Sam Houston State University
Department of Economics and International Business
Working Paper Series

Income Inequality and Economic Growth in the U.S. :A Panel Cointegration Approach

Mark W. Frank

SHSU Economics & Intl. Business Working Paper No. SHSU_ECO_WP05-03
March 2005

Abstract:
The purpose of this paper is to examine the empirical relationship between income inequality and economic growth using U.S. state-level data during the post-war period. We construct a sample of 48 U.S. states with annual observations over the period 1945 to 2001. With this sample the number of time series observations is relatively large and of the same order of magnitude as the number of groups. This allows for the exploitation of new cointegrated dynamic panel data techniques. Our findings indicate that the long-run relationship between inequality and growth is negative in nature, though this negative relationship appears to be larger for low-income states.

Income Inequality and Economic Growth in the U.S.: A Panel Cointegration Approach[*]

Mark W. Frank, Ph.D.[†]

Abstract: The purpose of this paper is to examine the empirical relationship between income inequality and economic growth using U.S. state-level data during the post-war period. We construct a sample of 48 U.S. states with annual observations over the period 1945 to 2001. With this sample the number of time series observations is relatively large and of the same order of magnitude as the number of groups. This allows for the exploitation of new cointegrated dynamic panel data techniques. Our findings indicate that the long-run relationship between inequality and growth is negative in nature, though this negative relationship appears to be larger for low-income states.

Keywords: Income Inequality, Economic Growth, Cointegrated Panels.

---

[*] The author gratefully acknowledges the generous comments and insights offered by Donald G. Freeman and Edward F. Blackburne. The construction of the income distribution data was accomplished with the help of David A. Mathews, Jennifer M. George, and Swapna S. Easwar. The data may be accessed online at http://www.shsu.edu/eco_mwf/inequality.html. All errors remain my responsibility
[†] Department of Economics and International Business; Sam Houston State University; Box 2118; Huntsville, TX 77341;Email: markfrank@shsu.edu

Income Inequality and Economic Growth in the U.S.: A Panel Cointegration Approach

I. Introduction

There is now a large and growing literature, both theoretical and empirical, examining the relationship between income inequality and economic growth. Early on, this relationship was usually assumed to be negative. Galor and Zeira (1993), also Aghion and Bolton (1997), argue that credit market imperfections limit the ability of low-income individuals to invest in human capital, leaving productivity gains unexploited. The political economy models of Alesina and Rodrik (1994) and Persson and Tabellini (1994) stress the efficiency losses from re-distributional schemes and government intervention as median voters use the political system to flatten the income distribution. Gupta (1990) and Alesina and Perotti (1996) emphasize the potential for social unrest and political upheaval from increased inequality and the consequent diversion of resources toward social control. Empirical evidence, primarily cross-country regressions of economic growth over long periods on inequality and other control variables, tended to support the negative view. Bénabou (1996) provides a useful survey of much of this literature.

Over time, however, an alternate view of the inequality-growth nexus developed, with researchers emphasizing the positive aspects of inequality for growth. In one variation of this view, inequality may reflect more flexible labor markets that bring about higher levels of work effort and entrepreneurial energy leading to stronger economic growth (Metzler, 1998; Siebert, 1998). Separately, Galor and Tsiddon (1997) develop a model in which technological shocks concentrate productivity growth and factor payments in the advancing sectors of the economy. Barro (2000) proposes that because political power follows from economic power, concentration of income can lead to government policies favoring economic growth. Some recent empirical work tends to support these alternative views, with positive relationships between growth and inequality found by Forbes (2000) for a panel of countries, and Partridge (1997) for a panel of U.S. states.

Still other empirical work, however, notably by Barro (2000), Quah (2001), and Panizza (2002) find little or no stable relationship between inequality and growth; results appear to be extremely sensitive to the econometric specification or the data set (Deininger and Squire, 1998; Barro, 2000). In general then, the evolution of the empirical literature on inequality and growth has moved from finding mainly negative relationships, to finding some positive relationships, to finding little or no relationship. The ambiguity is unfortunate, because inequality is clearly increasing, at least in the U.S., and whether and by how much this change in inequality is associated with a change in economic performance is an important question.

[**Figure 1 about here**]

Figure 1 illustrates changes in both real income per capita and income inequality among the 48 states over the period 1945 to 2001. Shaded areas show periods of recession as defined by the National Bureau of Economic Research. The solid line (left scale) shows the yearly trend in the average logarithm of real income per capita for the 48 states. In 2001, the average state income per capita ($16,361 in 1982-4 constant dollars) was three times greater than the average state income in 1949 ($5,491), the lowest year for the period. The dashed line (right scale) shows the yearly average among the 48 states of the gini coefficient, an inequality measure encompassing the entire income distribution.[1] Average inequality among the states has grown substantially over this period, from a low of 0.402 in 1953, to a high of 0.572 in 2000. Clearly, current levels of inequality have been rising at an unprecedented rate in the post-war period.[2]

However, one must be cautious in attempting to infer relationships from aggregate U.S. data. Aggregate growth in the U.S. has been influenced by any number of factors during the past 50 years, and any attempt to partial out the effect of changes in income inequality is vulnerable to the problems of multicollinearity among the regressors, and the potential endogeneity of inequality itself. For these reasons, we use pooled U.S. state-level data, which offers enhanced variability and additional controls for heterogeneity, and utilize a methodology to address endogeneity issues, as well as long-run and short-run forces, as discussed below.

Figure 2 shows the individual state-level trends in the log of real per capita income and income inequality. It is clear that both income and income inequality have been rising within each state during the past half century. Moreover, the apparent long run relationship between income and income inequality seen in Figure 1, is also apparent within each of the forty-eight states in Figure 2.

[**Figure 2 about here**]

The greater homogeneity of U.S. states vis-a-vis international panels mitigates the difficulty in adequately capturing the structural differences across the latter group confronted by earlier studies such as Forbes (2000). Corruption levels, labor market flexibility, tax neutrality, tradition of entrepreneurship, and many other factors are only poorly measured, if at all, and these sources of heterogeneity are much more likely to contribute to omitted variable bias across countries than across U.S. states. Therefore, estimation using U.S. state-level data is more likely to accurately estimate the ceteris paribus effect of a change in inequality on the change in economic growth.

U.S. state level data have been explored before, notably by Partridge (1997) and Panizza (2002). Partridge (1997) estimates a panel of 48 states measured at ten year intervals using decennial U.S. Census data with controls for initial income, education, and industrial structure. Partridge finds that initial inequality is positively associated with subsequent 10-year cumulative growth in state income. These results were among the first empirical findings that challenged the view that inequality was harmful for economic growth. Panizza (2002), however, using decennial income data from the U.S. Census as well as from IRS tax returns, "concludes that, at the U.S. cross-state level, there is no clear, robust relationship between inequality and growth and that small differences in the method used to measure income inequality and in the econometric specification yield substantial differences in the estimated relationship between inequality and growth." (P. 25) Empirically, therefore, the relationship between inequality and economic growth at the U.S. state level appears to remain an open question.

The purpose of this paper is to re-examine the U.S. state-level inequality/growth nexus by employing three new approaches to the data. First, following Barro (2000), we recognize inherent non-linearities in the data, which neither Partridge (1997) nor Panizza (2002) do.[3] A previous paper (Frank and Freeman, 2002), showed that the effect of inequality on growth was negative, and more pronounced at lower levels of income. Second, we use Internal Revenue Service data, which are available on an annual basis, to construct a new data set of gini coefficients for the 48 states over the period 1945 to 2001. This data set brings an unusual degree of detail and comprehensiveness to the inequality/growth literature. Rather than a sample of 48 cross-sections and 5 or 6 time periods, as is common in prior research, the data set used in this paper has 48 cross-sections and 57 time periods.

Third, because the number of time series observations is relatively large and of the same order of magnitude as the number of states, we are able to exploit new cointegrated dynamic panel data techniques. Prior empirical research on income inequality has relied on fixed effects estimators (e.g. Partridge 1997) or a combination of fixed effects estimators and instrumental variable estimators, such as Arellano and Bond (1991) (e.g. Forbes 2000, Panizza 2002, and Frank and Freeman 2002). These methods require pooling individual groups and allowing only the intercepts to differ across the groups. Unless the slope coefficients are in fact identical, these estimators can produce inconsistent and misleading estimates (see Pesaran and Smith 1995, and Baltagi 2001). To address these concerns we employ two alternative estimators, the mean group estimator of Pesaran and Smith (1995), and the pooled mean group estimator of Pesaran, Shin, and Smith (1999).

II. Methodology and Data

The data used in the estimations is collected annually for the years 1945 to 2001 (T = 57). The number of states is 48 (N = 48).[4] This brings the total number of observations to 2,736. Descriptive statistics for the variables in raw form are presented in Table 1.

[**Table 1 about here**]

Gini coefficients are computed from tax data reported in *Statistics of Income* published by the IRS.[5] This calculation of income by the IRS is a broad measure of income. In addition to wages and salaries, it includes capital income (dividends, interest, rents, and royalties) and entrepreneurial income (self-employment, small businesses, and partnerships).[6] Real state income per capita is taken from the Regional Accounts Data available at the web site of the Bureau of Economic Analysis, and deflated using the Consumer Price Index (1982-84 = 100).[7] The eight industry wage and salary variables are taken from the Regional Economic Accounts data available at the web site of the Bureau of Economic Analysis.[8]

Prior research on income inequality in the U.S. has relied on data from the Bureau of the Census to construct gini coefficients (e.g. Partridge 1997). Census data are available from the decennial publication *Census of the Populations* for the years 1969, 1979, 1989, and 1999. Data for the years 1949 and 1959 are not available from the Census, but are usually taken from Ahmad Al-Samarrie and Herman P. Miller (1967). The annual data that are used to construct the gini coefficients in this paper have the obvious advantage of much greater frequency, but for comparability purposes have the disadvantage of being from a different source, the Internal Revenue Service.[9]

It is reasonable to ask how the two data sources compare in their assessment of income inequality in the U.S. over the past five decades. Figure 3 compares the average yearly trend lines and data distribution of both gini coefficients.[10] With the exception of the year 1949, the average Census gini coefficient is smaller than the average IRS gini coefficient, though the trend is generally similar starting in 1969. Note also that 1969 is the first true year of the Bureau of the Census's calculation of the Census gini, the two prior years are taken from Al-Samarrie and Miller (1967). It has been argued by Panizza (2002) that the censoring of the IRS data at the low end of the distribution may explain the difference, but top-coding procedures used in the Census data may also contribute.[11]

Obviously, unlike the Bureau of the Census, the IRS will penalize respondents for income reporting errors.

[**Figure 3 about here**]

For the empirical analysis, we assume that the long-run growth-inequality relationship is

$$(1) \quad y_{it} = \theta_{0i} + \theta_{1i} gini_{it} + \theta_{2i}\left(gini_{it} \times y_{it}\right) + u_{it},$$

$$i = 1,2,\ldots,N, \qquad t = 1,2,\ldots,T,$$

where y_{it} is the logarithm of real state income per capita, and $gini_{it}$ is the state gini coefficient. All variables are differenced from their cross-section means to control for fixed time effects. Mean differencing is necessary given the year to year incremental changes in tax laws associated with the IRS income data and the long time span of the sample. Including the product of the gini coefficient and the level of income allows for non-linearity in the inequality/income relation, and is a procedure also used by Barro (1999). The inclusion of this term strengthens the principle conclusions, provides further evidence of omitted variable bias in previous work, and permits an interesting interpretation of the results.

If the variables are $I(1)$ and cointegrated, then the error term is an $I(0)$ process for all i. Imposing a lag of one on all terms, the ARDL(1,1,1) equation is

$$(2) \quad y_{it} = \gamma_i + \delta_{10i} gini_{it} + \delta_{11i} gini_{i,t-1} + \delta_{20i}\left(gini_{it} \times y_{it}\right) + \delta_{21i}\left(gini_{i,t-1} \times y_{i,t-1}\right) + \lambda_i y_{i,t-1} + \varepsilon_{it}.$$

The resulting error correction equation is

$$(3) \quad \Delta y_{it} = \phi_i\left[y_{i,t-1} - \theta_{0i} - \theta_{1i} gini_{i,t-1} - \theta_{2i}\left(gini_{i,t-1} \times y_{i,t-1}\right)\right]$$

$$- \delta_{11i} \Delta gini_{i,t-1} + \delta_{20i}\left(\Delta gini_{i,t-1} \times \Delta y_{i,t-1}\right) + \varepsilon_{it}$$

where

$$\theta_{0i} = \frac{\gamma_i}{1-\lambda_i}, \quad \theta_{1i} = \frac{\delta_{10i} + \delta_{11i}}{1-\lambda_i}, \quad \theta_{2i} = \frac{\delta_{20i} + \delta_{21i}}{1-\lambda_i}, \text{ and } \phi_i = -(1-\lambda_i).$$

The parameter ϕ_i is the error-correcting speed of adjustment term. One would expect this parameter to be significantly negative if the variables show a return to a long-run equilibrium. Obviously, if $\phi_i = 0$, then there would be no evidence for a long-run relationship. Since we are primarily interested in the nature of the long-run relationship between income inequality and real income per capita, the long-run coefficients θ_{1i} and θ_{2i} will be of particular importance.

The recent literature on dynamic panel estimation in which both N and T are relatively large suggests several approaches to the estimation of equation (*3*).[12] On one extreme, a fixed effects (FE) estimation approach could be utilized in which the time series data for each state is pooled and only the intercepts are allowed to differ across states. If the slope coefficients are in fact not identical, however, then the FE approach could produce inconsistent and potentially misleading results. On the other extreme, the model could be estimated separately for each individual state, and a simple arithmetic average of the coefficients could be calculated. This is the mean group (MG) estimator proposed by Pesaran and Smith (1995). With this estimator the intercepts, slope coefficients, and error variances are all allowed to differ across states.

More recently, Pesaran, Shin, and Smith (1999) have proposed a pooled mean group (PMG) estimator that combines both pooling and averaging. This intermediate estimator allows the intercepts, short-run coefficients and error variances to differ across states (as would the MG estimator), but pools the data and constrains the long run coefficients to be the same across states (as would a FE estimator). In the following section, we will estimate equation (*3*) using each of these three estimators.

III. Empirical Results

Table 2 presents evidence indicating that real income per capita and the gini coefficient are nonstationary and cointegrated (see Figure 2 also). With respect to a null hypothesis of trend stationarity, Hadri (2000) constructs several residual-based Lagrange Multiplier tests applicable to panel data with homoscedastic, heteroscedastic, or serially dependant error processes.[13] The test statistics for each of these three cases are reported in Table 2. Each test is statistically significant beyond the 1% level.

[**Table 2 about here**]

With respect to a null hypothesis of no cointegration, both Kao (1999) and Pedroni (1995, 2004) provide applicable tests. The Kao (1999) test reported in Table 2 is an augmented Dickey-Fuller (ADF) type test applicable to panel data. The Pedroni (1995, 2004) test is a pooled Phillips and Perron-type test. Both tests are statistically significant beyond the 1% level. Taken together, these tests indicate that real income per capita and income inequality are both nonstationary and cointegrated among the 48 states for the period 1945 to 2001.

Empirical estimates of the mean group, pooled mean group, and fixed effects estimators are presented in Tables 3 and 4. Table 3 shows the estimation results for the one-lag ARDL without the interaction term (columns 1 – 3), and with the interaction term (columns 4 – 6). Table 4 differs from Table 3 only in that the Schwarz Bayesian

Criterion (SBC) was used to select the lag lengths. Appendix Table A1 shows the full mean group results for each state under the ARDL (1,1,1) model.

[**Table 3 about here**]

When the interaction term is omitted (columns 1 – 3 of Tables 3), the results do vary across estimators. In Table 3, the long-run gini coefficient is negative in the MG and dynamic FE estimations, but positive in the pooled MG estimation. (Although only the MG estimator of gini is statistically significant). When SBC is used to select the lags (Table 4, columns 1 – 3), the long-run gini coefficients are all negative, and significantly so in both the pooled MG and static FE estimations.

Recall that the long-run coefficients of the MG estimator are unrestricted, while the long-run coefficients of the pooled MG estimator are restricted to be the same for all states. To compare the MG and pooled MG estimators, a Hausman test may be conducted to evaluate the additional restrictions of the pooled MG estimator (see Pesaran, Shin, and Smith, 1999). Under the null hypothesis of the Hausman test, there are no differences in the estimators and the pooled estimator is consistent and efficient. In the ARDL (1,1) estimations in Table 3 (columns 1 and 2), the Hausman test statistic is a significant 5.78 (p-value = 0.02). Of all the results obtained, the only estimator showing a positive long-run gini coefficient was the pooled MG estimator in column 2 of Table 3. This Hausman test sheds doubt upon the reliability of this positive long-run gini coefficient.

The same test may also be applied to the SBC estimations of Table 4 (columns 1 and 2). Note that in this case, the two long-run gini coefficients are negative and nearly identical. Here the Hausman test statistic is an insignificant 0.49 (p-value = 0.48). This evidence indicates support for the additional restrictions incurred in the pooled MG estimation vis-à-vis the MG estimation.

[**Table 4 about here**]

The long-run estimates of θ_{1i} and θ_{2i} are remarkably consistent across estimation methods when the interaction term is included (columns 4 – 6 of Tables 3 and 4). In the ARDL (1,1,1) models of Table 3, the MG and dynamic FE estimates for θ_{1i} and θ_{2i} are nearly identical. In all cases in both Tables, moreover, the estimates for the long-run gini are significantly negative and large in magnitude, while the estimates for the interaction term are positive and significant. In comparison to the MG estimator, the more restrictive pooled MG estimator produces very similar long-run coefficients, though they are slightly less in magnitude in both the ARDL (1,1,1) estimation (columns 4 and 5 of Table 3) and the SBC estimation (columns 4 and 5 of Table 4).

The speed of adjustment parameter, ϕ_i, is consistently negative and significant in both Tables, but does vary in magnitude. In general, the pooled MG ϕ_i is pushed closer to zero than the MG ϕ_i. Moreover, when the interaction term is included, the MG ϕ_i is nearly double the magnitude of the pooled MG ϕ_i.

The models in Table 4 include interaction terms between inequality and the real state income per capita, similar to specifications estimated by Barro (2000). The general idea is that inequality may have different effects depending on the level of economic development. In all six models, the interaction terms are positive and significant, indicating that the negative effect of inequality on growth is greater for lower-income states; Barro (2000) finds similar results for a panel of countries. As Barro notes, the lesser effect of inequality at higher income levels may stem from the better developed credit markets and the greater degree of income mobility at higher levels of development.

[**Table 5 about here**]

To test the robustness of these estimates, in Table 5 we include eight state-level industry wage and salary variables. The inclusion of these variables changes the principle results very little. The coefficients on the industry variables tend to show that those states who are more closely associated with manufacturing and construction production economies have experienced faster growth, but this conclusion is very tentative. Most importantly, the estimates for ϕ_i, θ_{1i}, and θ_{2i} are nearly identical across the three models, and quite similar to the parsimonious estimates in Tables 3 and 4, columns 4 – 6.

IV. Conclusions

This paper presents empirical evidence on the relationship between income inequality and economic growth using a panel of 48 states over the period 1945 to 2001. Our measure of inequality is constructed from individual tax filing data available from the Internal Revenue Service. Because this data is annual, we gain an unusual degree of detail and comprehensiveness. Rather than a sample of 48 cross-sections with 5 or 6 time periods, as is common in prior research, we are able to construct a sample that is large in both cross-sections and time periods (T = 57, N = 48).

This unusual panel size enables the employment of new cointegrated panel data techniques, a first in the inequality/growth literature. Prior empirical research on income inequality has relied on fixed effects estimators and the instrumental variable estimators of Arellano and Bond (1991). These estimators require pooling the individual groups and allowing only the intercepts to differ across groups. Because the slope coefficients are in fact not identical, these estimators can produce inconsistent and misleading estimates. To address these concerns we have employed two alternative estimators, the mean group estimator of Pesaran and Smith (1995), and the pooled mean group estimator of Pesaran, Shin, and Smith (1999).

The results indicate that the long-run relationship between inequality and growth is negative in nature, though this negative relationship appears to be larger for low-income states. Moreover, when the nonlinearity of this relationship is recognized, the estimates are quite robust to alternative estimation techniques, as well as the inclusion of numerous additional regressors.

These results contrast with the positive relationship found in prior empirical research, (see Forbes 2000, and Partridge 1997), though the robustness of these prior findings has been questioned by Barro (2000) and Panizza (2002). As we have discussed, each of these prior efforts has been limited to large N, small T panels.

The theoretical literature suggests several explanations for why the relationship between income growth and inequality would be negative. In the political economy models of Alesina and Rodrik (1994) and Persson and Tabellini (1994), for example, high levels of inequality push median voters to support higher taxes, thereby lowering income growth. In the imperfect credit models of Galor and Zeira (1993) and Aghion and Bolton (1997), low income individuals are unable to invest in their human capital, causing income inequality to increase and income growth to decrease. Finally, models by Gupta (1990) and Alesina and Perotti (1996) emphasize the political and social unrest consequences of high income inequality, though these mechanisms seem less plausible within the U.S. states. The task for future empirical research is to begin testing and quantifying these potential mechanisms.

References

Aghion, Philippe, and Patrick Bolton. 1997. A Theory of Trickle-Down Growth and Development. *Review of Economic Studies* 64 (2, April):151-72.

Akhand, H., and H. Liu. 2002. Income Inequality in the United States: What the Individual Tax Files Say. *Applied Economics Letters* 9:255-59.

Al-Samarrie, A., and H. Miller. 1967. State Differentials in Income Concentration. *American Economic Review* 57:59-72.

Alesina, A., and R. Perotti. 1996. Income Distribution, Political Instability and Investment. *European Economic Review* 81 (5):1170-89.

Alesina, A., and D. Rodrik. 1994. Distributional Politics and Economic Growth. *Quarterly Journal of Economics* 109:465-90.

Arellano, M., and S. Bond. 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58:227-97.

Baltagi, B. 2001. *Econometric Analysis of Panel Data*. Second. England: Wiley.

Barro, R. 2000. Inequality and Growth in a Panel of Countries. *Journal of Economic Growth* 5:5-32.

Benabou, R. 1996. Inequality and Growth. *NBER Working Papers* #5658.

Deninger, K, and L. Squire. 1996. A New Data Set Measuring Income Inequality. *World Bank Economic Review* 10:565-91.

Forbes, K. 2000. A Reassessment of the Relationship Between Inequality and Economic Growth. *American Economic Review* 90:869-87.

Frank, M., and D. Freeman. 2002. Relationship of Inequality to Economic Growth: Evidence from U.S. State-Level Data. *Pennsylvania Economic Review* 11:24-36.

Freeman, D. 2000. Alternative Panel Estimates of Alcohol Demand, Taxation, and the Business Cycle. *Southern Economic Journal* 67:325-44.

Galor, O., and J. Zeira. 1993. Income Distribution and Macroeconomics. *Review of Economic Studies* 60:35-52.

Galor, Oded, and Daniel Tsiddon. 1997. Technological Progress, Mobility, and Economic Growth. *American Economic Growth* 87 (3, June):363-82.

Gottschalk, P., and T. Smeeding. 1997. Cross-National Comparisons of Earnings and Income Inequality. *Journal of Economic Literature* 35:633-87.

Gupta, D. 1990. *The Economics of Political Violence*. New York: Prager.

Hadri, K. 2000. Testing for Stationarity in Heterogeneous Panel Data. *Econometrics Journal* 3:148-61.

Kakwani, N. C. 1980. *Income Inequality and Poverty: Methods of Estimation and Policy Applications*. New York: Oxford University Press for the World Bank.

Kao, C. 1999. Spurious Regression and Residual-Based Tests for Cointegration in Panel Data. *Journal of Econometrics* 90:1-44.

Kuznets, S. 1955. Economic Growth and Income Inequality. *American Economic Review* 45:1-28.

Martinez-Zarzoso, I., and A. Bengochea-Morancho. 2004. Pooled Mean Group Estimation of an Environmental Kuznets Curve for CO2. *Economics Letters* 82:121-26.

Meltzer, A. 1998. Discussion on 'Economic Consequences of Income Inequality.' Income Inequality: Issues and Policy Options. Kansas City, KS: Federal Reserve Bank of Kansas City.

Panizza, U. 2002. Income Inequality and Economic Growth: Evidence from American Data. *Journal of Economic Growth* 7:25-41.

Partridge, M. 1997. Is Inequality Harmful for Growth? Comment. *American Economic Review* 87:1019-32.

Pedroni, P. 1995. Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Test, with and Application to the PPP Hypothesis. Indiana University Working Papers in Economics.

Pedroni, P. 2004. Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Test with and Application to the PPP Hypothesis. *Econometric Theory* 20:597-625.

Persson, T., and G. Tabellini. 1994. Is Inequality Harmful for Growth? Theory and Evidence. *American Economic Review* 84:600-21.

Pesaran, M., and R. Smith. 1995. Estimating Long-Run Relationships From Dynamic Heterogeneous Panels. *Journal of Econometrics* 68:79-113.

Pesaran, M., Y. Shin, and R. Smith. 1999. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *American Statistical Association* 94:621-34.

Piketty, Thomas, and Emmanuel Saez. 2003. Income Inequality in the United States, 1913-1998. *Quarterly Journal of Economics* 118 (1, February):1-39.

Quah, Danny. 2001. Some Simple Arithmetic on How Income Inequality and Economic Growth Mattrer. LSE Economics Working Paper.

Siebert, H. 1998. Comment on 'Economic Consequences of Income Inequality.' A Symposium Sponsored by the Federal Reserve Bank of Kansas City. Income Inequality: Issues and Policy Options. Kansas City, KS: Federal Reserve Bank of Kansas City.

Figure 1. Mean Real Income Per Capita and Income Inequality Among the 48 States, 1945 to 2001

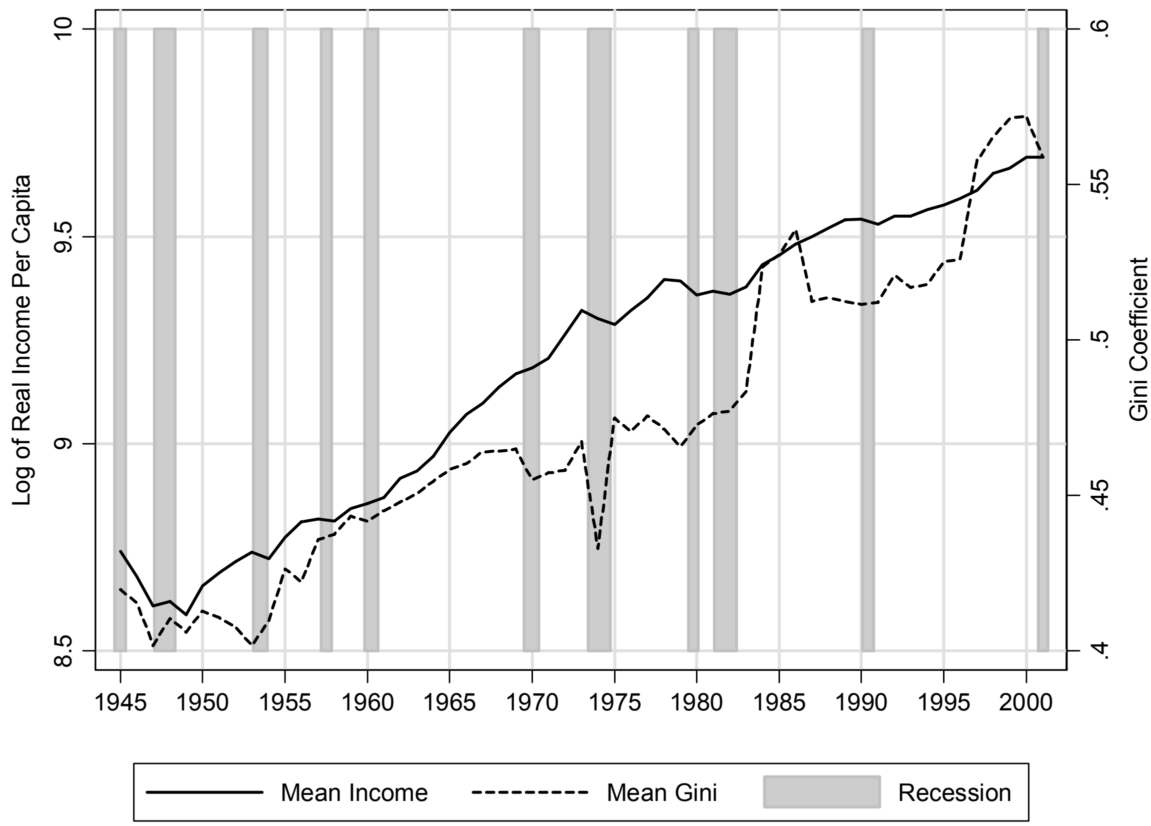

Figure 2. State-Specific Trends in Log Real Per Capita Income and Income Inequality

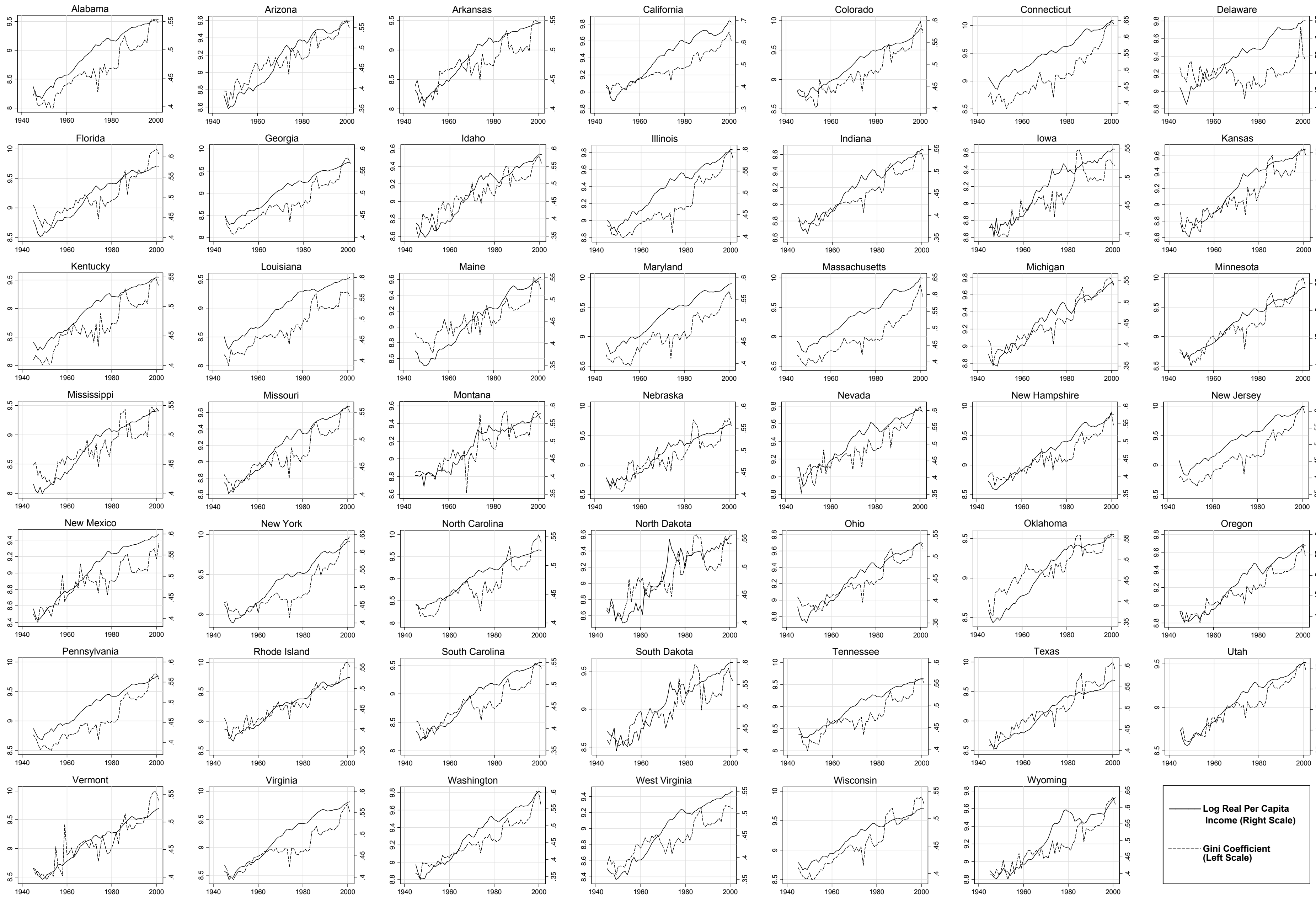

Figure 3. Distributional Comparison of the IRS Gini to the Census Gini, 1945 to 2001

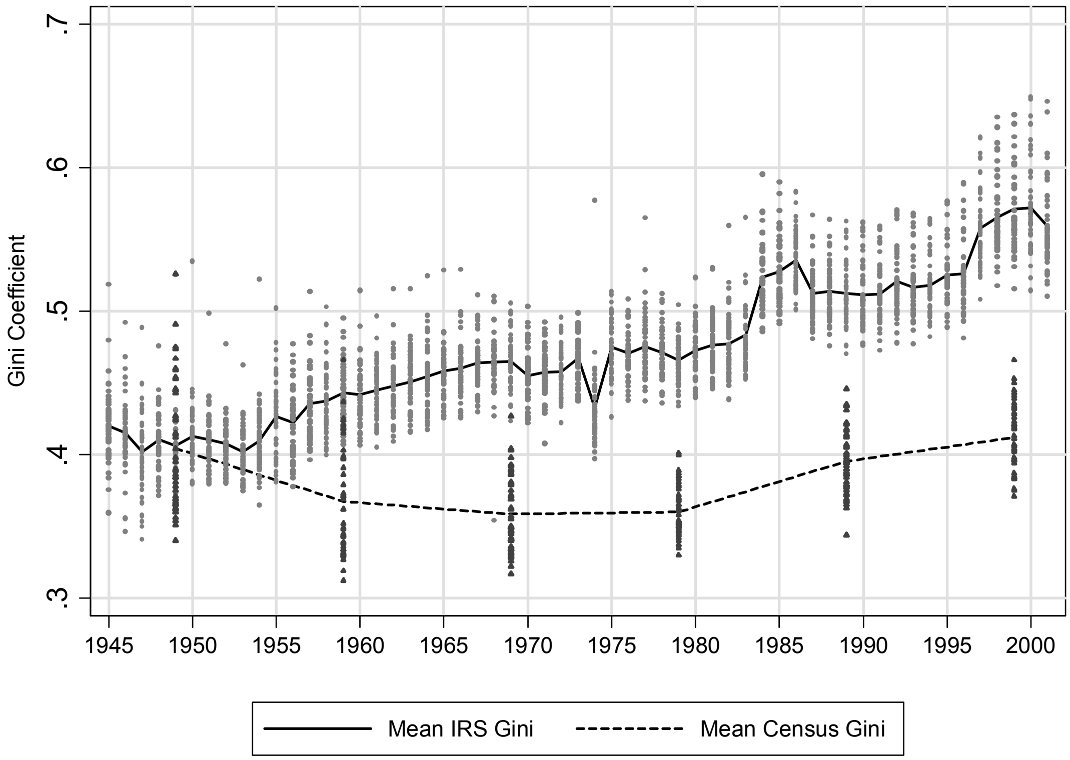

Table 1. Descriptive Statistics of the Variables in Raw Form (1982-84 = 100)

Variable	Mean	Standard Deviation	Minimum Annual Mean (Year)	Maximum Annual Mean (Year)
Real state income per capita	10,441	3,742	5,491 (1949)	16,375 (2000)
Gini	0.472	0.052	0.402 (1953)	0.572 (2000)
Farming	205,150	281,846	151,138 (1987)	2,705,12 (1946)
Construction	1,636,132	2,048,659	339,120 (1945)	3,132,220 (2001)
Manufacturing	7,666,546	9,510,521	3,893,355 (1946)	10,012,043 (2000)
Transportation	2,216,814	2,775,356	1,146,637 (1947)	3,735,767 (2000)
Trade	2,361,990	3,137,477	1,084,927 (1958)	4,003,021 (2000)
F.I.R.E.	1,966,200	3,975,799	375,278 (1945)	5,366,797 (2001)
Services	5,634,071	4,397,730	998,032 (1945)	16,562,089 (2001)
Government	8,923,996	4,230,961	2,140,346 (1947)	16,270,362 (2001)

Table 2. Stationarity and Cointegration Tests

Hadri (2000) Stationarity Tests	Homoscedastic Errors	Heteroscedastic Errors	Serial Dependence
H_0: Log of real state income per capita is stationary	101.289*	95.006*	10.431*
H_0: Gini is stationary	47.961*	41.800*	10.574*
Cointegration Tests	Kao (1999)	Pedroni (1995)	
H_0: No Cointegration	-5.857*	-45.282*	

* Significant at the 1% level.

Table 3. Alternative Estimates of Income Inequality and Real State Income Per Capita

	Without Interaction, ARDL (1,1)			With Interaction, ARDL (1,1,1)		
	MG (1)	Pooled MG (2)	Dynamic FE (3)	MG (4)	Pooled MG (5)	Dynamic FE (6)
Adjustment coefficient, (Φ)	-0.149** (1.721)	-0.124** (0.020)	-0.095** (0.008)	-0.266** (0.022)	-0.141** (0.018)	-0.088** (0.009)
Gini, long run (θ_1)	-3.867* (1.721)	0.234 (0.234)	-0.587 (0.370)	-17.920** (0.861)	-15.602** (0.316)	-17.809** (0.744)
Gini X log real state income per capita, long run (θ_2)				1.894** (0.085)	1.676** (0.034)	1.819** (0.080)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the log of real state income per capita.

Table 4. Alternative Estimates of Income Inequality and Real State Income Per Capita, Schwarz Bayesian Criterion

	Without Interaction, SBC			With Interaction, SBC		
	MG (1)	Pooled MG (2)	Static FE (3)	MG (4)	Pooled MG (5)	Static FE (6)
Adjustment coefficient, (Φ)	-0.116** (0.017)	-0.132** (0.016)		-0.310** (0.032)	-0.197** (0.035)	
Gini, long run (θ_1)	-1.352 (1.340)	-0.424* (0.221)	-0.440** (0.077)	-17.971** (0.894)	-16.216** (0.214)	-18.610** (0.145)
Gini X log real state income per capita, long run (θ_2)				1.887** (0.091)	1.745** (0.023)	1.967** (0.015)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. The maximum number of lags in each estimation is three. Dependent variable in each estimation is the log of real state income per capita.

Table 5. Income Inequality and Real State Income Per Capita

	ARDL (one lag)		
	MG (1)	Pooled MG (2)	Dynamic FE (3)
Adjustment coefficient, (Φ)	-0.738** (0.038)	-0.176** (0.026)	-0.124** (0.010)
Gini, long run (θ_1)	-17.212** (0.555)	-17.032** (0.306)	-16.595** (0.647)
Gini X log real state income per capita, long run (θ_2)	1.869** (0.062)	1.815** (0.033)	1.725** (0.070)
Farming, long run	0.002 (0.006)	0.012** (0.003)	-0.010 (0.009)
Construction, long run	0.021** (0.005)	0.030** (0.005)	0.035** (0.012)
Manufacturing, long run	0.014* (0.014)	0.016** (0.004)	0.026** (0.011)
Transportation, long run	-0.012 (0.015)	0.001 (0.008)	0.046* (0.022)
Trade, long run	-0.032* (0.015)	-0.025** (0.007)	0.001 (0.019)
Fire, long run	-0.037** (0.014)	-0.020** (0.008)	-0.074** (0.018)
Services, long run	-0.015 (0.016)	-0.078** (0.011)	0.011 (0.020)
Government, long run	0.010 (0.017)	0.024* (0.011)	-0.074** (0.025)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the log of real state income per capita.

V. Appendix

Table A1. State-Specific Mean Group Estimates, ARDL (1,1,1)

State	Adjustment coefficient, (Φ)	Gini, long run (θ_1)	Gini X real state income, long run (θ_2)	Log likelihood
AL	-0.269**	-28.654**	2.842**	202.680
AZ	-0.309**	-15.240**	1.698**	191.490
AR	-0.122*	-23.010**	2.450**	177.140
CA	-0.114	-18.965**	1.869**	201.210
CO	-0.204**	-8.883**	1.052**	190.520
CT	-0.097*	-10.867	1.005	180.130
DE	-0.237*	-6.910	0.887	151.470
FL	-0.227**	-14.899**	1.550**	193.270
GA	-0.377**	-21.567**	2.269**	221.770
ID	-0.559**	-15.060**	1.658**	184.730
IL	-0.022	-28.236	3.113	213.250
IN	-0.189**	-14.254**	1.422**	227.300
IA	-0.555**	-18.027**	1.874**	199.890
KS	-0.310**	-13.890**	1.509**	206.990
KY	-0.043	-18.755	1.899	203.290
LA	-0.100	-15.492*	1.865**	180.670
ME	-0.087	-11.547	1.063	190.490
MD	-0.378**	-14.132**	1.556**	202.230
MA	-0.353**	-18.061**	1.798**	194.150
MI	-0.443**	-19.412**	2.096**	197.970
MN	-0.588**	-17.678**	1.982**	221.050
MS	-0.184**	-22.817**	2.346**	174.980
MO	-0.149*	-9.709*	1.148**	243.740
MT	-0.316**	-18.359**	1.985**	171.110
NE	-0.203**	-17.410**	1.872**	195.490
NV	-0.271**	-25.425**	2.683**	169.910
NH	-0.500**	-19.337**	2.056**	175.590
NJ	-0.331**	-15.335**	1.532**	190.850
NM	-0.321**	-13.567**	1.511**	174.380
NY	-0.021	-39.230	3.611	192.960
NC	-0.257**	-23.419**	2.520**	210.220
ND	-0.377**	-17.476**	1.869**	165.340
OH	-0.174**	-14.899**	1.585**	230.560
OK	-0.224**	-12.111**	1.396**	177.900
OR	-0.237**	-19.308**	2.089**	217.890
PA	-0.523**	-16.112**	1.731**	214.410
RI	-0.626**	-18.208**	2.033**	207.860
SC	-0.068	-29.360**	3.089**	185.860
SD	-0.441**	-18.400**	1.986**	173.680
TN	-0.263**	-22.935**	2.530**	198.640
TX	-0.193**	-14.087**	1.435**	199.600
UT	-0.244*	-13.920**	1.489**	200.830
VT	-0.101	-21.717**	2.302**	186.590
VA	-0.200*	-20.247**	2.198**	220.300
WA	-0.213*	-17.995**	1.924**	194.370
WV	-0.106	-7.571	0.655	177.800
WI	-0.266**	-16.129**	1.657**	231.410
WY	-0.366**	-21.525**	2.246**	184.660
Mean Group	-0.266**	-17.920**	1.894**	9398.630

*, **: Significant at the 0.05, 0.01 level, respectively. Dependent variable in each estimation is the log of real state income per capita.

Notes

[1] There are many possible interpretations of the gini coefficient (see Kakwani 1980), but perhaps the most common is the gini coefficient as one minus twice the area under the Lorenz curve, the later being a plot of the cumulative proportion of income received against the cumulative proportion of income units, arranged in ascending order of income.

[2] Our gini coefficients are constructed from state-level distributional data taken from tax returns compiled by the IRS. Piketty and Saez (2003) look at various indicators of income inequality for the entire U.S. also using IRS tax return data, and find a pattern similar to Figure 1. They measure only top income shares (top 10%, top 90-95%, top95-99%, and top 1%), not gini coefficients. Their measures start in 1913, not 1945, and are calculated for the U.S. as a whole, not for individual states. Despite these differences, they find consistently increasing income inequality since 1945 for the top 90-95% and top 95-99% (as do we), but large spikes in income inequality starting in the 1980s for the top 10% and top 1% (see Figures 1 and 2, pages 11-12).

[3] Of course, the famous Kuznets (1955) curve between the level of income and income inequality is highly nonlinear.

[4] The IRS tax data used to construct the gini coefficients is available starting in 1916, but there are several reasons to not sample before 1945. First, war time wage controls were used extensively throughout the period 1941-1944. Secondly, before World War II only a small fraction of individuals had to file tax returns. See Piketty and Saez (2003) for a discussion of these issues.

[5] The Gini coefficients are calculated using data on the number of returns and the adjusted gross income (before taxes) by state and by size of the adjusted gross income. This distributional data is available annually from various publications by the Internal Revenue Service. For the years 1945 to 1981, the data is available in the *Statistics of Income, Individual Income Tax Returns* annual series. For the years 1982 to 1987, the data series was not published but is available by request from the Internal Revenue Service. For the years 1988 to 2001, the data is available in the *Statistics of Income Bulletin* quarterly series.

[6] The distribution of wage and salary income by state, an informative but more narrow measure of income, is not available prior to 1970.

[7] We use the BEA's calculation of per capita state income instead of an IRS-based measure of state per capita income because IRS data is based on tax units, not individuals. Under currently tax law, for example, a tax unit can be defined as a married couple living together, or as a single adult. Moreover, each may or may not have dependents.

[8] The mining industry wage and salary variable is not included because of missing data. Government is the sum of national, state, and local government wages and salaries.

[9] Panizza (2002) also experiments with the IRS-based gini coefficients, but only at ten year spacings.

Notes

[10] The correlation between the IRS and Census gini indexes for the six years of commonality is 0.52. While seemingly small, it is higher than the 0.44 found by Panizza (2002) for similar data, or the 0.48 between estimates for OECD country data of Deninninger and Squire (1996) and Gottschalk and Smeeding (1997).

[11] Akhand and Liu (2002) compare the IRS-based income inequality data with inequality data from the Current Population Survey (CPS), a third possible source for data. They find the IRS data to be superior because of significant response errors in the CPS. According to Akhand and Liu, the CPS data is systematically biased downward by as much as 32% because of "over-reporting of earnings by individuals in the lower tail of the income distribution and under-reporting by individuals in the upper tail of the income distribution" (p. 258).

[12] For general discussions of this literature see Baltagi (2001) chapter 12. For recent empirical applications see Martinez-Zarzoso and Bengochea-Morancho (2004) and Freeman (2000).

[13] These are known as the Z-tau test statistics in Hadri (2000).