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

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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.

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 analyses of economic growth over long periods, 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 averaged over the 48 states for 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 thick dashed line (right scale) shows the yearly trend in the average 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 0.407 in 1956, to a high of 0.581 in 2000.

Increasing inequality in the U.S. is well noted. Piketty and Saez (2003) for example, find consistently increasing income inequality since 1945 in the U.S. for the top 90-95% and top 95-99% of income earners, and large spikes in income inequality starting in the 1980s for the top 10% and top 1%.[2] The state-level data portrayed in Figure 1 shows a steady increase in inequality beginning in the early 1950s, and proceeding at a pace similar to the rise in real per capita income. For the first third of the sample (1945 through the early 1960s), inequality and real per capita income increased at similar rates. For the second third of the sample (early 1960s through the early 1980s), inequality was outpaced by the rise in real per capita income. However, for the final third of the sample (early 1980s through 2001), it is inequality that outpaces the rise in real per capita income.

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.

The greater homogeneity of U.S. states mitigates the difficulty in adequately capturing the structural differences across international panels of 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.

[Figure 2 about here]

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. The Pearson's correlation between log real income per capita and the gini coefficient, for example, is between 0.80 and 0.95 for all states except Delaware ($r = 0.21$). The average Pearson's correlation for the remaining 47 states is 0.90.

[Table 1 about here]

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 data in ten year intervals 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] Previous research by 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 2.

[Table 1 about here]

Gini coefficients are computed from tax data reported in *Statistics of Income* published by the IRS.[5] The IRS reports state-level income data in grouped form. A lower limit estimate of the gini can be constructed based on the assumption that all individuals in a group receive exactly the average income of the group. An upper limit estimate of the gini can be constructed based on the assumption that individuals within the group receive income equal to either the lower or upper bound of the group interval (see chapter 5 in Cowell, 1995). These upper and lower limit estimates of the gini coefficient are presented in Figure 1 as the thinly dashed lines. The gini coefficient we use in the analysis is the compromise gini coefficient proposed by Cowell and Mehta (1982), and shown in Figure 1 as the thick dashed line.[6]

The income reported 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).[7] Portions of the year-to-year fluctuations in the gini coefficient may simply reflect enforcement and other incremental tax policy changes, while other fluctuations may reflect reporting changes by the IRS. For all of these reasons, it becomes important in the analysis to mean-difference the inequality data.

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).[8] The middle quintile share of income is derived by fitting a three-parameter Singh and Maddala (1976) distribution to the IRS tax filing data. The remaining nine variables are industry wage and salary variables taken from the Regional Economic Accounts data available at the web site of the Bureau of Economic Analysis.[9]

Some of the earlier empirical research 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.

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 begin by assuming that the long-run income and income inequality relationship is

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

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

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 (2000). The inclusion of this term strengthens the principal 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 yields the autoregressive distributed lag model, ARDL(1,1,1):

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

The resulting error correction equation is

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

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

where

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

Notice with equation (3) that the left-hand side variable is the growth rate of real income per capita, while the right-hand side includes lagged income and income inequality. These right-hand side variables are expressed as first differences and in levels to capture the short-run and long-run dynamics, respectively.[12] The parameter ϕ is the errorcorrecting 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 $\phi = 0$, 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_1 and θ_2 will be of particular importance. Notice, however, that while the error-correction framework addresses nonstationarity and endogeneity concerns, it is neutral with respect to causality.[13] A more meaningful treatment of causality will be an important area for future empirical research.

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*).[14] 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) proposes several residual-based Lagrange Multiplier tests applicable to panel data with homoscedastic, heteroscedastic, or serially dependant error processes.[15] 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 3 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 nonstationary and cointegrated among the 48 states for the period 1945 to 2001.[16]

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 (interaction term included).

[Table 3 about here]

When the interaction term is omitted, the results vary in magnitude, though not in sign. In the ARDL (1,1) estimates (columns 1 – 3 of Table 3), the long-run gini coefficient is negative and significant in both the MG and dynamic FE estimations, but insignificant in the pooled MG estimation. When SBC is used to select the lags (columns 1 – 3 of Table 4), the long-run gini coefficients are significantly negative in both the pooled MG and static FE estimations.

While the long-run coefficients of the pooled MG estimator are restricted to be the same for all states, the MG long-run coefficients are unrestricted. 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 6.28 (p-value = 0.01). Of the results presented in Table 3, the only estimator showing an insignificant long-run gini coefficient is the pooled MG estimator in column 2. This Hausman test sheds doubt upon the reliability of this insignificant long-run gini coefficient.

The same test may also be applied to the SBC estimations (Table 4 columns 1 and 2). Note that in this case, the MG and pooled MG gini coefficients are negative, but only the pooled MG is significantly so. Here the Hausman test statistic is an insignificant 0.39 (p-value = 0.53). This evidence indicates support for the additional restrictions incurred in the pooled MG estimation vis-à-vis the MG estimation, and sheds doubt on the insignificant MG estimator presented in column 1 of Table 4.

[Table 4 about here]

The inclusion of the interaction term (columns 4 – 6 of Tables 3 and 4) is 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 term is 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.[17] 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.

When the interaction term is included, the estimates for the long-run gini (θ_1) are significantly negative and large in magnitude in all cases, while the estimates for the interaction term (θ_2) are positive and significant in all cases. In comparison to the MG estimator, the more restrictive pooled MG estimator produces surprisingly similar long-run coefficients (see columns 4 – 5 of Tables 3 and 4).

Across all of the models presented in Tables 3 and 4, the speed of adjustment parameter, ϕ, is consistently negative and significant, but does vary in magnitude. In general, the pooled MG ϕ is pushed closer to zero than the MG ϕ. Moreover, when the interaction term is included, the MG ϕ is nearly double the magnitude of the pooled MG ϕ.

In a general sense, the results from Tables 3 and 4 indicate that the long-run relationship between growth and inequality is negative in nature. To interpret these results further, notice that the inclusion of the interaction term in equation (*1*) means that the partial derivative of real income per capita with respect to inequality depends on the level of income:

$$\partial y_{it} / \partial gini_{it} = \theta_1 + \theta_2 \left(gini_{it} \times y_{it} \right).$$

Using the parameter estimates from the ARDL (1,1,1) model estimated via pooled MG (column 5 of Table 3), suppose a state has a real income per capita that is two standard deviations below the average of other states (or $2,936 over our sample period, in constant 1982-84 dollars). If that state experiences a 0.1 increase in the gini coefficient, its long run growth rate of real income per capita would fall by 1.76% per year, *ceteris paribus*. (A change in the gini coefficient of 0.1 is slightly less than a two standard deviation increase in inequality for the sample period.) Suppose, on the other hand, that a state has a real income per capita that is two standard deviations *above* the average of the other states (or $17,896 over our sample period). If this wealthier state experiences an increase in inequality of 0.1, its long run growth rate of real income per capita would fall by only 1.46%.

The nature of this non-linear relationship between income growth, inequality, and the level of income is more fully expressed in Figure 4. Figure 4 uses the pooled MG ARDL (1,1,1) parameter estimates (column 5 of Table 3) to show the impact of a 0.1 unit increase in the gini coefficient on the long run growth rate of real income per capita, given the level of real income per capita.[18] Though the relationship between inequality and growth is always negative in nature, the decrease in income growth is greater for lower income states than for higher income states.

[Figure 4 about here]

Table 5 presents several alternative specifications of the ARDL (1,1,1) pooled MG estimation. The first column of Table 5 is the baseline pooled MG estimation from column 5 of Table 3. Columns 2 and 3 replace the compromise gini coefficient with the lower limit and upper limit estimates of the gini coefficient, respectively (these are the thinly dashed lines of Figure 1). In both of these cases, the results are nearly identical to the baseline specification. Since prior empirical work was limited to decennial census data to construct the gini coefficient, one may wonder what effect the greater time frequency of our data has on our conclusions. Columns 3 – 5 of Table 5 break the sample into 3-year, 5-year, and 7-year period averages. In column 4, the 57 time-series observations of the panel are condensed into nineteen 3-year average-periods. For the 5-year averages of column 5, the panel is condensed to eleven periods covering the period 1946-2000. The 7-year averages of column 6, the panel is condensed into eight periods covering the span 1945-2000.[19] In each of these three cases, the results are consistent in sign and significance, though there is an degree of variation in magnitude.

[Table 5 about here]

To further test the robustness of these estimates, Table 6 includes several additional variables in a one-lag ARDL model using the MG, pooled MG, and FE estimators. Of these additional regressors, the middle quintile share of income has been used in the prior empirical work of Partridge (1997) and Panizza (2002). The remaining nine variables are state-level industry wage and salary variables. The inclusion of these additional variables changes the principal results very little.[20] The estimates for θ_1 and θ_2 are nearly identical across the three estimators, and quite similar to the parsimonious estimates in Tables 3 and 4, columns 4 – 6. It is noteworthy that the middle quintile share of income is insignificant in all three estimations. This finding concurs with the findings of Panizza (2002), but differs from the positive and significant finding of Partridge (1997). Furthermore, many of the wage and salary variables are significant across the estimations. Having high wages and salaries in the service sector, for example, is positively related to short-run changes in real per capita income. By contrast, having high wages and salaries in farming and finance and real estate (F.I.R.E), is negatively related to short-run changes in real per capita income.

[Table 6 about here]

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. The annual frequency of the state-level data allows 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.

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

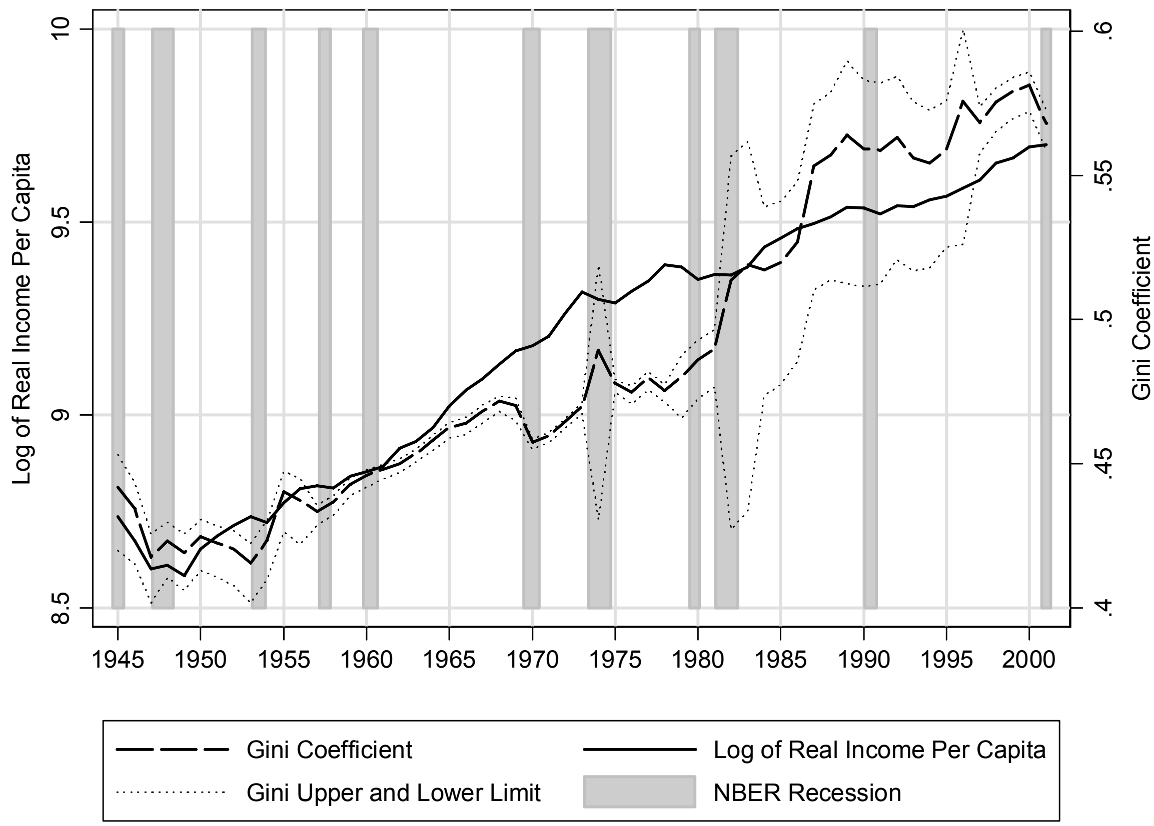

Figure 2. State-Specific Trends in Log Real Income Per Capita and Income Inequality, 1945 to 2001

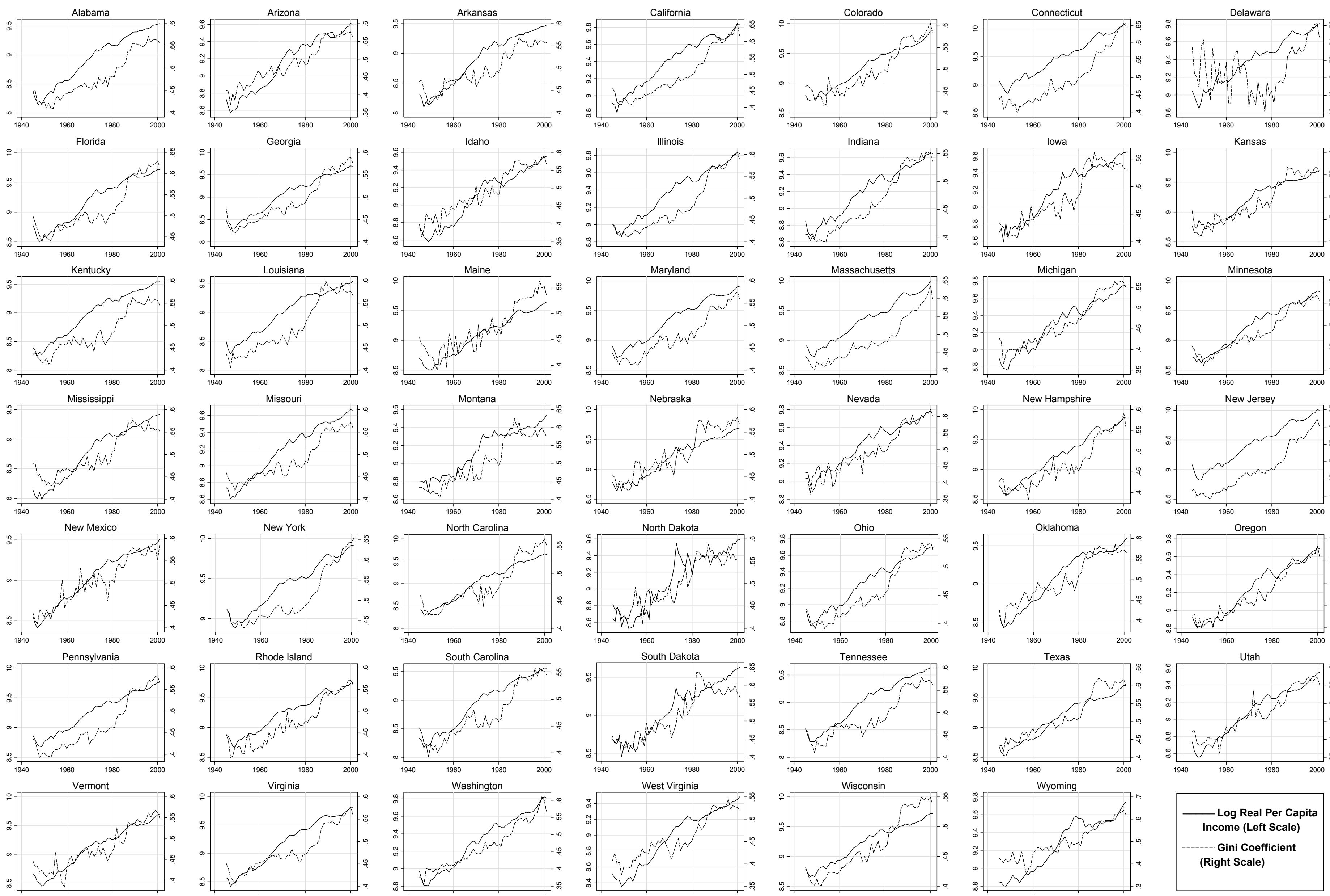

Figure 3. Distributional Comparison of the IRS Gini to the Census Gini, 1945 to 2001

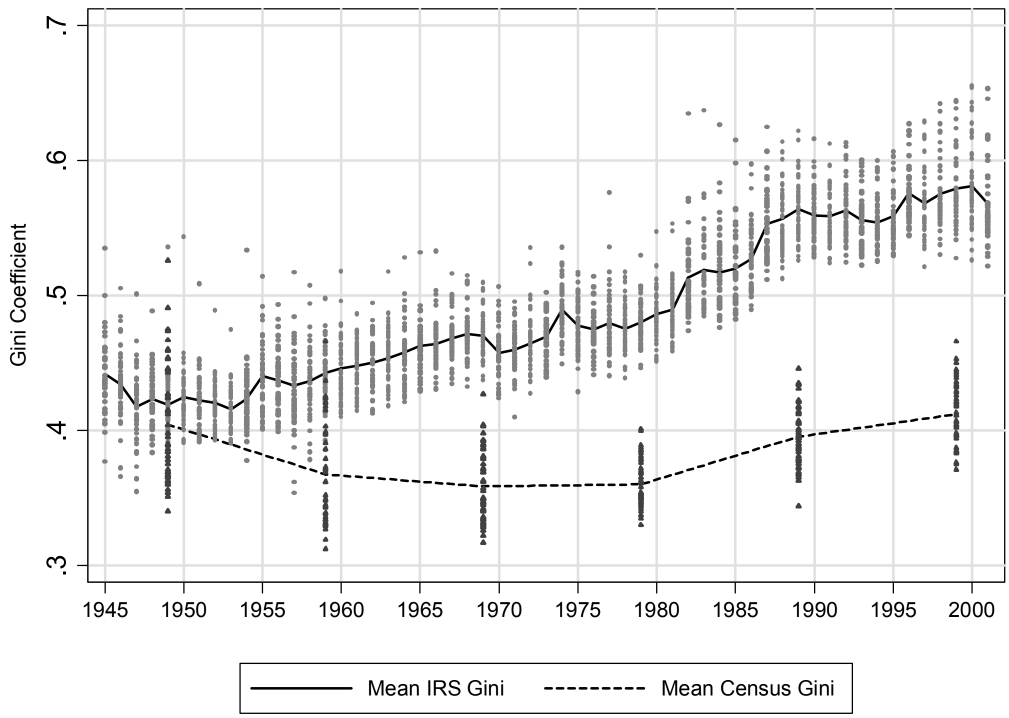

Figure 4. Long Run Change in the Growth Rate of Real Income Per Capita from a 0.1 Increase in the Gini Coefficient, by Level of Real Income Per Capita

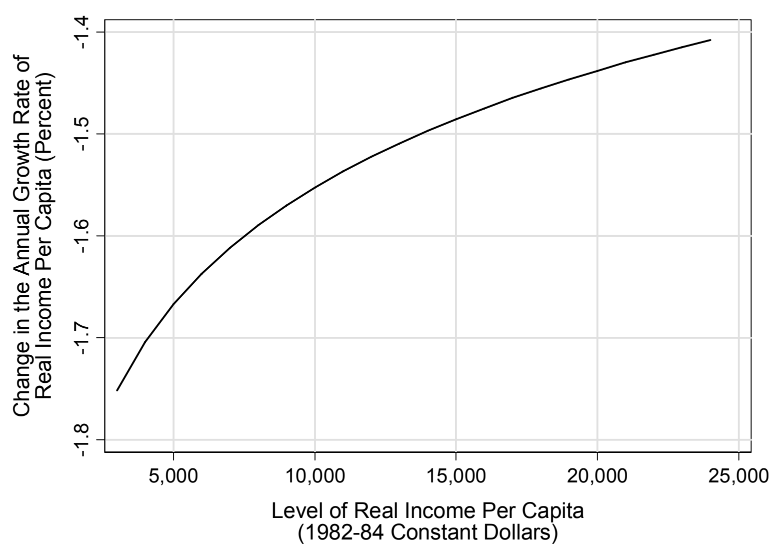

Table 1. Descriptive Statistics of the Variables (1982-84 = 100)

Variable	Mean	Standard Deviation	Minimum Annual Mean (Year)	Maximum Annual Mean (Year)
Gini	0.488	0.058	0.407 (1956)	0.581 (2000)
Real state income per capita	10,416	3,740	5,463 (1949)	16,497 (2001)
Middle Quintile Share of Income	0.145	0.015	0.118 (1996)	0.161 (1953)
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)
Federal Government	5,353,358	7,015,488	1,441,168 (1947)	9,131,843 (2001)
State and Local Government	3,570,639	5,236,169	631,319 (1945)	7,138,518 (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	101.606*	95.559*	10.497*
H_0: Gini is stationary	86.342*	83.655*	12.014*
Cointegration Tests	Kao (1999)	Pedroni (1995)	
H_0: No Cointegration	-5.893*	-31.101*	

* Significant at the 1% level.

Table 3. ARDL 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)	-0.155** (0.022)	-0.124** (0.020)	-0.097** (0.008)	-0.239** (0.026)	-0.120** (0.018)	-0.052** (0.008)
Gini, long run (θ_1)	-3.204** (1.156)	-0.364 (0.227)	-0.862* (0.356)	-16.004** (1.413)	-15.457** (0.345)	-16.450** (1.067)
Gini X log real state income per capita, long run (θ_2)				1.720** (0.143)	1.653** (0.037)	1.650** (0.118)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the mean-differenced annual growth rate of real income per capita.

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

	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)	-0.150** (0.019)	-0.123** (0.018)		-0.268** (0.035)	-0.176** (0.036)	
Gini, long run (θ_1)	-1.467 (1.127)	-0.773** (0.210)	-0.532** (0.077)	-14.860** (1.613)	-15.755** (0.202)	-18.056** (0.140)
Gini X log real state income per capita, long run (θ_2)				1.594** (0.162)	1.680** (0.022)	1.919** (0.015)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the mean-differenced annual growth rate of real income per capita. The maximum number of lags in each estimation is three.

Table 5. Alternative ARDL(1,1,1) Estimates of Income Inequality and Real State Income Per Capita

	Baseline (1)	Lower Gini (2)	Upper Gini (3)	3 Year Average (4)	5 Year Average (5)	7 Year Average (6)
Adjustment coefficient, (Φ)	-0.120**	-0.122**	-0.134**	-0.171**	-0.232**	-0.281**
	(0.018)	(0.017)	(0.019)	(0.025)	(0.058)	(0.062)
Gini, long run (θ_1)	-15.457**	-15.561**	-15.857**	-13.947**	-17.303**	-13.264**
	(0.345)	(0.365)	(0.325)	(0.393)	(0.127)	(0.050)
Gini X log real state income per capita, long run (θ_2)	1.653**	1.653**	1.699**	1.410**	1.800**	1.417**
	(0.037)	(0.039)	(0.035)	(0.042)	(0.014)	(0.006)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the mean-differenced annual growth rate of real income per capita. The baseline specification in column 1 corresponds to column 5 of Table 3.

Table 6. Extended ARDL Estimates of Income Inequality and Real State Income Per Capita

	MG (1)	Pooled MG (2)	Dynamic FE (3)
Adjustment coefficient, (Φ)	-0.710**	-0.598**	-0.077**
	(0.028)	(0.030)	(0.009)
Gini, long run (θ_1)	-16.559**	-16.712**	-16.466**
	(0.318)	(0.186)	(0.825)
Gini X log real state income per capita, long run (θ_2)	1.814**	1.819**	1.710**
	(0.032)	(0.020)	(0.089)
Middle Quintile, long run (θ_3)	-0.069	-0.013	0.657
	(0.079)	(0.044)	(0.485)
Farming, short run	-0.006**	-0.007**	-0.002*
	(0.002)	(0.002)	(0.001)
Construction, short run	0.008**	0.007**	0.001
	(0.002)	(0.002)	(0.001)
Manufacturing, short run	0.006	0.008	0.004**
	(0.005)	(0.004)	(0.001)
Transportation, short run	-0.003	-0.005	0.001
	(0.006)	(0.005)	(0.002)
Trade, short run	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
F.I.R.E., short run	-0.018**	-0.016**	-0.008**
	(0.006)	(0.005)	(0.002)
Services, short run	0.018**	0.017**	0.005**
	(0.005)	(0.004)	(0.001)
Federal Government, short run	0.004	0.008	-0.003
	(0.006)	(0.005)	(0.002)
State and Local Government, short run	-0.015**	-0.020**	0.001
	(0.006)	(0.005)	(0.002)

*, **: Significant at the 0.05, 0.01 level, respectively. Standard errors in parentheses. Dependent variable in each estimation is the mean-differenced annual growth rate of real 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	-0.247**	-27.958**	2.741**	210.41
AZ	-0.256*	-14.384**	1.599**	196.18
AR	-0.112	-23.574**	2.501**	184.97
CA	-0.053	-21.779	2.155	208.12
CO	-0.130	-7.807	0.972*	199.56
CT	-0.018	17.986	-2.071	188.02
DE	-0.112	-6.918	0.871	181.00
FL	-0.107	-13.837**	1.454**	207.25
GA	-0.513**	-20.814**	2.208**	222.11
ID	-0.436**	-14.395**	1.569**	189.00
IL	-0.035	-37.543	4.020	225.62
IN	-0.152	-14.346**	1.405**	229.42
IA	-0.711**	-17.577**	1.831**	200.56
KS	-0.292**	-13.056**	1.426**	207.88
KY	-0.036	-22.509	2.275	204.29
LA	-0.110	-13.620**	1.649**	182.79
ME	-0.100	-13.722	1.312	183.44
MD	-0.273**	-14.826**	1.638**	208.77
MA	-0.308**	-15.985**	1.560**	195.29
MI	-0.289**	-19.218**	2.107**	213.26
MN	-0.710**	-18.177**	2.038**	228.14
MS	-0.085	-25.856**	2.708**	181.26
MO	-0.183*	-12.638**	1.459**	245.50
MT	-0.230*	-17.652**	1.889**	188.84
NE	-0.158*	-16.333**	1.731**	197.40
NV	-0.189*	-25.698**	2.729**	182.44
NH	-0.398**	-18.469**	1.944**	179.12
NJ	-0.251**	-13.064**	1.289**	202.23
NM	-0.282**	-12.655**	1.425**	177.15
NY	0.014	19.469	-1.341	206.12
NC	-0.183**	-23.152**	2.496**	227.46
ND	-0.400**	-16.551**	1.774**	164.74
OH	-0.079	-13.478**	1.429**	241.07
OK	-0.229**	-10.374**	1.234**	184.82
OR	-0.337**	-19.408**	2.078**	220.35
PA	-0.442**	-16.335**	1.744**	221.29
RI	-0.650**	-17.762**	1.947**	199.78
SC	-0.097	-30.384**	3.225**	189.85
SD	-0.602**	-18.337**	1.974**	173.32
TN	-0.327**	-22.382**	2.505**	203.31
TX	-0.147**	-10.826**	1.120**	218.66
UT	-0.284**	-12.981**	1.391**	206.78
VT	-0.121	-25.507**	2.692**	188.62
VA	-0.216*	-19.959**	2.173**	220.83
WA	-0.216*	-18.039**	1.930**	194.85
WV	-0.063	3.023	-0.304	188.69
WI	-0.201*	-17.556**	1.776**	237.96
WY	-0.140	-21.244**	2.242**	184.03
Mean Group	-0.239**	-16.004**	1.720**	9692.57

*, **: Significant at the 0.05, 0.01 level, respectively. Dependent variable in each estimation is the mean-differenced annual growth rate of real 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 latter being a plot of the cumulative proportion of income received against the cumulative proportion of income units, arranged in ascending order of income.

[2] Piketty and Saez (2003) construct time series data on top income shares in the U.S. beginning in the year 1913. Our panel of data is also IRS-based, but the gini coefficients we calculate start in 1945, and are constructed for each state.

[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 state-level distributional data is available annually from various publications by the Internal Revenue Service. For the periods 1945 to 1973, and 1975 to 1981, the data is available in the *Statistics of Income*, *Individual Income Tax Returns* annual series. The 1974 volume of this series was never published, but the data is available from the 1974 edition of *Statistics of Income: Small Area Data*. Data for the years 1982 to 1987 was tabulated by the IRS, but never included in any of the publicly available IRS publications. Upon our request, however, Charles Hicks with the IRS graciously provided the data. For the years 1988 to 2001, the data is available in the *Statistics of Income Bulletin* quarterly series.

[6] Following Cowell (1995), the lower limit gini is

$$G_L = \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\frac{n_i n_j}{n\mu}\left|\mu_i - \mu_j\right|,$$

where n is the number of individuals, μ is mean income, and subscripts i and j denote within group values. The upper limit gini is

$$G_U = G_L + \sum_{i=1}^{k}\frac{n_i^2\left(a_{i+1}-\mu_i\right)\left(\mu_i - a_i\right)}{n^2\mu\left(a_{i+1}-a_i\right)}$$

where the lower bound of group i is a_i, and the upper bound is a_{i+1}. The compromise gini is $G_U\ 2/3 + G_L\ 1/3$. Cowell and Mehta (1982) provide strong empirical and theoretical support for the compromise gini. The upper and lower gini coefficients are both sensitive to the number of groupings used by the IRS (see Gastwirth, 1972). This is evident in Figure 1, where the difference between G_U and G_L is large during years with an unusually small number of IRS groups (1974 and 1982-1987).

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

[8] 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 current 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.

[9] The mining industry wage and salary variable is not included because of missing data.

[10] The Pearson's correlation between the IRS and Census gini indexes for the six years of commonality is 0.52. This is larger than the 0.44 found by Panizza (2002) for similar data, or the 0.48 between estimates for OECD country data of Deninginger 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] Note that equation (*3*) has important differences from the empirical work of Panizza (2002), Forbes (2000), and Partridge (1997). These prior investigations regressed the growth of real per capita income on lagged levels of income and income inequality, usually in a fixed effects or GMM framework. With the larger time dimension of our sample, however, we discover in the next section that the gini coefficient over this time period is in fact $I(1)$ and cointegrated with real per capita income, meaning the techniques used in the prior investigations would be inappropriate with our sample. The error correction framework of equation (*3*) is particularly useful in this instance because it deals with the endogeneity concerns, the cointegration concerns, and because the variables within the error correction term can be expressed in level form, is able to speak to the long-run relationships between inequality and growth as prior empirical work has done.

[13] The seminal paper by Sims (1980) provides a discussion of the advantages of our VAR-based approach over other simultaneous equation modeling approaches.

[14] 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).

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

[16] Though the evidence is strong that the gini coefficient is nonstationary over the period 1945-2001, it cannot be nonstationary indefinitely. Unlike real income per capita, the gini coefficient is bound between zero and one, and thus cannot increase *ad infinitum*.

[17] The state-specific MG results presented in Appendix Table A1 shows that the relationship between the gini coefficient and real income per capita is robust across states. The long run estimate of gini (θ_1) is negative and significant for 39 of the 48 states (or 81% of the time), while the long run estimate of the interaction term (θ_2) is positive and significant in 40 of the 48 states (or 83% of the time). In no state is the gini coefficient significantly positive, and in no state is the interaction term significantly negative. Hence, removing the cross-sectional dimension of the data does significantly alter the relationship between inequality and growth.

[18] To derive the partial of real income per capita with respect to inequality, note that the real income per capita levels shown on the horizontal axis of Figure 4 must be log-transformed and mean-differenced before using the pooled MG theta parameters presented in column 5 of Table 3.

[19] To estimate equation (*3*) at least eight time-period observations are required. Therefore the 7-year average model is the longest time-span that can be estimated within the error-correction framework. Alternatively, it is possible to estimate the model in 10-year average periods using the GMM-based approach of Arellano and Bond (1991). Arellano and Bond's estimator deals with the endogeneity of income and income inequality, but neglects the nonstationarity of each. For the 10-year average model this is less of the concern since the panel condenses to five time periods covering the span 1950 to 1999. After mean-differencing the variables, and including as regressors lagged real per capita income in log form, the gini coefficient, and the interaction of gini and log real per capita income, the gini parameter estimate is found to be -16.174 (standard error = 0.501), while the interaction parameter estimate is 1.668 (standard error = 0.052). These results are remarkably consistent with the baseline specification in Table 5.

[20] The middle quintile income share is found to be nonstationary and cointegrated with logged real per capita income, and therefore is included with the other long-run variables within the error-correction term. By contrast, the nine wage and salary variables are treated as short-run regressors.