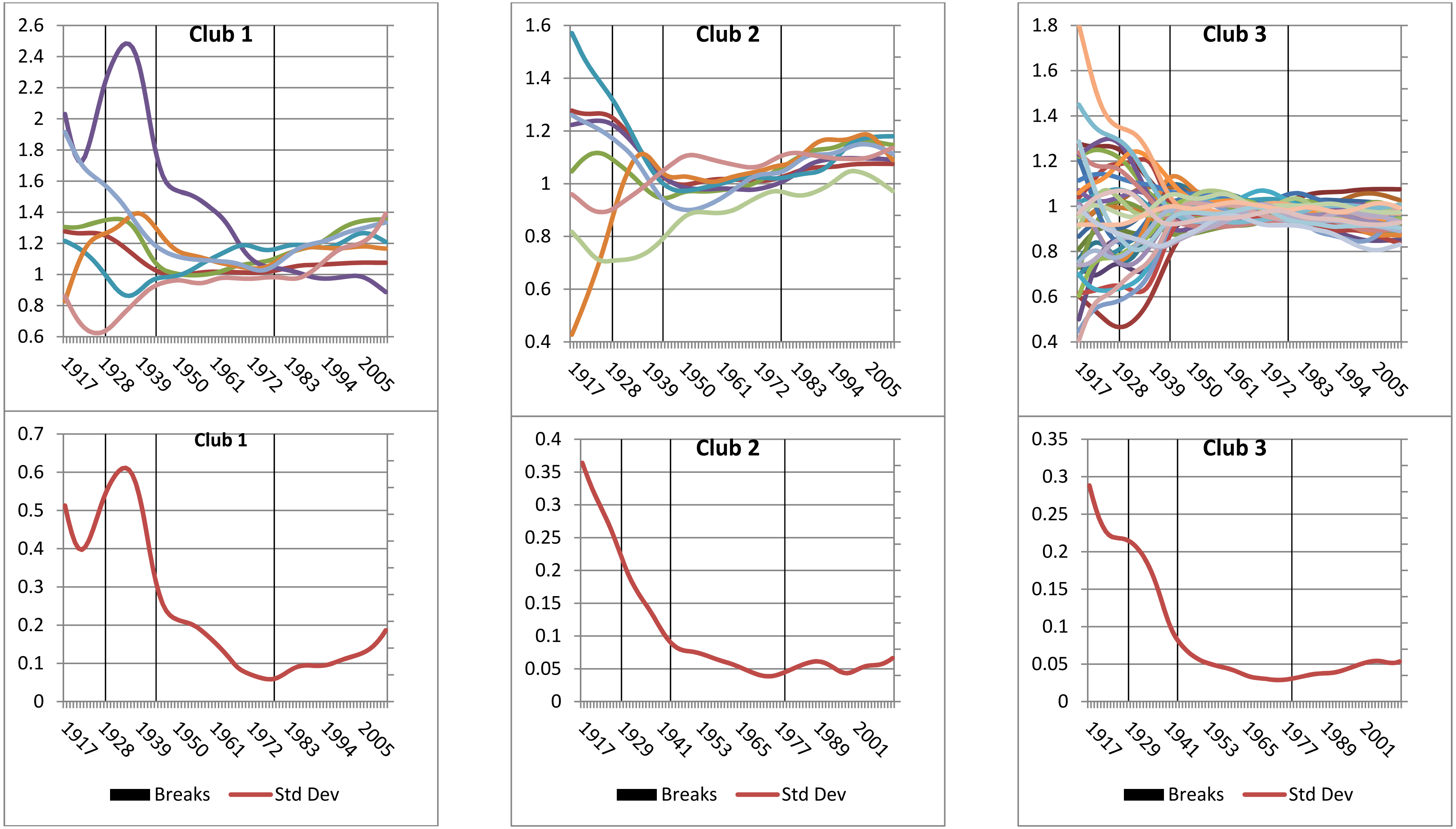


Figure 5. Relative Transition Curves and Standard Deviations: Mean deviation index

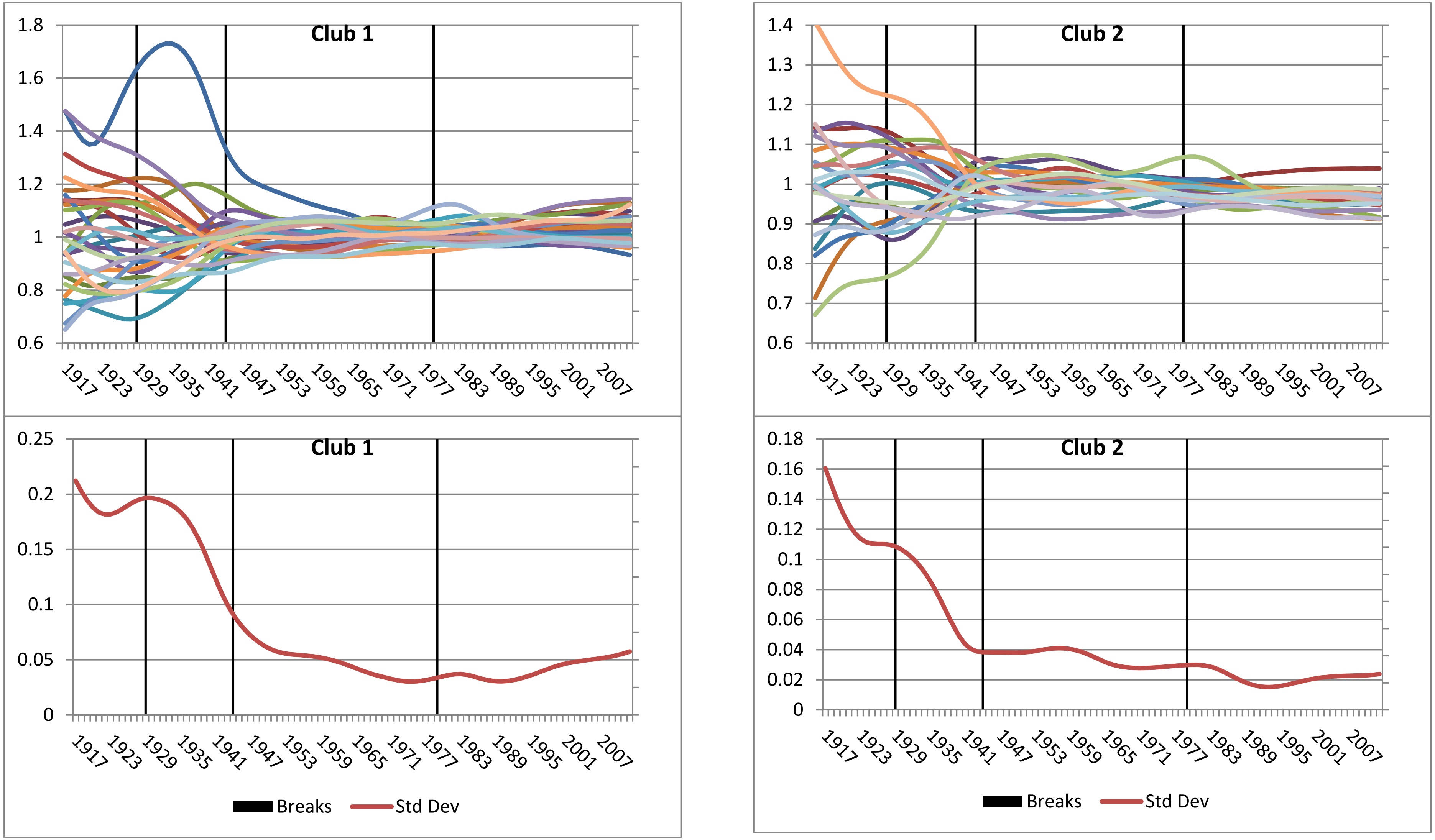


Figure 6. Relative Transition Curves and Standard Deviations: Theil index

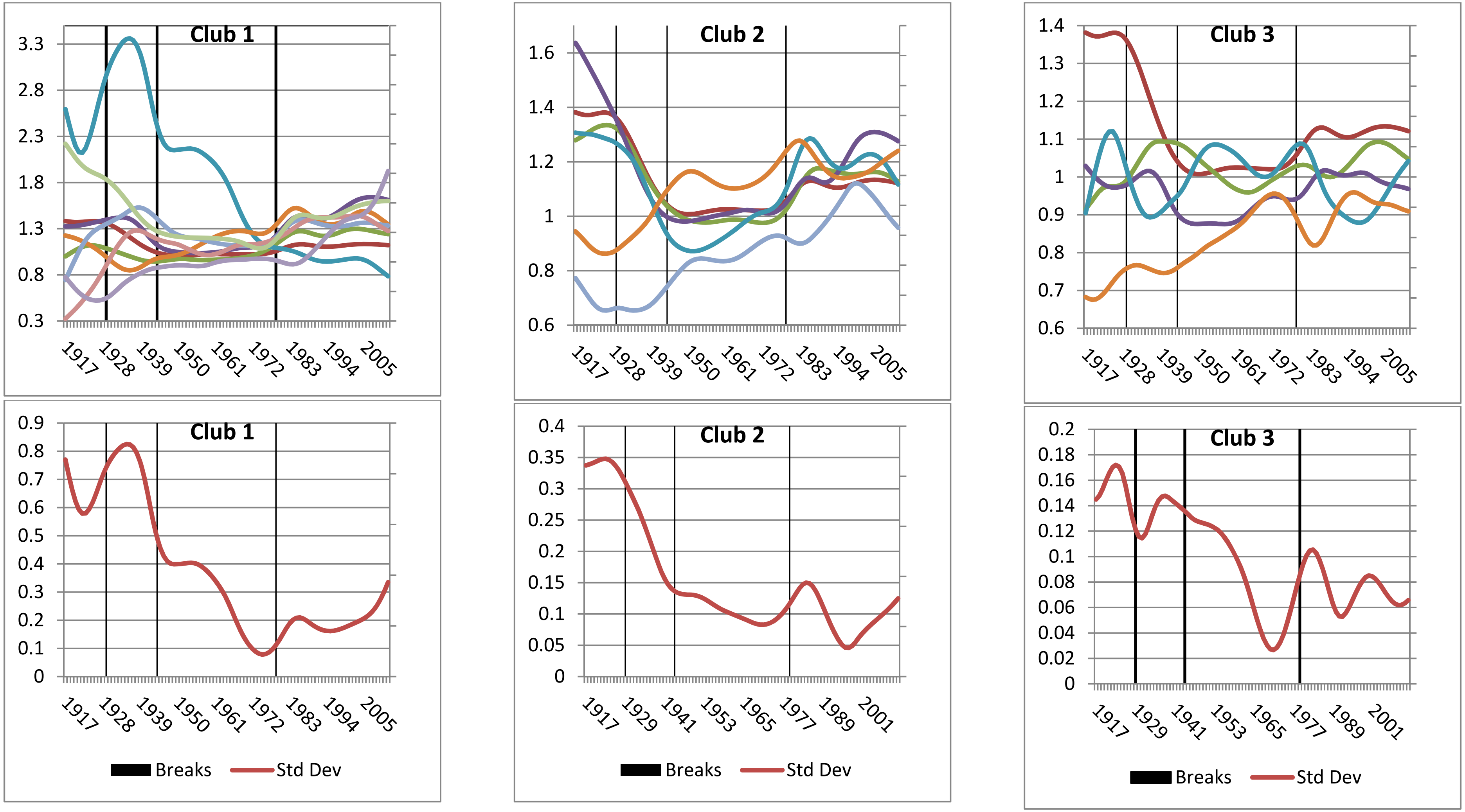


Figure 6. Relative Transition Curves and Standard Deviations: Theil index (continued)