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Pitfalls in Testing for Cointegration between Inequality and the Real Income*

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Abstract

Frank (2009) constructed a comprehensive panel of state-level income inequality measures using individual tax filing data from the Internal Revenue Service. Employing an array of cointegration exercises for the data, he reported a positive long-run relationship between income inequality and the real income per capita in the US. This paper questions the validity of his findings. First, we suggest a mis-specification problem in his approach regarding the order of integration in the inequality index, which shows evidence of nonstationarity only for the post-1980 data. Second, we demonstrate that his findings are not reliable because the panel cointegration test he uses requires cross-section independence, which is inappropriate for the US state-level data. Employing panel tests that allow cross-section dependence, we find no evidence of cointegration between inequality and the real income.

JEL Classification: D31; O40

Keywords: Inequality; Economic Growth; Cointegration; Cross-Section Dependence; Nonstationarity

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1 Introduction

The unprecedented rise in US income inequality since the early 1980's has been attracting the attention of researchers and policy makers over the last decades. One key question in the academic and public debates surrounding inequality is regarding its relation to economic growth. The current empirical literature provides mixed evidence, finding the correlation to be either negative or positive, or sometimes insignificant.[1]

Early researches on this topic predominantly found a negative correlation. Many of them used modified versions of the cross-country economic growth model proposed by Barro (1991) augmented with an inequality variable. See, among others, Alesina and Perotti (1994), Alesina and Rodrik (1994), Persson and Tabellini (1994), Birdsall, Ross, and Sabot (1995), and Deininger and Squire (1998). However, Forbes (2000), later on, questioned the validity of these findings, pointing at measurement error (or omitted variable) biases in the earlier works due to the fact that inequality was measured differently in the countries studied in those cross-country analyses.

More recent studies point towards a positive relationship between income inequality and economic growth, following the significant work of Deininger and Squire (1996) who constructed an improved database of cross-country inequality measures. Using these data, Forbes (2000) reports that income inequality and growth are positively correlated, while Barro (2000) reports a positive correlation in wealthier countries and a negative one in low-income countries. On the other hand, using a cross-state panel for the US, Panizza (2002) reports that the relationship between inequality and growth is not robust, questioning the validity of previous findings. Therefore, the profession has as yet failed to reach consensus.

More recently, Frank (2009) constructed a new valuable data set for state-level income inequality measures, i.e., top percentile shares of income for the 1945-2004 period, using highly confidential data from the Internal Revenue Service (IRS).[2] [3] Employing this data set for panel cointegration tests, he reported strong evidence of a positive correlation between income inequality and the real income per capita.

The present paper questions the validity of Frank's (2009) findings, employing more rigorous econometric procedures for the same data set.

First, we note that income inequality and the real income are assumed to be nonstationary

[1] See, name a few, Garcia-Penalosa, Caroli, and Aghion (1999) and Quadrini and Rios-Rull (2015) for a review on the theoretical literature.

[2] We use his updated data until 2011 in the present paper.

[3] Leigh (2007) find that the trends in top income shares correspond other common measures of inequality as the Gini coefficient, and Burkhauser, Feng, Jenkins, and Larrimore (2012) find that the growth in the income share of the top income percentile substantially outpaced inequality measured by the Gini coefficient.

in his work, which is necessary for cointegration analyses.[4] We demonstrate that the income inequality measures in most 49 US states follow a nonstationary stochastic process since the 1980's, while it is better approximated by a stationary process for the period prior to 1980.[5] This implies that Frank's (2009) conclusion of a positive relationship might not be valid because he uses cointegration tests for the entire sample period, ignoring a possible change in the stochastic process for inequality. Similar observations were also reported in Piketty and Saez (2003) and Atkinson, Piketty, and Saez (2011).

Second, the panel cointegration tests used by Frank require cross-section independence. In what follows, we show that this assumption is inappropriate for US state-level data that Frank has analyzed. When this assumption fails to hold, statistical inferences may suffer from severe size distortion. Applying panel cointegration tests that allow cross-section dependence, we obtain virtually no evidence of a positive correlation between inequality and the real income.

The remainder of this paper is organized as follows. Section 2 describes the data and provides preliminary discussions. In Section 3, we first describe our econometric procedures. Then, we report and discuss our empirical results. Section 4 concludes.

2 Data Descriptions and Preliminary Discussions

We employ annual observations of the state-level inequality data for 49 US states, which was compiled by Frank (2009). Using highly confidential IRS data, he constructed the top decile share of income data, that is, the percentage of total *income* held by the top 10% income earners in each state. Observations range from 1945 to 2011.[6] Also, we obtained the state-level real income per-capita data from the Federal Reserve Economic Data (FRED) for the same sample period to measure economic growth in the US. The real income per capita is log-transformed.

We noticed a substantial degree of common tendency from each of the 49 state-level inequality measures. Similar comovements were observed from the real income variables. This observation has an important implication on our econometric test procedures, because panel cointegration tests that require cross-section independence perform poorly when the

[4]He implemented a panel unit root test for these variables from 1945 to 2004, which fails to reject the null of nonstationarity. If the true data generating process has changed from a stationary to a nonstationary process, implementing the test for the full sample will result in invalid statistical inferences.

[5]Unit root tests are known to have low power in small samples. That is, these tests may imply non-stationarity even when the alternative hypothesis (stationarity) is correct. Since we have stationarity for inequality in small samples (pre-1980s), this greatly strengthens our argument because the test rejects the null of nonstationarity even though the test suffers from low power in small samples.

[6]We obtained the data from Frank's website at: http://www.shsu.edu/eco_mwf/inequality.html

true (panel) data-generating process is given a common factor structure. One may estimate a vector of common factors via the method of the principal components to study the patterns of the cross-section dependence. It turns out that the cross-section average of the data resembles the first common factor (see Pesaran, 2007). In order to see the common dynamics of these variables, we report the cross-section averages of the inequality and income variables in Figure 1.

We noticed that the cross-section mean of the real GDP per capita is continuously trending upward since the beginning of the data in 1945, while the top decile share of income exhibits a positive trend only after 1980. The inequality variable exhibits ups and downs around 32% until around 1980. Put it differently, the real GDP per capita seems to follow a non-stationary stochastic process for the entire sample period, whereas the stochastic nature of the inequality measure might have changed from a stationary process to a nonstationary process around 1980.

We are not the first who observed such a change in inequality dynamics. Piketty and Saez (2003) also noticed a positive trend in the top 10% pre-tax income share since 1980's based on individual tax returns data. Atkinson, Piketty, and Saez (2011) summarize the literature that documents concurrent trends in other English speaking countries, but not in continental Europe or Japan.[7] Burkhauser, Feng, Jenkins, and Larrimore (2012) report remarkably similar trends from the Current Population Survey (CPS) data.[8]

Figure 1 around here

This observation casts doubt on the validity of cointegration test results in Frank (2009) for the entire sample period, since a cointegration relationship requires a set of nonstationary variables. We implement an array of econometric tests in the next section to investigate these issues.

In addition to these data, we also employ the two measures of state-level human capital data used in Frank (2009), the proportion of the population having finished high school and the percentage of those having earned college degrees, for the sample period from 1945 to 2004, which were obtained from Mark Frank's website.[9] We extend our benchmark model

[7] Atkinson, Piketty, and Saez (2011) provide a literature review on long-run trends in the share of top-income earners, e.g., Piketty and Saez (2006), for more than 20 countries.

[8] Piketty and Saez (2006) suggest that top labor compensations in the United States has increased due to increased ability of executives in setting their own salaries, which extracts rents at the expense of shareholders. Atkinson, Piketty, and Saez (2011) also note that this positive trend in inequality might be due to changes in taxation policy, politics, and globalization.

[9] Updated data for these series are not available unfortunately.

using these series to replicate the results of Frank (2009), which confirms findings from our benchmark model. As we can see in Figure 2, the cross-section means of these human capital series exhibit an upward trend since the beginning of the data in 1945. That is, these series seem to follow a nonstationarity stochastic process.

Figure 2 around here

3 Empirical Findings

3.1 Unit Root Tests

This section implements formal econometric tests for the stochastic properties of our key variables focusing on the state-level inequality data in the US. For this purpose, we report an array of univariate and panel unit root tests for the two sub-sample periods, the pre-1980 and the post-1980 samples. These tests are crucial for the validity of the panel cointegration tests we implement afterward.

3.1.1 Univariate Unit Root Tests

We first employ the DFGLS test proposed by Elliott, Rothenberg, and Stock (1996) for the two sub-samples: the pre-1980 (1945-1979) and the post-1980 (1980-2011) periods. The DFGLS test is known to be asymptotically more powerful than the augmented Dickey-Fuller (ADF) test. We use 1980 as an *ad hoc* break point based on our eye-ball inspection of the inequality graph in Figure 1. We do not attempt to estimate the structural break date, because, to the best of our knowledge, no econometric procedures are available when the data generating process (DGP) changes from a stationary process to a nonstationary one in the middle of the data. However, many researchers acknowledge that the late 1970's or early 1980's as the time when income inequality in the US started to grow rapidly. See, for example, e.g. Piketty and Saez (2003), Frank (2009), and Saez and Zucman (2014).

The DFGLS test is based on the following regression model for each US state.

$$\Delta \tilde{y}_t = \alpha + \rho y_{t-1} + \sum_{j=1}^{p} \beta_j \Delta \tilde{y}_{t-j} + \varepsilon_t, \tag{1}$$

where $\tilde{y}_t$ is locally *demeaned* data under the local alternative of $\tilde{\alpha} = 1 + \hat{c}/T$. T is the sample size and we use $\hat{c} = -7$ as recommended by Elliott, Rothenberg, and Stock (1996). The DFGLS test statistic is defined as,

$$ADF = \frac{\hat{\rho}}{s.e.(\hat{\rho})}, \tag{2}$$

where $\hat{\rho}$ is the ordinary least squares (OLS) estimate of ρ and $s.e.(\hat{\rho})$ is the OLS standard error. We report the test results in Tables 1 and 2.[10]

In the pre-1980's sample period, the DFGLS test rejects the null of nonstationarity in the inequality series for 41 out of 49 states at the 10% significance level, which is over 83% of the total samples (see Table 1).[11] That is, we obtained very strong evidence of stationarity for the pre-1980's inequality series. On the other hand, we find no evidence of stationarity for the post 1980's inequality series as the test fails to reject the null for all 49 states even at the 10% significance level (see Table 2). Therefore, it seems that the inequality series exhibit nonstationarity only for the post-1980's data.

As to the real income series, we observe very weak evidence of stationarity in both sub-samples. The DFGLS test fails to reject the null for most states both in the pre- and the post-1980's data.[12] We obtained similar empirical evidence in favor of nonstationarity for the human capital data used in Frank (2009) for the sample period from 1945 to 2004.[13] That is, the test implies that the real income and the human capital data obey a nonstationary stochastic process, which is consistent with the upward trend that is observed in Figures 1 and 2.

In a nutshell, our univariate unit root test supports the nonstationarity of the inequality variable only for the post-1980's samples, while the real income and human capital data seem to follow a nonstationary process for the entire sample period. Therefore, cointegration tests for the full sample period in Frank (2009) may suffer from a mis-specification problem.

Tables 1 and 2 around here

3.1.2 Panel Unit Root Test

We note that the pre-1980 and the post-1980 sub-samples include 35 and 32 annual observations, respectively. Since the univariate unit root test has low power in small samples, we

[10] We report test results with one lag. The test with two lags yields qualitatively similar results. Results with two lags are available in the not-for-publication appendix.

[11] We also implemented the ADF test. The test rejects the null of nonstationarity in the inequality series for 32 out of 49 states, which is over 65% of the total observations. Since the DFGSL test is asymptotically more powerful than the ADF test, such weaker evidence seems to be due to low power of the ADF test. The ADF test results with 1 and 2 lags are available upon request.

[12] All test results are available from authors upon request.

[13] These test results are also available from authors upon request.

investigate the possibility that weak evidence of stationarity is due to lack of power. For this purpose, we implement a panel unit root test proposed by Pesaran (2007). By adding more observations in a panel framework, we may expect greater power gains from using panel test as suggested by Taylor and Sarno (1998) for example. However, it is crucially important to do a pre-test about the cross-section structure of the panel data, because panel tests that require cross-section independence suffer from severe size distortion in the presence of the cross-section dependence.

Employing the formal test proposed by Pesaran (2004), we establish the existence of cross-section dependence in our data. Consider the following test statistic.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{i,j} \right) \xrightarrow{d} N(0,1) \tag{3}$$

where $\hat{\rho}_{i,j}$ is the pair-wise correlation coefficients from the residuals of the ADF regressions for each state.

The test results in Table 3 imply a strong presence of cross-section dependence in the panels for inequality, real income per capita, and the two measures of human capital. The test statistics rejects the null of the cross-section independence at the 1% significance level for all series. Total average $\hat{\rho}$ is 0.473 and 0.524 for inequality and the real income, respectively. For the two human capital series, average $\hat{\rho}$ was much greater for the high school degree attainment in comparison with that of the college degree attainment data, although the cross-section independence null was still strongly rejected for both human capital series. We also report average correlations of each state in Figures 3 through 6, which show high degree cross-section dependence in all variables.

Table 3, Figures 3, 4, 5, and 6 around here

Since all data including the inequality and the real income series are characterized by cross-section dependence, we employ the so-called second generation panel unit root tests, because the first generation panel unit root tests such as the ones by Im, Pesaran, and Shin (2003), Levin, Lin, and James Chu (2002), and Maddala and Wu (1999) require cross-section independence, which is clearly rejected for our state-level data in Table 3. In this paper, we implement a panel unit root test proposed by Pesaran (2007) with the following least squares regression model.

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{p} \theta_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{4}$$

where $y_{i,t}$ is a variable in state $i \in \{1, 2, ..., N\}$ at time t and $\bar{y}_t$ denotes the common factor at time t, which is proxied by the cross-section mean, $N^{-1} \sum_{i=1}^{N} y_{i,t}$. Note that this is a version of the ADF regression model extended by the cross-section mean in order to control for the effect of the common factor on the panel unit root test. The panel test statistic is then computed as follows.

$$t(N,T) = N^{-1} \sum_{i=1}^{N} t_i(N,T) \tag{5}$$

where $t_i(N,T)$ is the t-statistic for β_i from the regression equation (4) for state $i \in \{1, 2, ..., N\}$.

It should be noted that the panel unit root test using this procedure requires an assumption that the common factor is *stationary*. When this assumption holds, the panel unit root test based on (5) provides meaningful inferences on the stationarity of the panel $\{y_{i,t}\}_{i=1,..,N,t=1,..,T}$. If this assumption fails, however, stationarity evidence from idiosyncratic components does not necessarily provide evidence in favor of stationarity.

Therefore, we first report the unit root test results for the common factors of the inequality and the real income data as well as the human capital data in Table 4. Table 5 provides Pesaran's (2007) panel unit root test results based on (5). Note that the ADF test rejects the null of nonstationarity only for the inequality common factor during the pre-1980 period. Combined with this, strong evidence of panel stationarity for the idiosyncratic components implies that only the inequality for the pre-1980 period obeys a stationary stochastic process. The test results imply strong evidence of nonstationarity for all other variables in both sub-sample periods.[14]

In a nutshell, we conclude that there is a possible mis-specification problem in Frank's (2009) approach, who uses panel cointegration tests for the state-level data for the inequality from 1945 to 2004 that includes both the pre- and the post-1980 periods. Cointegration tests require nonstationarity in all variables in the cointegrating relationship. Our unit root tests imply that one may employ a panel cointegration framework only for the post-1980 sample period, because the inequality series show clear evidence of stationarity for the pre-1980 samples.

Tables 4 and 5 around here

[14]High school human capital variable exhbits very strong evidence of nonstationarity as the test fails to reject the null of nonstationarity for both the common factor and the idiosyncratic components.

3.2 Cointegration Test

In addition to the nonstationarity issue, Frank's (2009) findings may not be valid because he employed cointegration tests that require cross-section independence. In this section, we implement robust cointegration tests that incorporate cross-section dependence in the data. We demonstrate that Frank's finding of a positive relationship between inequality and the real income is not empirically supported when correct econometric procedures are used.

As explained above, it is appropriate to test for cointegration only for the post-1980 sample period, because inequality obeys a stationary stochastic process in the pre-1980 period. Nonetheless, we implement the cointegration test using the full sample to replicate the empirical findings reported in Frank (2009). Then, we compare the results with those from rigorous test procedures that allow cross-section dependence which clearly exists in the US state-level data as shown in the previous section.

We first implement our analysis for the sample period between 1945 and 2011 using inequality and the real income data, because Mark Frank's human capital data are available only until 2004. We also provide test results for the same specification used in Frank (2009) to highlight the mis-specification issues in his work.

For this purpose, we employ the error correction-based panel cointegration tests proposed by Westerlund (2007).[15] The tests allow for a large degree of heterogeneity between the cross-sectional units and can account for cross section dependence via bootstraps. The tests assume the following data-generating process.

$$\Delta y_{it} = \delta_i' \mathbf{d}_t + \alpha_i (y_{i,t-1} - \beta_i' \mathbf{x}_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta \mathbf{x}_{i,t-j} + e_{it}, \tag{6}$$

where $\mathbf{d}_t$ is a vector (or scalar) of deterministic components. α_i denotes the error correction parameter with the cointegrating vector $[1 \quad -\beta_i']'$. p_i and q_i are the numbers of lags and leads, respectively. (6) can be rewritten as follows.

$$\Delta y_{it} = \delta_i' \mathbf{d}_t + \alpha_i y_{i,t-1} - \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it}, \tag{7}$$

where $\lambda_i' = -\alpha_i \beta_i'$. Note that $\alpha_i < 0$ implies that there is an error correction when deviations from the long-run equilibrium occur. If $\alpha_i = 0$, there is no cointegration because there is no adjustment toward the long-run equilibrium when shocks occur.

Westerlund (2007) propose two types of the cointegration test with the null hypothesis $H_0 : \alpha_i = 0, \forall i$, that is, there is no cointegration for all i. Note that the test can be

[15] We used the stata code following instructions from Persyn and Westerlund (2008).

implemented without paying much attention on the cointegration vector β_i itself. They propose the following two tests: the group mean tests and the panel tests. The *group mean test* does not require homogeneity in α_i estimates. That is, the alternative hypothesis is $H_A : \alpha_i < 0$, for at least one i. On the other hand, his *panel test* requires homogeneity with $H_A : \alpha_i = \alpha < 0, \forall i$.

Our test results in Table 6 clearly reveal our point. When we impose a cross-section independence assumption, both the group mean test and the panel test strongly reject the null of no cointegration. However, the test that incorporates cross-section dependence via bootstraps fails to reject the null of no cointegration whichever specifications are employed.[16] Put it differently, Frank's empirical results seem to be caused by size distortion caused by imposing a wrong cross-section independence assumption in addition to the mis-specification problem which was explained in the previous section. Accounting for cross-section dependence in our cointegration tests, we find no statistically meaningful evidence for cointegration between inequality and the real income.

Table 6 around here

Next, we present further test results using the exact same model specification used in Frank (2009). That is, we added the two measures of human capital to the cointegration model for the sample period between 1945 and 2004. Results are provided in Table 7. We obtained qualitatively similar results. 3 out of 4 cases, the test fails to reject the null of no cointegration when cross-section dependence is allowed. The test continues to reject the null hypothesis when the panel test is implemented with an intercept. However, the panel test requires homogeneity of the error correction coefficient α, which can be restrictive. Therefore, empirical findings presented in Table 7 seem to be overall consistent with those in Table 6.[17]

Table 7 around here

[16] We implemented the same tests with different combinations of leads and lags and different types of kernels and bandwidths. Results are similar with each other.

[17] We also performed this test for the post-1980 samples, which yielded qualitatively similar results. The test fails to reject the null of no cointegration for 3 out of 4 cases in both the two-variable and the four-variable models at the 5% significance level.

4 Conclusion

This paper revisits the cointegrating relationship between income inequality and economic growth using Frank's (2009) state-level inequality measures data constructed from confidential individual tax filing data from the IRS.

We question the validity of his findings that imply a positive long-run relationship between inequality and economic growth raising the following two issues. First, his cointegration analyses may have a mis-specification problem as to the order of integration of the data. As is well documented, cointegrating tests can be implemented among the integrated nonstationary variables. Via an array of univariate and panel unit root tests, we demonstrate that the nature of the stochastic process in the income inequality series has changed around 1980. More specifically, the inequality index seems to obey a stationary process during the pre-1980 sample period, while the real income data follows a non-stationary process for the entire sample period. That is, the econometric model in Frank (2009) may be mis-specified for the pre-1980 data.

Second, we note that Frank's panel cointegration tests require cross-section independence, which is strongly rejected by our test for the US state-level data. Employing rigorous panel cointegration tests that allow cross-section dependence via bootstraps, we find no such evidence of a stable long-run relationship using the same data series. We obtained the same positive cointegration results only when cross-section independence is assumed. Put it differently, the strong evidence of cointegration found in Frank (2009) is likely to be caused by size distortion by imposing a wrong assumption of cross-section independence. Using the exactly same model specification with two measures of human capital as in Frank (2009), we obtained qualitatively similar results as those from our benchmark model, which highlights our points.

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Table 1. DFGLS Test for the Inequality Index: 1945 to 1979

State	DFGLS	State	DFGLS
Alabama	-2.245**	Nebraska	-2.079**
Arizona	-2.547**	Nevada	-2.663***
Arkansas	-2.265**	New Hampshire	-2.178**
California	-1.220	New Jersey	-1.810*
Colorado	-1.904*	New Mexico	-1.939*
Connecticut	-2.476**	New York	-2.330**
Delaware	-1.170	North Carolina	-1.472
District of Columbia	-1.051	North Dakota	-2.006**
Florida	-1.696*	Ohio	-2.133**
Georgia	-1.442	Oklahoma	-3.160***
Idaho	-2.406**	Oregon	-1.720*
Illinois	-2.241**	Pennsylvania	-2.148**
Indiana	-1.903*	Rhode Island	-1.765*
Iowa	-1.773*	South Carolina	-1.896*
Kansas	-1.579	South Dakota	-2.003**
Kentucky	-2.629***	Tennessee	-2.191**
Louisiana	-2.450**	Texas	-1.622*
Maine	-3.243***	Utah	-1.400
Maryland	-1.850*	Vermont	-1.875*
Massachusetts	-2.094**	Virginia	-2.035**
Michigan	-2.564**	Washington	-1.161
Minnesota	-1.757*	West Virginia	-2.290**
Mississipi	-1.798*	Wisconsin	-2.396**
Missouri	-1.757*	Wyoming	-2.245**
Montana	-1.876*		

Note: We report the DFGLS test results with an intercept. *, **, and *** denote rejections of the null hypothesis of nonstationarity in the 10%, 5%, and 1% significance level, respectively.

Table 2. DFGLS Test for the Inequality Index: 1980 to 2011

State	DFGLS	State	DFGLS
Alabama	-1.502	Nebraska	-1.127
Arizona	-1.311	Nevada	-1.131
Arkansas	-0.182	New Hampshire	-1.055
California	-0.759	New Jersey	-0.685
Colorado	-0.817	New Mexico	-0.782
Connecticut	-0.540	New York	-0.580
Delaware	-1.162	North Carolina	-0.962
District of Columbia	-0.862	North Dakota	0.305
Florida	-1.075	Ohio	-1.117
Georgia	-0.739	Oklahoma	-0.645
Idaho	-0.828	Oregon	-0.952
Illinois	-0.899	Pennsylvania	-1.287
Indiana	-1.063	Rhode Island	-1.043
Iowa	-1.263	South Carolina	-1.214
Kansas	-0.865	South Dakota	-0.692
Kentucky	-1.479	Tennessee	-1.052
Louisiana	-1.575	Texas	-0.764
Maine	-1.041	Utah	-1.192
Maryland	-0.972	Vermont	-1.134
Massachusetts	-0.785	Virginia	-1.139
Michigan	-0.639	Washington	-1.252
Minnesota	-0.974	West Virginia	-0.418
Mississipi	-1.307	Wisconsin	-0.997
Missouri	-0.990	Wyoming	-1.100
Montana	-0.734		

Note: We report the DFGLS test results with an intercept. *, **, and *** denote rejections of the null hypothesis of nonstationarity in the 10%, 5%, and 1% significance level, respectively.

Table 3. Cross-Section Dependence Test Results

	Inequality	Real Income	High School	College
CD	129.68***	143.86***	133.10***	28.48***
Average $\hat{\rho}$	0.473	0.524	0.525	0.112

Note: CD is Pesaran's (2004) cross-section dependence statistic. *** denotes a rejection of the cross-section independence at the 1% significance level. The sample period is from 1945 to 2011 for inequality and the real income, while it is from 1945 to 2004 for the human capital variables, obtained from Mark Frank's website.

Table 4. Unit Root Test Results: Common Components

	Inequality	Real Income	High School	College
1945 – 1979	-2.541*	0.488	-1.188	1.301
1980 – 2011	-2.072	-1.638	-1.986	-0.152

Note: The common components are identified by taking the cross-section means of the series. The first common factors estimated via the method of the principal components are qualitatively similar to the cross-section means. * denotes a rejection of the nonstationarity null hypothesis at the 10% significance level. The sample period is from 1945 to 2011 for inequality and the real income, while it is from 1945 to 2004 for the human capital variables, obtained from Mark Frank's website. The ADF test fails to reject the null of nonstationarity for the full sample data.

Table 5. Panel Unit Root Test Results: Idiosyncratic Components

	Inequality	Real Income	High School	College
1945 – 1979	-3.310***	-2.694***	-1.625	-2.806***
1980 – 2011	-2.473***	-2.075*	-1.930	-2.722***

Note: Test statistics are from Pesaran (2007) that controls the cross-section dependence. * and *** denote rejections of the nonstationarity null hypothesis at the 10% and 1% significance level, respectively. Critical values are obtained from Pesaran (2007).

Table 6. Panel Cointegration Test Results

	Tests with an intercept		
	Statistics	p-value	p-value with CSD
Group Mean Test	-2.005	0.048	0.548
Panel Test	-13.972	0.000	0.258

	Tests with an intercept and time trend		
	Statistics	p-value	p-value with CSD
Group Mean Test	-3.103	0.000	0.156
Panel Test	-19.177	0.000	0.438

Note: The test is implemented using inequality and the real income data from 1945 to 2011. We implement Westerlund's (2007) t-test type panel cointegration test statistics. Number of leads and lags are determined by the AIC. p-value is not sized correctly when cross-section independence fails to hold. p-value with CSD denotes p-values with cross-section dependence via 500 bootstraps. The null hypothesis is no cointegration for both tests. The group mean test does not require homogeneity and the alternative hypothesis is there is at least one cointegration. The panel test does require homogeneity and the alternative hypothesis is the common cointegration exists for all panel seris.

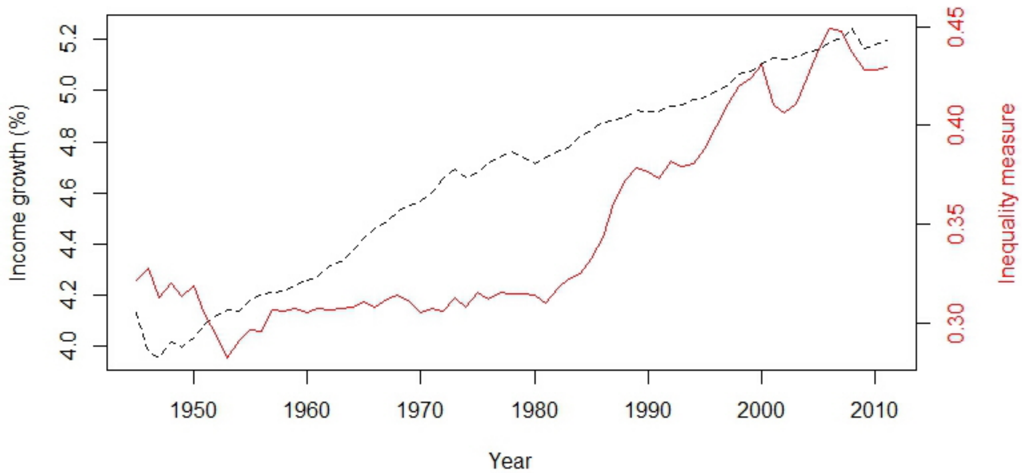
Table 7. Panel Cointegration Test Results with Frank's (2008) Model

	Tests with an intercept		
	Statistics	p-value	p-value with CSD
Group Mean Test	-2.613	0.003	0.178
Panel Test	-18.192	0.000	0.034

	Tests with an intercept and time trend		
	Statistics	p-value	p-value with CSD
Group Mean Test	-2.865	0.100	0.560
Panel Test	-19.007	0.020	0.420

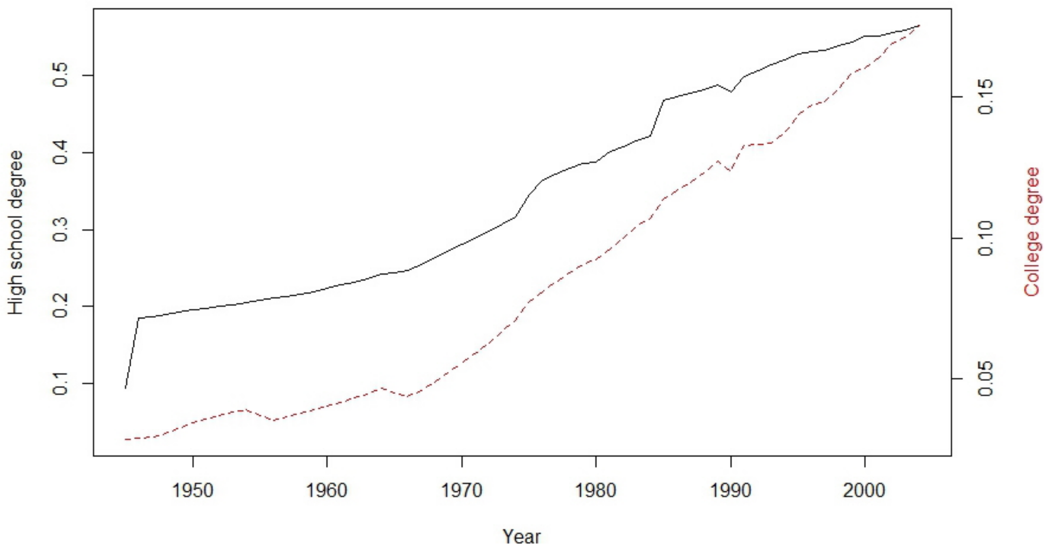
Note: The test is implemented using inequality,the real income, and the human capital data from 1945 to 2004.We implement Westerlund's (2007) t-test type panel cointegration test statistics for the empirical model used in Frank (2008). That is, we added two sets of human capital variables in the cointegration model for the same sample period (1945 - 2004) as in Frank (2008). Human capital data were obtained from Mark Frank's website. Number of leads and lags are determined by the AIC. p-value is not sized correctly when cross-section independence fails to hold. p-value with CSD denotes p-values with cross-section dependence via 500 bootstraps. The null hypothesis is no cointegration for both tests. The group mean test does not require homogeneity and the alternative hypothesis is there is at least one cointegration. The panel test does require homogeneity and the alternative hypothesis is the common cointegration exists for all panel seris.

Figure 1. Inequality (Solid) and Real Income per capita (Dashed)



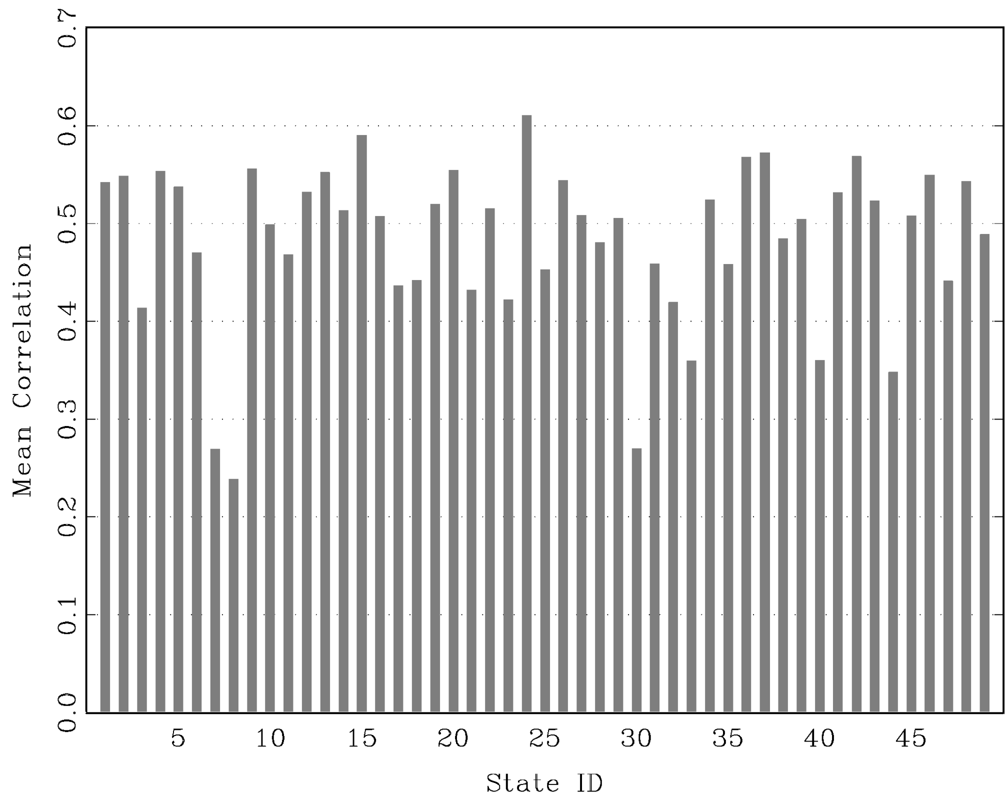
Note: Cross-section averages of the 49 state-level data are presented.

Figure 2. High School (Solid) and College (Dashed) Degree Ratios



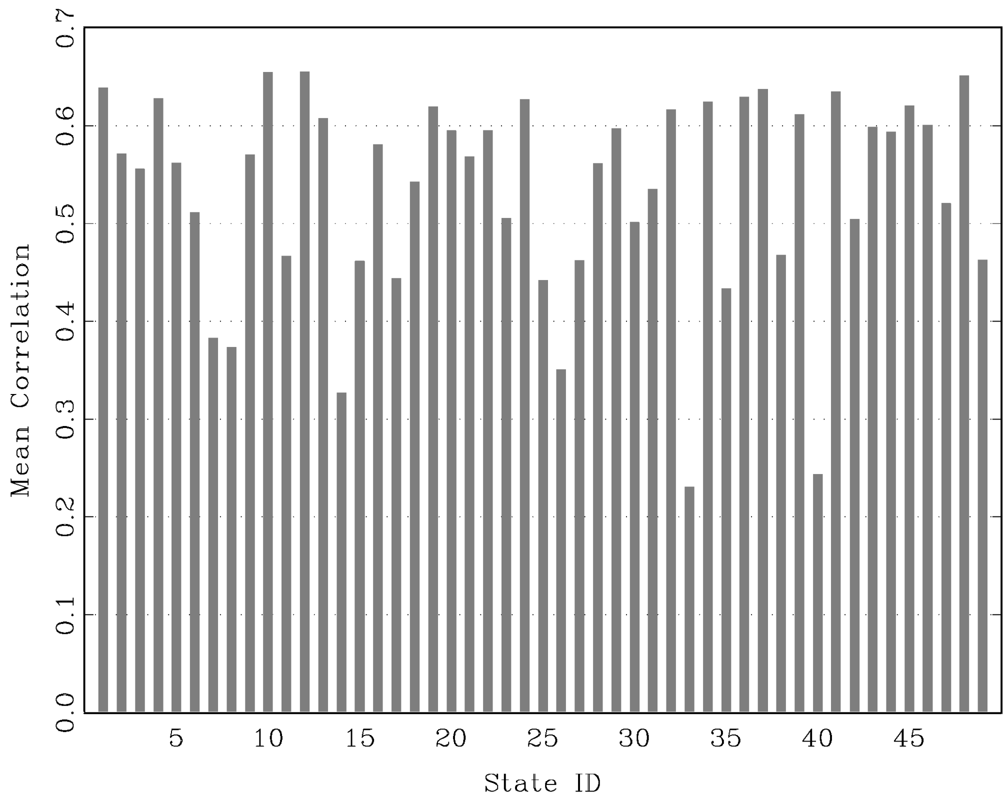
Note: Cross-section averages of the 49 state-level data are presented.

Figure 3. Mean Correlation Coefficients: Inequalty Series



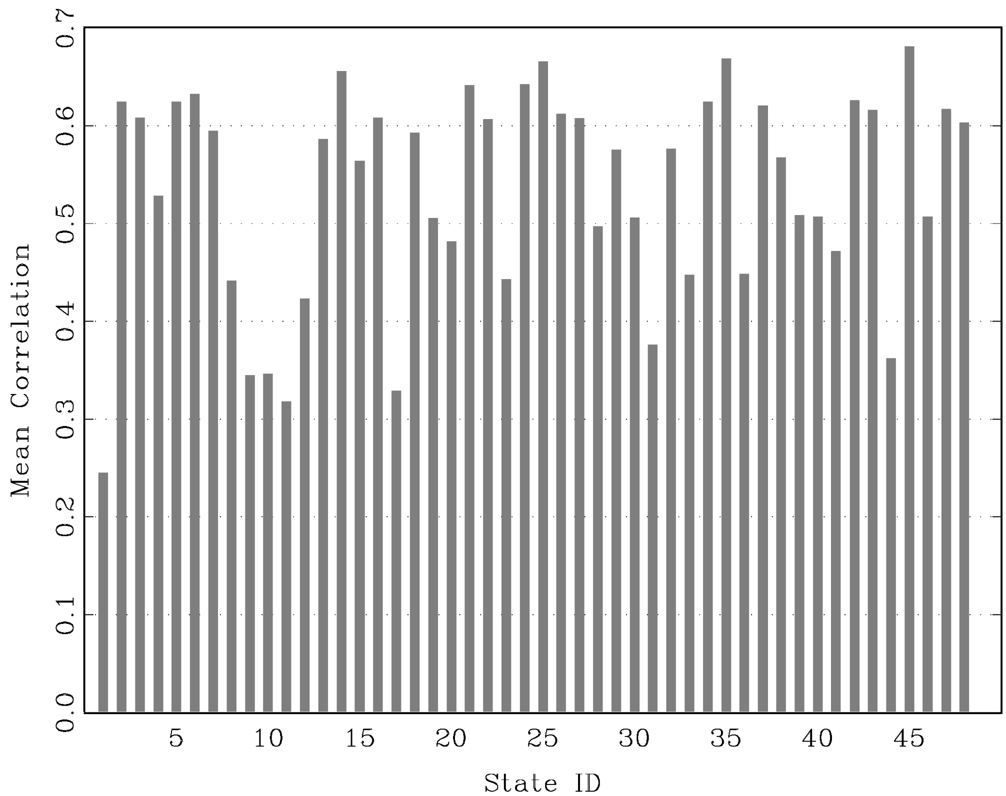
Note: We report the mean correlation coefficient of each state with respect to other 48 states.

Figure 4. Mean Correlation Coefficients: Real Income Series



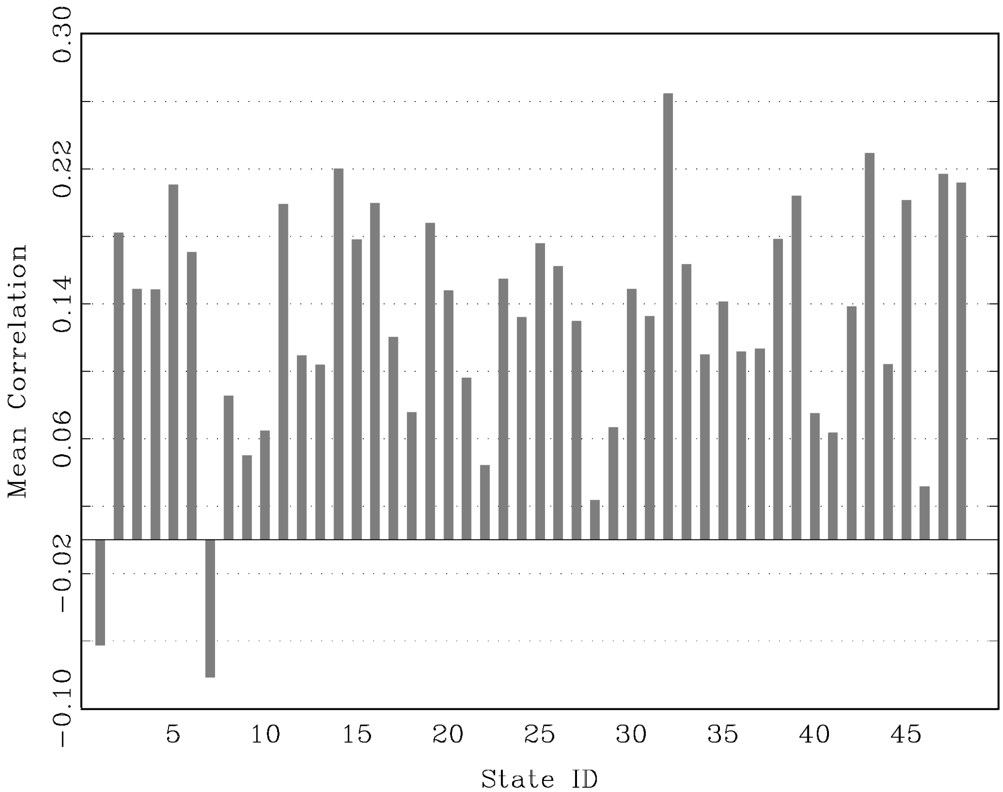
Note: We report the mean correlation coefficient of each state with respect to other 48 states.

Figure 5. Mean Correlation Coefficients: High School Ratio



Note: We report the mean correlation coefficient of each state with respect to other 48 states.

Figure 6. Mean Correlation Coefficients: College Ratio



Note: We report the mean correlation coefficient of each state with respect to other 48 states.