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Causality between Output and Income Inequality across U.S. States:

Evidence from a Heterogeneous Mixed Panel Approach

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Abstract

In this paper, we investigate the causal relationship between output, proxied by personal income, and income inequality in a panel data of 48 states from 1929 to 2012. We employ the causality methodology proposed by Emirmahmutoglu and Kose (2011), as it incorporates possible slope heterogeneity and cross-sectional dependence in a multivariate panel. Evidence of bi-directional causal relationship exists for several inequality measures -- the Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil's entropy Index and Top 10% -- but no evidence of the causal relationship for the Top 1 % measure. Also, this paper finds state-specific causal relationships between personal income and inequality.

JEL classification code: C33, D31, D63

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1. Introduction

The issue of income inequality has drawn great interest from researchers, politicians, and policy makers, since the well-being of an individual often depends on the distribution of income. Many researchers show that the U.S. economy experienced increasing income inequality over the last 30 years. Consequently, the determinants of income inequality and political and/or economic solutions to reduce inequality have become important discussions.

Researchers consider many possible explanations for this widening gap, yet no consensus exists on what can explain its emergence and on what can reduce differences among individuals. Most of the existing literature examines the effects of income inequality on economic growth in personal income, since personal income exerts a large effect on consumer consumption, and since consumer spending drives much of the economy. Studies provide evidence that more income inequality slows economic growth over the medium and long terms (Alesina and Perotti, 1996; Alesina and Rodrik, 1994; Person and Tabellini, 1992; Birdsall et al., 1995; Clarke, 1995; Deininger and Squire, 1996; Easterly, 2007; Wilkinson and Pickett, 2007; Berg et al., 2012). In contrast, some studies provide evidence that more income inequality promotes economic growth (Lazear and Rosen, 1981; Hassler and Mora, 2000; Kaldor, 1955; Bourguignon 1981; Saint-Pal and Verdier, 1993; Barro, 2000). Depending on the specific research method and sample, this literature discovers a complex set of interactions between inequality and economic growth and highlights the difficulty of capturing a definitive causal relationship. Inequality either promotes, slows, or does not affect growth.

Studies also exist that examines the causality between income growth and inequality using panel data. Using cross-country data, Dollar and Kraay (2002) document that the share of income going to the poorest fifth of the income distribution does not change when mean income fluctuates. Their finding implies that income of the poor grows at the same rate as the growth rate of the economy. On the other hand, Parker and Vissing-Jorgensen (2009), using U.S. income tax returns, find that the top-end of the income distribution carries a high share of aggregate income fluctuations. Although inequality rose in almost all U.S. states and regions between 1980 and the present, some states and regions experienced substantially greater increases in inequality than did others (see, for example, Partridge et al., 1996; Partridge et al., 1998; Morrill, 2000). The decentralisation of the analysis to states and regions allows geographic policy differences to emerge. At the same time, a cross-state consistency also can exist in how those policies respond to the macroeconomic economic shocks such as the Great Recession. Although many researchers analyse state differences in poverty, health insurance, social mobility, and taxes, less study occurs on state differences in causality between personal income and inequality.

Even though many researchers analyse causality relationships using cross-state data, a couple of issues are not addressed such as the possible existence of heterogeneity, cross-sectional dependence, and interdependencies. We use a modified version of the panel causality developed by Emirmahmutoglu and Kose (2011), which was originally designed to analyse causality in a bivariate-setting, to control not only for heterogeneity and cross-sectional dependence across state, but also to permit interactions between personal income and inequality.

Since U.S. states experience significant spatial effects given their high level of integration, we need to address the concern expressed in Pesaran (2004), who notes that ignoring cross-sectional dependency may lead to substantial bias and size distortions. Furthermore, unlike traditional causality approaches that rely on cointegration techniques, the bootstrap methodology does not require testing for cointegration, hence obviating pre-test bias (Emirmahmutoglu and Kose, 2011). The bootstrap methodology also provides evidence for the entire panel as well as each of the cross-sectional units comprising the panel. Thus, we can consider state-specific policies, since we possess causality test results for each of the series in the panel. A multivariate panel setup allows for greater inference due to the greater degrees of freedom, stemming from the larger data set that a panel provides. The panel also allows us to control for omitted variables.

Our sample period covers a series of different events – the Great Depression (1929-1944), the Great Compression (1945-1979), the Great Divergence (1980-present), the Great Moderation (1982-2007) and the Great Recession (2007-2009). Goldin and Margo (1991) categorized the Great Compression as the time after the Great Depression, when income inequality fell significantly compared to the Great Depression. Krugman (2007) identified the period after the Great Compression as the Great Divergence, when income inequality grew. Piketty and Saez (2003) argue that the Great Compression ended in the 1970s and then income inequality worsened in the United States. Many studies show high income inequality during the 1920s, strong growth and shared prosperity for the early post-war period, followed by slower growth and growing inequality since the 1970s[1].

This paper is structured as follows. Section 2 describes data. Section 3 discusses the methodology. Section 4 reports and analyses the empirical results. Concluding remarks appear in Section 5.

2. Data

Our analysis relies on the natural logarithm of U.S. per capita real personal income and the six income inequality measures[2] - Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil's entropy Index, the Top 10% income share, and the Top 1% income share -- as proxies for inequality across the income distribution (Leigh, 2007). The annual data cover 1929 – 2012. Income inequality measures and income share measures come from the

[1] For example, see Dew-Becker and Gordon (2005), Gordon (2009)

[2] We take natural logarithms to correct for potential heteroskedasticity and dimensional differences between the series. Also, by taking natural logarithms, we can interpret the coefficients as elasticities.

online data segment of Professor Mark W. Frank's website.[3] U.S. per capita nominal personal income comes from the Bureau of Economic Analysis (BEA), which we deflate using the U.S. aggregate Consumer Price Index (Index 1982-84=100). By using cross-state panel data, we minimize the problems associated with data comparability often encountered in cross-country studies related to income inequality.

3. Methodology

As we use cross-state panel dataset, cross-sectional dependency may create some bias in identifying causal linkages between personal income and inequality. The high degree of economic integration across U.S. states can cause spillover effects of shocks originating in one state to other states and these effects, if ignored, may produce misleading inferences due to misspecification. Also, the homogeneity restriction, which imposes constant parameters with cross-section-specific characteristics, can produce similar outcomes (Granger, 2003; Breitung, 2005). To determine the appropriate specification, we test for cross-sectional dependence and slope homogeneity.

3.1 Testing for cross-sectional dependence

To test for cross-sectional dependence, researchers typically use the *Lagrange Multiplier* (*LM*) test of Breusch and Pagan (1980). To compute the *LM* test, we implement the following panel-data estimation:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \text{ for } i = 1,2, \dots, N\,; t = 1,2, \dots, T, \qquad (1)$$

where i is the cross-section dimension, t is the time dimension, x_{it} is $k \times 1$ vector of expnatory variables, α_i and β_i are the individual intercepts and slope coefficients that we allow to vary across states, respectively. In the *LM* test, we test the null hypothesis of no-cross-sectional dependence -- $H_0: Cov(u_{it}, u_{jt}) = 0$ for all t and $i \neq j$ --- against the

[3] http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed the dataset based on Internal Revenue Service (IRS) data, which omits some individuals earning less than a threshold level of gross income. For this reason, we focus more on the top income shares as primary indicators of inequality measures. We examine six inequality measures as each offers a different insight as to the inequality of income.

alternative hypothesis of cross-sectional dependence $H_1: Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. To test the null hypothesis, Breusch and Pagan (1980) developed the *LM* test as follows:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2, \tag{2}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from Ordinary Least Squares (OLS) estimation of equation (1) for each i. Under the null hypothesis, the *LM* statistics possesses an asymptotic chi-squared distribution with $(\frac{N(N-1)}{2})$ degrees of freedom. Note that the *LM* test is valid for *N* relatively small and *T* sufficiently large.

The *Cross-sectional Dependence* (*CD)* test may decrease in power under certain situations -- when the population average pair-wise correlations are zero, but the underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008). In addition, in stationary dynamic panel data models, the *CD* test fails to reject the null hypothesis when the factor loadings contain zero mean in the cross-sectional dimension. To overcome these problems, Pesaran et al. (2008) propose a bias-adjusted test, which is a modified version of the *LM* test by using the exact mean and variance of the *LM* statistic. The bias-adjusted *LM* test is

$$LM_{adj} = \sqrt{(\frac{2T}{N(N-1)})} \sum_{I=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}}, \tag{3}$$

where μ_{Tij} and v_{Tij}^2 are the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, respectively, which Pesaran et al. (2008) provides. Under the null hypothesis with first $T \to \infty$ and $N \to \infty$, $the\ LM_{adj}$ test is asymptotically normally distributed.

3.2 Testing slope homogeneity

We next check whether the slope coefficients are homogeneous in a panel data analysis. The causality from one to another variable with the joint restriction imposed for entire panel generates the strong null hypothesis (Granger, 2003). Moreover, the homogeneity assumption for the parameters cannot capture heterogeneity due to region-specific characteristics (Breitung, 2005).

The most well-known way to test the null hypothesis of slope homogeneity -- $H_0: \beta_i = \beta$ for all i -- against the hypothesis of heterogeneity -- $H_1: \beta_i \neq \beta$ for a non-zero fraction of pair-wise slopes for $i \neq j$ -- employs the standard *F* test. The *F* test is valid when the cross-section dimension (*N*) of the panel is relatively small and the time dimension (*T*) is relatively large; the explanatory variables are strictly exogenous; and the error variances are homoscedastic. By relaxing the homoscedasticity assumption in the *F* test, Swamy (1970) developed the slope homogeneity test on the dispersion of individual slope estimates from a suitable pooled estimator. Both the *F* and Swamy's test require panel data, where *N* is small relative to *T*. Pesaran and Yamagata (2008) proposed a standardized version of Swamy's test (the $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid when $(N, T) \rightarrow \infty$ without any restrictions on the relative expansion rates of *N* and *T* as the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, the first step computes the following modified version of the Swamy's test as in Pesaran and Yamagata (2008)[4]:

$$\tilde{S} = \sum_{i=1}^{N} (\widetilde{\widehat{\beta}}_i - \tilde{\beta}_{WFE})' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} (\widetilde{\widehat{\beta}}_i - \tilde{\beta}_{WFE}), \tag{4}$$

where $\widetilde{\widehat{\beta}}_i$ is the pooled OLS estimatoer, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator, M_τ is an identity matrix, and $\tilde{\sigma}_i^2$ is the estimator of σ_i^2. Then the standardized dispersion statistic is as follows:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right). \tag{5}$$

Under the null hypothesis with the condition of $(N, T) \rightarrow \infty$ (as long as $\sqrt{N}/T \rightarrow \infty$) and the error terms are normally distributed, the $\tilde{\Delta}$ test is asymptotically normally distributed. Under the normally distributed errors, the small sample properties of the $\tilde{\Delta}$ test improve when using

[4] See Pesaran and Yamagata (2008) for the details of estimators and for Swamy's test.

the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right), \qquad (6)$$

where $E(\tilde{z}_{it}) = k$ and $var(\tilde{z}_{it}) = 2k(T - k - 1)/T + 1$.

If cross-sectional dependence and heterogeneity exist, then the panel causality test that imposes the homogeneity restriction and does not account for spillover effects may produce misleading inferences. Table 1 summarizes the results of these selected tests. We can reject the nulls of slope homogeneity and cross-sectional independence, hence, confirming the evidence of heterogeneity as well as spillover effects across the U.S. states. The findings reported in Table 1 motivate the decision to rely on the methodology for causal analysis proposed by Emirmahmutoglu and Kose (2011), which addresses heterogeneous mixed panels and cross-sectional dependence.

3.3 Panel Granger causality analysis

The panel Granger causality test proposed by Emirmahmutoglu and Kose (2011) uses the Meta analysis of Fisher (1932). Emirmahmutoglu and Kose (2011) extend the Lag Augmented VAR (LA-VAR) approach by Toda and Yamamoto (1995), which uses the level VAR model with extra *d*max lags to test Granger causality between variables in heterogeneous mixed panels. Consider a level VAR model with $k_i + d\text{max}_i$ lags in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j=1}^{k_i+d\text{max}_i} A_{11,ij}\, x_{i,t-j} + \sum_{j=1}^{k_i+d\text{max}_i} A_{12,ij}\, y_{i,t-j} + u_{i,t}^x \text{ and} \qquad (7)$$

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i+d\text{max}_i} A_{21,ij}\, x_{i,t-j} + \sum_{j=1}^{k_i+d\text{max}_i} A_{22,ij}\, y_{i,t-j} + u_{i,t}^y, \qquad (8)$$

where i $(i = 1, \ldots, N)$ denotes individual cross-sectional units; t $(t = 1, \ldots, T)$ denotes time period; μ_i^x and μ_i^y are two vectors of fixed effects; $u_{i,t}^x$ and $u_{i,t}^y$ are column vectors of error terms; $k_i$is the lag structure, which we assume to know and may differ across cross-sectional units; and $d\max_i$ is the maximal order of integration in the system for each *i*. Following the bootstrap procedure in Emirmahmutoglu and Kose (2011), we test for causality from *x* to *y* as follows:

Step 1. We determine the maximal order $d\max_i$ of integration of variables in the system for each cross-section unit based on the Augmented Dickey Fuller (ADF) unit-root test and select the lag orders k_i's via Akaike information criterion or Schwarz information criterion (AIC or SIC) by estimating the regression (2) using the OLS method.

Step 2. We re-estimate Equation (2) using the $d\max_i$ and k_i under the non-causality hypothesis and attain the residuals for each individual as follows:

$$\hat{u}_{i,t}^{y} = y_{i,t} - \hat{\mu}_i^{y} - \sum_{j=1}^{k_i+d\max_i} \hat{A}_{21,ij}\, x_{i,t-j} - \sum_{j=1}^{k_i+d\max_i} \hat{A}_{22,ij}\, y_{i,t-j} \tag{9}$$

Step 3. We center the residuals using the suggestion of Stine (1987) as follows:

$$\tilde{u}_t = \hat{u}_t - (T-k-l-2)^{-1} \sum_{j=1}^{k_i+d\max_i} \hat{u}_t, \tag{10}$$

where $\hat{u}_t = (\hat{u}_{1t}, \hat{u}_{2t}, \dots, \hat{u}_{Nt})', k = \max(k_i)$ and $l = \max(d\max_i)$. Furthermore, we develop the $[\tilde{u}_{it}]_{N\times T}$ from these residuals. We select randomly a full column with replacement from the matrix at a time to preserve the cross covariance structure of the errors. We denote the bootstrap residuals as $\tilde{u}_t^*$ where (t=1,…, T).

Step 4. We generate a bootstrap sample of $y_{i,t}^*$ under the null hypothesis:

$$y_{i,t}^* = \hat{\mu}_i^{y} + \sum_{j=1}^{k_i+d\max_i} \hat{A}_{21,ij}\, x_{i,t-j} + \sum_{j=1}^{k_i+d\max_i} \hat{A}_{22,ij}\, y_{i,t-j}^* + u_{i,t}^*\,, \tag{11}$$

where $\hat{\mu}_i^{y}, \hat{A}_{21,ij}$, and $\hat{A}_{22,ij}$ are the estimates from step 2.

Step 5. For each individual, we calculate Wald statistics to test for the non-causality null hypothesis by substituting $y_{i,t}^*$ for $y_{i,t}$ and estimating Equation (2) without imposing any parameter restrictions. Using individual *p*-values that correspond to the Wald statistic of the i^{th} individual cross-section, we calculate the Fisher test statistic λ as follows:

$$\lambda = -2\sum_{i=1}^{N} \ln(p_i)\,, i = 1, \dots, N. \tag{12}$$

We generate the bootstrap empirical distribution of the Fisher test statistics by repeating steps 3 to 5 10,000 times and specifying the bootstrap critical values by selecting the appropriate percentiles of these sampling distributions. Using simulation studies, Emirmahmutoglu and Kose (2011) demonstrate that the performance of LA-VAR approach under both cross-section independency and dependency seem to perform satisfactory for the entire range of values for *T* and *N*.

4. Empirical Analysis

As mentioned in the methodology section, we first need to examine for possible cross-sectional dependence and slope heterogeneity, using four different tests ($CD_{BP}, CD_{LM}, CD, LM_{adj}$) with a null hypothesis of no cross-sectional dependence. The results conclude that we can reject the null hypothesis at the 1-percent level of significance (see Table 1, 4 rows from the top). This outcome implies that evidence exists of cross-sectional dependence, meaning that a shock originating in one state may spillover into other states. As shown in the methodology section, the causality tests of Emirmahmutoglu and Kose (2011) control for this dependency.

Also, Table 1 (3 rows from the bottom) shows the results of the slope homogeneity tests. According to $\tilde{\Delta}$ test, we can reject the null hypothesis of homogenous slopes at the 1-percent level of significance. Furthermore, at least one of the tests rejects null hypothesis of slope homogeneity with the $\tilde{\Delta}_{adj}$ test and the Swamy Shat test. This implies that imposing slope homogeneity on the panel causality analysis may result in misinterpretation. Hence, we need to consider possible state-specific characteristics.

Establishing the existence of cross-sectional dependence and heterogeneity across the 48 U.S. states suggests the suitability of the bootstrap panel causality approach developed by Emirmahmutoglu and Kose (2011), which accounts for these econometric issues. Table 2 through 7 report the bootstrap test causality results. We chose the appropriate lag length using the Akaike Information Criterion for each state.

The overall causality results between income inequality and personal income suggest that we can reject both the null of no Granger causality from inequality to income and from income to inequality at 1-percent level of significance (i.e. bi-directional causality) except for Top 1% income share, suggesting the possible existence of a trend relationship between increasing income and widening income inequality.

Table 2 shows the causality between personal income and the Atkinson Index. Under AIC and SBC, the asymptotic chi-square values applied with the Fisher test are higher for inequality led hypothesis. This suggests that individual states results are more consistent for the inequality led hypothesis than the income led hypothesis. That is, only 3 states out of 48 display insignificant Wald statistics (high *p*-values) for the inequality led hypothesis, namely New Mexico, North Dakota, and Wyoming. For the income led hypothesis, 6 states display insignificant Wald statistics, namely Arizona, Florida, Maryland, Missouri, New Hampshire, and Wyoming. Thus, Wyoming confirms the neutrality hypothesis.

Table 3 shows causality between personal income and the Gini coefficient. Under AIC and SBC, the asymptotic chi-square values applied with the Fisher test are higher for inequality led hypothesis. This suggests that individual results are more consistent for the inequality led hypothesis than the income led hypothesis. That is, 4 states display insignificant Wald statistics (high *p*-values) for inequality led hypothesis, namely Kansas, Montana, Nebraska, and Wyoming. For the income led hypothesis, 11 states display an insignificant Wald statistics, namely Arkansas, Colorado, Iowa, Louisiana, Maryland, Mississippi, Missouri, South Carolina, Texas, Wisconsin, and Wyoming. Once again, Wyoming confirms to the neutrality hypothesis.

Table 4 shows causality between personal income and the Relative Mean Deviation. Under AIC and SBC, the asymptotic chi-square values applied with the Fisher test are higher for inequality led hypothesis. This suggests that individual results are more consistent for the inequality led hypothesis than the income led hypothesis. Only South Dakota displays an insignificant Wald statistic (high *p*-value) for the inequality led hypothesis. For the income led hypothesis, only 3 states out of 48 states display an insignificant Wald statistics, namely Iowa, Texas, and Wyoming. No state conforms to the neutrality hypothesis in this case.

Table 5 shows causality between personal income and Theil's entropy. Under AIC and SBC, the asymptotic chi-square values applied with the Fisher test are higher for the inequality led hypothesis. This suggests that individual results are more consistent for the inequality led hypothesis than the income led hypothesis. 12 states display insignificant Wald statistics (high *p*-values) for the inequality led hypothesis, namely Arkansas, Idaho, Indiana, Maryland, Mississippi, Nebraska, New Mexico, North Carolina, Oregon, South Dakota, Vermont, and Wyoming. For the income led hypothesis, 30 states display an insignificant Wald statistics, namely Arizona, Colorado, Connecticut, Florida, Idaho, Indiana, Iowa, Louisiana, Maryland, Massachusetts, Minnesota, Mississippi, Missouri, Nevada, New Hampshire, New Jersey, New York, North Dakota, Ohio, Oregon, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Washington, Wisconsin, and Wyoming. Thus, we confirm the neutrality hypothesis for 8 states, namely, Idaho, Indiana, Maryland, Mississippi, Oregon, South Dakota, Vermont, and Wyoming.

Table 6 shows causality between personal income and Top 10% income share. 4 states display insignificant Wald statistics (high *p*-values) for the inequality led hypothesis, namely Arizona, Montana, South Dakota, and Wyoming. For the income led hypothesis, 4 states display an insignificant Wald statistics, namely Arizona, Florida, New York, and Utah. Thus, we confirm the neutrality hypothesis only for Arizona.

Table 7 shows that the overall results confirm no causality between Top 1% income share and Income.

The differences of the results underline the advantages of panel over individual regressions such as capturing more complex dynamic models, identifying unobserved effects, and mitigating multicollinearity problems (Baltagi, 2008).

5. Conclusion

In this paper, we followed the procedure of Emirmahmutoglu and Kose (2011), a panel Granger causality methodology that controls for heterogeneity and cross-sectional dependence, to test for the existence and direction of causal relationships between income and income inequality, using annual data for the 48 U.S. states from 1929-2012. The panel data literature has shown possible cross-sectional dependence with panel data resulting in biased estimates (Pesaran; 2006).

In this study, we found evidence of bi-directional causal relationship exists for the Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil’s entropy Index, and Top 10% measures of inequality. For Top 1% income share, we found no evidence of a causal relationship. Also, we found state-specific causal relationships between personal income and inequality.

The reason for focusing on inequality across states reflects the fact that inequality-related policy can occur at the state and local levels, which can produce different inequality profiles across states. For instance, federal tax and transfer policies affect inequality. States can selectively adopt and/or implement some federal policies or supplement them with state policies. For example, states (and local municipalities) can increase the minimum wage applicable within its borders as seen with the recent adoption of $15 minimum wage in some cities. Progressive state personal income tax policies can alter the progressivity of the federal code. As another example, states responded differently to the Affordable Care Act (Obama Care) with respect to providing or not providing Medicaid to state residents.

As another example, most immigrants from Mexico settled in California and Texas and the immigration probably increased inequality. Legalisation of immigration for many U.S. residents would attract those who currently work off the books onto the IRS tax rolls, which, in turn, would increase the state-level Earned Income Tax Credits, reducing inequality. As immigration policy is a federal government issue, however, state-level efforts to address rising inequality by immigrants through the tax might face limitations. In the long term, states can make changes to their policy on human-capital investment that can raise middle-class incomes and reduce inequality (Heinrich and Smeedling, 2014). Better access to education and health service and well-targeted social policies can help rise the income share for the poor and the middle income group. No one-size-fits-all policy exists to tackling inequality issues, however.

Since some of the literature supports a positive effect of inequality on growth, some degree of inequality may not prove beneficial. For instance, returns to education and differentiation in labour earnings can motivate human capital accumulation and economic growth, despite its association with higher income inequality (Lazear and Rosen, 1981). Rising inequality, however, can result in large social cost, as income inequality can significantly undermine individual's educational and occupational choices. Further, a possibility exists that income inequality does not generate the "right" incentives if it rests on rents (Stiglitz, 2012). In that case, individuals have an incentive to divert their efforts toward protection, such as resource misallocation and corruption. Thus, the appropriate policies depend on the underlying drivers and state-specific policy and institutional settings.

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Table 1. Cross-sectional Dependence and Homogeneity Tests (Inequality and Income)

	Atkin05	Gini	Rmeandev	Theil	Top 10%	Top1%
CD_{BP}	42343.951***	34514.356***	29210.937***	28955.723***	42343.951***	45076.726***
CD_{LM}	867.752***	702.910***	591.252***	585.879***	867.752***	925.288***
CD	202.945***	181.227***	163.112***	163.445***	202.945***	208.543***
LM_{adj}	1708.916***	1735.807***	1656.264***	1569.867***	1583.094***	1600.792***
$\tilde{\Delta}$	178.457***	168.938***	189.290***	106.396***	73.039***	100.942***
$\tilde{\Delta}_{adj}$	2.188***	2.072***	2.321***	1.304*	0.895	1.237*
Swamy Shat	1796.522***	1703.247***	1902.657	1090.463***	763.639***	1037.030***

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 2. Results of Granger causality between Personal Income and Atkinson Index

State	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause Atkinson Index						Inequality led hypothesis H0: Atkinson Index does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	8	25.243	***	26.764	***	16.262	**	12.778		16.581	***	9.122	
Arizona	5	6.528		6.528		5.55		22.237	***	22.237	***	23.579	***
Arkansas	8	37.695	***	7.663	**	30.128	***	14.198	*	7.196	**	14.125	*
California	8	27.116	***	10.139	*	23.986	***	23.346	***	24.117	***	27.374	***
Colorado	8	19.89	**	7.427		17.301	**	28.372	***	25.05	***	22.622	***
Connecticut	8	15.266	*	3.236		11.833		26	***	1.031		24.24	***
Delaware	8	23.568	***	23.568	***	20.911	***	24.067	***	24.067	***	33.252	***
Florida	8	8.477		4.639		11.371		34.657	***	34.386	***	32.549	***
Georgia	8	19.321	**	27.941	***	12.241		15.135	*	16.351	***	13.013	
Idaho	7	15.137	**	15.137	**	20.856	***	13.499	*	13.499	*	15.404	**
Illinois	8	17.215	**	16.62	**	8.689		39.786	***	18.825	***	16.121	**
Indiana	7	14.512	**	10.298	*	14.711	**	21.553	***	20.149	***	22.656	***
Iowa	8	18.628	**	9.075		11.481		14.893	*	11.82	*	10.521	
Kansas	8	27.39	***	8.618	*	22.049	***	15.191	*	14.026	***	17.118	**
Kentucky	7	13.669	*	13.669	*	9.226		31.324	***	31.324	***	33.187	***
Louisiana	8	25.906	***	25.906	***	20.825	***	68.666	***	68.666	***	55.252	***
Maine	8	26.861	***	18.057	***	15.615	**	25.112	***	8.675	*	24.205	***
Maryland	7	9.416		1.279		8.296		13.485	*	16.189	***	9.895	
Massachusetts	8	15.779	**	9.284	*	9.363		25.205	***	15.596	***	16.121	**
Michigan	7	21.779	***	21.779	***	20.834	***	16.496	**	16.496	**	13.123	*
Minnesota	8	22.488	***	6.961		19.037	**	32.389	***	35.564	***	27.528	***
Mississippi	8	28.768	***	6.793		13.947	*	20.589	***	14.99	**	15.462	*
Missouri	5	4.49		4.49		4.792		29.07	***	29.07	***	24.523	***
Montana	8	22.544	***	9.095	***	18.146	**	18.376	**	0.143		15.233	*
Nebraska	8	25.576	***	3.62	*	19.23	**	13.819	*	0.077		11.274	
Nevada	8	12.658		0.704		15.767	**	25.026	***	0.116		27.156	***
N. Hampshire	8	9.119		2.469		8.477		17.807	**	16.075	***	9.797	
New Jersey	8	29.883	***	1.277		19.935	**	25.051	***	1.099		15.531	*
New Mexico	7	24.556	***	14.876	***	27.617	***	9.042		7.024		11.722	
New York	8	24.731	***	14.514	**	13.476	*	18.166	**	15.847	***	10.262	
North Carolina	7	34.874	***	26.277	***	36.815	***	8.911		14.632	**	7.357	
North Dakota	3	7.647	*	5.484	**	8.86	**	1.939		2.672		2.612	
Ohio	6	8.631		9.71	*	7.847		19.974	***	19.883	***	11.476	*
Oklahoma	8	13.681	*	4.459		19.044	**	53.313	***	13.453	***	38.353	***
Oregon	8	22.257	***	23.711	***	14.618	*	16.886	**	12.787	**	16.204	**
Pennsylvania	8	27.514	***	9.639	*	15.984	**	24.827	***	25.649	***	14.635	*
Rhode Island	8	21.403	***	0.851		25.862	***	29.094	***	0.428		25.027	***
South Carolina	8	19.82	**	11.37	**	9.879		21.9	***	22.958	***	18.047	**
South Dakota	8	18.99	**	20.228	***	16.508	**	13.829	*	11.351		13.566	*
Tennessee	8	10.567		15.4	***	5.952		32.855	***	28.916	***	18.181	**
Texas	7	14.116	**	1.445		9.594		19.126	***	15.481	***	18.662	***
Utah	8	31.591	***	31.591	***	14.81	*	31.403	***	31.403	***	39.529	***
Vermont	8	27.173	***	2.639		21.117	***	19.313	**	0.033		15.121	*
Virginia	8	29.202	***	15.693	***	30.481	***	35.329	***	23.939	***	44.449	***
Washington	8	15.371	*	6.278		8.104		25.357	***	26.354	***	23.325	***
West Virginia	7	16.507	**	17.826	***	13.157	*	22.013	***	17.089	***	12.96	*
Wisconsin	8	16.69	**	8.075		8.056		21.937	***	21.205	***	10.718	
Wyoming	6	4.027		6.261		4.044		3.275		2.108		3.407	
Fisher test statistic value		460.96						592.007					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		220.318		176.509		157.391		217.998		174.965		155.848	
Fisher test statistic value		339.978						544.594					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		190.624		156.549		141.928		194.822		163.103		145.22	
Fisher test statistic value		327.115						473.219					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		193.25		160.971		147.621		192.065		162.099		147.444	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.
3. The number of appropriate lag orders in level VAR systems are selected by minimizing the Schwarz Baysian criteria. Lag order 8 is used for all states.

Table 3. Results of Granger causality between Personal Income and Gini Coefficient

State	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause Gini Coefficient						Inequality led hypothesis H0: Gini Coefficient does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	8	19.887	**	17.559	**	22.351	***	22.256	***	13.508	*	19.545	**
Arizona	7	10.473		10.282	**	9.076		27.38	***	18.692	***	24.208	***
Arkansas	5	7.233		6.858		5.596		11.678	**	11.801	**	10.328	*
California	8	22.147	***	22.147	***	22.624	***	32.812	***	32.812	***	35.881	***
Colorado	8	10.196		10.196		11.024		55.989	***	55.989	***	46.064	***
Connecticut	8	15.452	*	15.452	*	16.522	**	39.298	***	39.298	***	33.853	***
Delaware	8	32.253	***	32.253	***	29.065	***	29.988	***	29.988	***	48.714	***
Florida	8	17.96	**	18.095	***	7.772		42.687	***	31.849	***	40.247	***
Georgia	8	14.704	*	26.133	***	11.949		30.804	***	25.738	***	23.324	***
Idaho	8	25.735	***	24.052	***	39.289	***	36.555	***	27.708	***	24.445	***
Illinois	8	26.938	***	24.456	***	23.009	***	43.683	***	12.701	**	18.715	**
Indiana	8	13.929	*	16.592	**	14.242	*	31.284	***	26.709	***	15.142	*
Iowa	8	9.659		10.183		10.213		18.077	**	19.575	***	15.543	**
Kansas	8	30.99	***	21.377	***	29.793	***	10.668		6.91		11.849	
Kentucky	7	13.531	*	13.531	*	10.233		29.003	***	29.003	***	27.639	***
Louisiana	8	7.223		7.223		13.309		49.444	***	49.444	***	39.748	***
Maine	8	21.894	***	17.475	***	15.222	*	23.82	***	3.243		21.952	***
Maryland	8	10.677		3.068		10.587		32.318	***	22.196	***	18.708	**
Massachusetts	8	25.499	***	14.45	***	27.519	***	31.296	***	12.94	**	20.578	***
Michigan	7	20.019	***	20.019	***	18.064	**	23.333	***	23.333	***	19.581	***
Minnesota	8	23.947	***	23.947	***	22.838	***	30.771	***	30.771	***	23.545	***
Mississippi	7	4.567		3.003		5.253		12.434	*	16.857	**	10.653	
Missouri	6	7.814		5.031		6.565		30.093	***	29.495	***	25.475	***
Montana	8	7.483		4.165	**	10.477		7.974		0.865		7.731	
Nebraska	8	27.569	***	0.031		27.134	***	11.697		0.124		10.912	
Nevada	8	33.182	***	32.823	***	31.505	***	23.092	***	20.313	***	26.067	***
N. Hampshire	8	12.864		1.522		14.006	*	36.156	***	23.675	***	25.262	***
New Jersey	8	29.34	***	1.706		25.357	***	38.293	***	1.74		26.72	***
New Mexico	8	13.825	*	9.112	*	14.015	*	22.624	***	9.25	*	18.665	**
New York	8	38.057	***	23.227	***	34.05	***	23.141	***	12.155	**	15.091	*
North Carolina	7	12.02		17.3	***	15.188	**	8.688		12.087	**	8.074	
North Dakota	7	13.617	*	5.479	**	11.182		9.373		3.958	**	11.883	
Ohio	7	15.987	**	14.907	**	14.34	**	28.587	***	21.887	***	35.665	***
Oklahoma	8	12.962		2.988		15.727	**	26.494	***	15.802	***	15.483	*
Oregon	8	25.954	***	29.587	***	28.088	***	15.414	*	32.636	***	16.437	**
Pennsylvania	8	22.906	***	19.1	***	22.825	***	26.292	***	19.752	***	16.124	**
Rhode Island	8	23.26	***	0.285		24.934	***	46.823	***	0.018		37.505	***
South Carolina	8	5.384		2.539		7.358		20.272	***	15.253	***	21.077	***
South Dakota	8	22.612	***	23.157	***	23.249	***	11.926		12.378	*	8.772	
Tennessee	8	13.75	*	19.254	***	14.084	*	24.44	***	19.887	***	11.48	
Texas	7	9.824		9.824		6.037		13.694	*	13.694	*	12.533	*
Utah	8	48.434	***	34.767	***	33.875	***	38.466	***	26.511	***	39.858	***
Vermont	8	16.903	**	9.453	*	17.442	**	25.032	***	12.377	**	17.925	**
Virginia	8	16.962	**	14.577	**	16.99	**	55.66	***	36.194	***	43.315	***
Washington	8	19.015	**	13.797	**	19.705	**	18.105	**	19.295	***	14.616	*
West Virginia	7	13.35	*	17.523	***	6.929		19.205	***	17.19	***	13.024	*
Wisconsin	8	5.435		6.18		8.418		22.367	***	25.542	***	10.575	
Wyoming	4	2.139		2.139		2.139		2.045		2.045		2.557	
Fisher test statistic value		405.633						724.19					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		225.97		180.168		159.523		224.271		182.758		161.691	
Fisher test statistic value		403.825						609.102					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		193.456		160.408		144.1		198.094		163.79		148.543	
Fisher test statistic value		382.65						546.644					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 10%	
		205.921		168.096		151.267		206.634		170.309		153.597	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 4. Results of Granger causality between Personal Income and Relative Mean Deviation

state	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause the Relative Mean Deviation						Inequality led hypothesis H0: the Relative Mean Deviation does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	8	28.149	***	14.627	**	23.048	***	24.951	***	41.917	***	19.38	**
Arizona	7	17.213	**	17.213	**	16.157	**	30.047	***	30.047	***	25.985	***
Arkansas	8	15.508	*	7.795		16.975	**	31.824	***	33.372	***	31.76	***
California	8	30.529	***	30.529	***	29.334	***	33.28	***	33.28	***	28.322	***
Colorado	8	15.053	*	15.053	*	18.418	**	51.176	***	51.176	***	40.199	***
Connecticut	8	19.107	**	19.107	**	21.47	***	44.127	***	44.127	***	29.442	***
Delaware	8	42.638	***	42.638	***	46.287	***	33.777	***	33.777	***	54.156	***
Florida	8	13.616	*	13.616	*	16.197	**	56.789	***	56.789	***	53.687	***
Georgia	8	14.005	*	14.005	*	11.296		72.398	***	72.398	***	62.814	***
Idaho	8	35.665	***	35.595	***	50.548	***	60.299	***	33.387	***	38.491	***
Illinois	8	28.096	***	8.531		22.72	***	72.855	***	28.827	***	38.574	***
Indiana	8	32.506	***	17.017	**	23.154	***	48.274	***	36.978	***	21.639	***
Iowa	8	7.606		7.606		7.955		23.488	***	23.488	***	21.596	***
Kansas	8	51.205	***	51.205	***	36.928	***	21.615	***	21.615	***	17.971	**
Kentucky	7	15.917	**	15.917	**	13.515	*	51.057	***	51.057	***	42.928	***
Louisiana	8	20.228	**	20.228	**	25.578	***	61.421	***	61.421	***	43.11	***
Maine	8	21.815	***	16.558	**	22.828	***	29.503	***	20.784	***	23.558	***
Maryland	8	26.154	***	5.34		23.852	***	44.449	***	23.757	***	28.718	***
Massachusetts	8	14.103	*	9.795	*	17.495	**	46.562	***	20.412	***	32.301	***
Michigan	8	71.539	***	31.564	***	80.467	***	58.039	***	28.435	***	29.076	***
Minnesota	8	38.335	***	38.335	***	36.85	***	34.265	***	34.265	***	23.766	***
Mississippi	8	31.203	***	13.147	**	31.683	***	35.735	***	22.961	***	52.04	***
Missouri	8	15.018	*	7.1		14.546	*	52.076	***	44.011	***	32.87	***
Montana	8	14.412	*	6.791	***	16.013	**	17.637	**	0.229		14.897	*
Nebraska	8	28.939	***	28.939	***	29.36	***	18.448	**	18.448	**	17.022	**
Nevada	8	13.561	*	13.561	*	16.279	**	27.103	***	27.103	***	23.696	***
N. Hampshire	8	14.605	*	2.376		16.744	**	43.557	***	27.62	***	28.039	***
New Jersey	8	22.593	***	5.973		33.982	***	70.425	***	41.288	***	55.034	***
New Mexico	7	20.056	***	20.056	***	16.457	**	37.007	***	37.007	***	37.344	***
New York	8	21.771	***	6.895		13.177		51.467	***	34.689	***	38.247	***
North Carolina	8	23.031	***	30.513	***	29.145	***	18.953	**	22.925	***	33.549	***
North Dakota	8	18.655	**	6.802	***	20.378	***	11.417		3.054	*	9.937	
Ohio	8	40.161	***	11.247	**	37.793	***	51.38	***	25.62	***	29.73	***
Oklahoma	8	20.784	***	20.784	***	18.538	**	53.59	***	53.59	***	38.283	***
Oregon	8	26.285	***	32.143	***	19.443	**	37.192	***	56.901	***	33.422	***
Pennsylvania	8	30.813	***	30.813	***	28.284	***	52.64	***	52.64	***	26.244	***
Rhode Island	8	33.388	***	33.388	***	45.494	***	43.036	***	43.036	***	31.824	***
South Carolina	8	11.754		13.863	**	13.212		36.016	***	29.302	***	28.211	***
South Dakota	8	21.891	***	21.891	***	24.321	***	12.702		12.702		9.74	
Tennessee	8	9.462		16.611	***	8.278		68.402	***	62.575	***	40.406	***
Texas	7	8.706		8.706		7.386		38.555	***	38.555	***	35.399	***
Utah	8	62.683	***	62.683	***	40.606	***	30.458	***	30.458	***	35.671	***
Vermont	8	32.492	***	16.112	***	29.772	***	35.337	***	20.51	***	26.145	***
Virginia	8	28.294	***	28.294	***	33.7	***	99.248	***	99.248	***	101.589	***
Washington	8	16.836	**	9.852		13.935	*	33.563	***	27.803	***	30.008	***
West Virginia	8	27.015	***	17.296	***	34.261	***	32.821	***	24.227	***	35.979	***
Wisconsin	8	11.667		11.667		14.444	*	28.49	***	28.49	***	10.623	
Wyoming	6	2.94		1.602		2.977		11.677	*	3.208		11.566	*
Fisher test statistic value		631.99						inf					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		232.605		181.288		161.302		253.533		196.213		170.298	
Fisher test statistic value		515.951						inf					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		203.074		170.01		153.255		217.667		175.752		158.151	
Fisher test statistic value		634.493						inf					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV 0%	
		201.294		166.744		149.775		211.049		211.049		153.337	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 5. Results of Granger causality between Personal Income and Theil's Entropy Index

state	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause Theil's entropy Index						Inequality led hypothesis H0: Theil's entropy Index does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	8	8.645		9.458	*	8.762		6.806		10.801	*	5.293	
Arizona	6	5.656		7.794		4.92		19.333	***	14.939	**	16.692	**
Arkansas	8	15.441	*	1.086		13.206		9.604		0.944		5.116	
California	5	10.725	*	13.195	**	10.115	*	15.797	***	15.744	***	14.322	**
Colorado	8	12.999		8.054		13.068		24.829	***	19.237	***	24.384	***
Connecticut	8	9.282		2.635		7.067		27.099	***	0.923		31.57	***
Delaware	8	27.436	***	27.436	***	21.024	***	16.415	**	16.415	**	18.619	**
Florida	8	6.624		4.064		7.144		27.708	***	32.26	***	27.291	***
Georgia	8	15.36	*	17.382	***	14.269	*	17.319	**	8.198		16.457	**
Idaho	7	6.493		6.493		10.823		10.725		10.725		7.144	
Illinois	6	12.717	**	12.717	**	9.18		18.203	***	18.203	***	18.859	***
Indiana	5	8.807		8.807		7.26		8.878		8.878		3.745	
Iowa	8	11.892		5.275		12.005		11.604		17.427	***	8.113	
Kansas	8	14.87	*	4.409		15.153	*	11.351		5.105		15.803	**
Kentucky	7	12.005		10.117	*	8.487		13.932	*	13.932	**	13.549	*
Louisiana	8	8.226		8.226		5.794		28.124	***	28.124	***	20.184	**
Maine	8	33.844	***	23.86	***	16.495	**	29.327	***	24.89	***	32.603	***
Maryland	7	7.085		3.098		6.473		8.731		1.877		8.554	
Massachusetts	8	9.087		1.679		6.5		20.992	***	0.776		12.316	
Michigan	7	13.755	*	12.168	**	14.973	**	15.71	**	15.171	**	14.612	**
Minnesota	7	9.216		4.037		8.829		24.147	***	30.052	***	25.188	***
Mississippi	8	6.282		2.939		3.996		9.261		4.172		5.358	
Missouri	5	5.142		5.142		4.78		16.747	***	16.747	***	13.538	**
Montana	8	7.393		6.053	**	5.279		16.833	**	0.209		15.046	*
Nebraska	8	13.751	*	1.953		12.025		12.289		0.562		11.618	
Nevada	8	10.561		0.906		12.251		21.458	***	0.148		18.858	**
N. Hampshire	8	7.043		2.329		6.619		13.622	*	13.977	***	7.492	
New Jersey	8	12.568		0.972		9.378		17.752	**	0.327		11.354	
New Mexico	7	15.423	**	10.88	**	15.149	**	5.272		3.679		5.223	
New York	8	11.66		8.589		6.914		13.075		10.402	*	7.232	
N. Carolina	7	21.734	***	14.201	**	23.919	***	4.187		7.423		3.401	
North Dakota	5	7.888		2.565		8.237		3.769		4.315	**	3.126	
Ohio	6	8.954		7.661		8.297		14.779	**	12.868	**	8.254	
Oklahoma	8	13.693	*	1.019		17.123	**	26.68	***	5.016		16.161	**
Oregon	8	9.83		5.375		8.063		7.078		7.6		7.056	
Pennsylvania	5	8.602		8.602		9.113		20.777	**c*	20.777	***	16.536	***
Rhode Island	8	13.567	*	0.257		16.219	**	18.294	**	0.176		15.348	*
S. Carolina	8	12.493		3.55		8.5		17.745	**	8.181	*	13.552	*
South Dakota	8	7.694		3.906		6.412		7.27		6.381		6.353	
Tennessee	5	8.671		8.671		7.208		10.367	*	10.367	*	6.856	
Texas	7	10.352		2.869		9.707		18.797	***	16.445	***	17.291	**
Utah	8	9.512		4.523		7.571		24.829	***	2.5		32.135	***
Vermont	8	10.863		3.792		9.244		12.964		1.302		10.313	
Virginia	8	21.911	***	9.036		19.394	**	34.717	***	31.896	***	35.845	***
Washington	8	5.707		3.303		3.261		25.911	***	23.161	***	24.473	***
West Virginia	7	10.983		12.707	**	9.095		10.899		10.095	*	7.086	
Wisconsin	8	3.138		3.998		1.504		13.782	*	10.308	*	7.813	
Wyoming	5	4.489		4.489		6.913		2.373		2.373		1.828	
Fisher test statistic value		202.651						360.295					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		202.863		166.808		150.332		194.826		161.299		146.306	
Fisher test statistic value		182.723						325.608					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		C10%	
		181.017		151.489		136.852		184.273		152.324		138.087	
Fisher test statistic value		166.494						299.788					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		195.072		163.16		148.601		184.903		155.609		141.827	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 6. Results of Granger causality between Personal Income and Top 10% Income Share

state	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause Top 10						Inequality led hypothesis H0: Top10 does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	8	30.204	***	15.645	**	21.126	***	15.121	*	12.367	*	25.563	***
Arizona	8	8.861		8.69		7.078		13.279		8.644		10.53	
Arkansas	8	31.152	***	14.916	**	21.402	***	24.521	***	14.038	**	21.988	***
California	8	20.806	***	17.368	***	13.388	*	13.976	*	2.968		14.761	*
Colorado	8	17.779	**	13.776	*	11.137		33.022	***	26.372	***	43.062	***
Connecticut	8	21.282	***	11.865	***	21.306	***	23.197	***	0.637		32.508	***
Delaware	8	53.424	***	53.424	***	49.834	***	29.735	***	29.735	***	34.973	***
Florida	8	12.773		5.174		9.024		22.774	***	21.731	***	23.158	***
Georgia	8	18.024	**	5.113	*	12.949		20.107	**	1.759		19.746	**
Idaho	8	23.788	***	9.326		27.543	***	18.707	**	7.425		14.669	*
Illinois	8	35.141	***	12.094	**	28.561	***	17.119	**	6.489		19.125	**
Indiana	8	30.106	***	10.874	*	21.738	***	24.834	***	7.723		31.706	***
Iowa	8	22.876	***	19.08	***	23.894	***	11.155		6.783		18.21	**
Kansas	8	20.696	***	20.696	***	21.302	***	23.557	***	23.557	***	36.126	***
Kentucky	7	18.726	***	8.168	*	14.871	**	12.194	*	2.809		13.871	*
Louisiana	8	19.768	**	12.296	**	13.625	*	34.085	***	12.186	**	34.256	***
Maine	6	33.116	***	33.116	***	29.674	***	17.875	***	17.875	***	16.539	**
Maryland	6	11.9	*	8.986	**	13.643	**	16.917	**	4.586		16.9	**
Massachusetts	8	15.354	*	9.641	***	13.152		16.434	**	1.471		19.374	**
Michigan	8	29.351	***	9.833	*	21.725	***	23.037	***	8.879		24.068	***
Minnesota	8	18.839	**	3.288	*	18.59	**	8.761		2.746	*	11.219	
Mississippi	8	18.581	**	12.311	**	12.733		27.259	***	10.583	*	30.474	***
Missouri	8	28.813	***	14.091	***	26.55	***	21.61	***	8.342	*	16.216	**
Montana	8	18.499	**	3.69		15.133	*	8.858		0.1		6.829	
Nebraska	8	14.708	*	4.972	**	11.613		21.622	***	3.072	*	28.692	***
Nevada	8	28.686	***	0.602		31.354	***	40.408	***	0.138		43.527	***
N. Hampshire	8	15.011	*	5.581		14.272	*	12.459		4.621		13.708	*
New Jersey	8	19.817	**	4.488		16.76	**	14.901	*	1.269		20.436	***
New Mexico	8	38.304	***	20.027	***	18.634	**	26.916	***	6.896		22.503	***
New York	8	13.233		1.446		10.458		23.244	***	12.578	**	30.074	***
North Carolina	8	25.813	***	14.553	**	20.285	***	21.171	***	18.847	***	22.958	***
North Dakota	8	12.288		6.337	*	9.758		18.522	**	12.061	***	20.451	***
Ohio	8	22.118	***	5.293		16.818	**	23.57	***	4.728		26.181	***
Oklahoma	8	21.455	***	7.606		16.414	**	42.613	***	8.8	*	35.26	***
Oregon	8	26.54	***	15.57	**	19.833	**	21.537	***	9.523		25.192	***
Pennsylvania	8	16.892	**	14.372	**	14.697	*	19.805	**	13.136	**	17.658	**
Rhode Island	8	26.306	***	12.154	***	25.566	***	17.419	**	0.557		28.954	***
South Carolina	8	26.772	***	16.123	**	18.945	**	42.875	***	27.277	***	47.694	***
South Dakota	8	14.198	*	6.339		15.308	*	12.496		5.708		10.972	
Tennessee	8	21.624	***	8.022		16.768	**	21.614	***	9.857	*	30.508	***
Texas	7	11.717		13.982	***	13.078	*	11.722		1.544		13.49	*
Utah	8	10.991		5.419		6.846		26.146	***	2.883		30.387	***
Vermont	8	14.959	*	1.484		15.925	**	13.765	*	0.932		19.048	**
Virginia	8	31.989	***	15.596	***	28.673	***	33.88	***	0.994		32.422	***
Washington	8	20.113	**	10.904	*	19.457	**	30.157	***	15.208	**	28.589	***
West Virginia	8	33.404	***	6.966		38.472	***	23.924	***	14.147	**	32.255	***
Wisconsin	8	22.77	***	22.77	***	16.026	**	12.937		12.937		14.667	*
Wyoming	4	9.934	**	9.934	**	7.896	*	1.305		1.305		2.396	
Fisher test statistic value		540.201						505.618					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		281.844		212.179		176.999		247.208		188.594		163.684	
Fisher test statistic value		361.418						243.683					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		196.409		162.499		146.44		187.813		157.424		142.62	
Fisher test statistic value		419.744						599.351					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		251.99		194.244		168.82		230.001		179.012		156.34	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 7. Results of Granger causality between Personal Income and Top 1% Income Share

state	Lag length	Income led hypothesis H0: Income sorted does not Granger Cause Top 1						Inequality led hypothesis H0: Top1 does not Granger Cause Income sorted					
		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2		AIC, dmax=1		SBC, dmax=1		AIC, dmax=2	
Alabama	7	1.589		3.441		3.002		8.4		12.367	*	8.765	
Arizona	8	3.085		1.171		2.81		12.114		8.644		13.969	*
Arkansas	5	4.021		1.729		4.141		2.751		14.038	**	2.889	
California	4	4.822		1.997		4.567		2.72		2.968		3.279	
Colorado	8	5.045		3.553		4.247		11.044		26.372	***	15.286	*
Connecticut	8	6.533		2.746		6.961		9.724		0.637		14.425	*
Delaware	8	24.83	***	10.129	***	23.733	***	16.53	**	29.735	***	17.553	**
Florida	8	9.556		0.661		8.566		16.181	**	21.731	***	19.259	**
Georgia	8	9.142		0.613		6.551		8.402		1.759		8.126	
Idaho	8	12.271		12.271		10.03		8.483		7.425		6.839	
Illinois	5	6.068		6.633		6.024		2.882		6.489		2.65	
Indiana	8	7.68		6.222		7.522		9.708		7.723		8.48	
Iowa	8	3.909		0.361		4.338		3.878		6.783		4.93	
Kansas	8	7.055		7.055		7.07		21.101	***	23.557	***	16.936	**
Kentucky	7	4.56		2.625		4.028		5.239		2.809		6.035	
Louisiana	8	8.162		9.803	**	5.212		15.234	*	12.186	**	19.918	**
Maine	6	16.135	**	16.135	**	15.288	**	19.316	***	17.875	***	17.14	***
Maryland	6	4.335		3.415		4.945		5.806		4.586		6.544	
Massachusetts	4	4.282		2.801		3.744		2.779		1.471		4.755	
Michigan	5	3.7		3.7		4.628		5.592		8.879		6.211	
Minnesota	8	5.384		1.912		5.515		4.774		2.746	*	4.211	
Mississippi	8	6.312		2.783		7.822		9.045		10.583	*	5.739	
Missouri	4	3.161		3.161		2.731		1.769		8.342	*	2.193	
Montana	8	10.077		0.073		8.698		9.828		0.1		8.523	
Nebraska	8	1.93		0.005		2.021		7.544		3.072	*	9.652	
Nevada	8	7.084		0.293		8.827		23.573	***	0.138		20.844	***
N. Hampshire	8	10.235		1.786		8.009		8.032		4.621		8.356	
New Jersey	4	1.815		2.282		1.081		1.508		1.269		2.03	
New Mexico	8	18.437	**	8.041	*	9.698		10.858		6.896		6.445	
New York	4	1.812		1.812		2.449		7.313		12.578	**	10.742	**
North Carolina	8	5.992		2.062		6.143		5.065		18.847	***	3.938	
North Dakota	3	4.589		0.333		2.952		4.465		12.061	***	3.169	
Ohio	8	4.846		3.608		4.238		11.844		4.728		8.733	
Oklahoma	8	13.094		2.618		8.503		17.758	**	8.8	*	14.247	*
Oregon	7	3.07		2.386		3.056		6.138		9.523		3.97	
Pennsylvania	8	8.559		3.489		7.554		9.134		13.136	**	6.779	
Rhode Island	8	12.245		3.15		14.969	*	10.821		0.557		13.925	*
South Carolina	8	11.607		3.119		8.816		17.616	**	27.277	***	15.228	*
South Dakota	8	6.436		0.482		7.494		7.212		5.708		6.065	
Tennessee	5	3.672		2.078		4.306		2.553		9.857	*	2.403	
Texas	8	11.923		5.789		7.823		12.666		1.544		13.357	
Utah	8	4.526		1.744		5.289		11.59		2.883		11.91	
Vermont	8	10.701		1.466		13.955	*	7.277		0.932		7.472	
Virginia	8	15.118	*	1.624		13.945	*	20.689	***	0.994		18.323	**
Washington	8	3.576		4.266		3.306		10.145		15.208	**	8.75	
West Virginia	5	2.79		2.79		2.646		4.616		14.147	**	5.102	
Wisconsin	8	6.976		3.481		7.889		5.833		12.937		6.251	
Wyoming	4	18.231	***	18.231	***	12.839	**	0.449		1.305		0.675	
Fisher test statistic value		115.424						149.679					
AIC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		234.786		179.873		158.107		200.43		164.751		146.759	
Fisher test statistic value		116.696						87.923					
SBC dmax=1		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		205.197		165.423		147.754		192.178		156.461		139.868	
Fisher test statistic value		95.33						148.621					
AIC dmax=2		CV 1%		CV 5%		CV10%		CV 1%		CV 5%		CV10%	
		227.524		176.982		154.646		203.913		164.843		147.944	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively.
2. Bootstrap critical values are obtained from 10,000 replications.

Table 8. List of states which cannot reject H0

Income does not Granger cause Atkinson Index	Atkinson Index does not Granger cause Income
Arizona, Florida, Maryland, Missouri, New Hampshire, Wyoming	New Mexico, North Dakota, Wyoming
Income does not Granger cause Gini Coefficient	**Gini Coefficient does not Granger cause Income**
Arkansas, Colorado, Iowa, Louisiana, Maryland, Mississippi, Missouri, South Carolina, Texas, Wisconsin, Wyoming	Kansas, Montana, Nebraska, Wyoming
Income does not Granger cause the Relative Mean Deviation	**the Relative Mean Deviation does not Granger cause Income**
Iowa, Texas, Wyoming	South Dakota
Income does not Granger cause Theil's entropy Index	**Theil's entropy Index does not Granger cause Income**
Arizona, Colorado, Connecticut, Florida, Idaho, Indiana, Iowa, Louisiana, Maryland, Massachusetts, Minnesota, Mississippi, Missouri, Nevada, New Hampshire, New Jersey, New York, North Dakota, Ohio. Oregon. Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Washington, Wisconsin, Wyoming	Arkansas, Idaho, Indiana, Maryland, Mississippi, Nebraska, New Mexico, North Carolina, Oregon, South Dakota, Vermont, Wyoming
Income does not Granger cause Top 10 % income share	**Top 10 % income share does not Granger cause Income**
Arizona, Florida, New York, Utah	Arizona, Montana, South Dakota, Wyoming
Income does not Granger cause Top 1 % income share	**Top 1 % income share does not Granger cause Income**
Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Washington, West Virginia, Wisconsin, Wyoming	California, Georgia, Idaho, Illinois, Indiana, Iowa, Kentucky, Maryland, Massachusetts, Michigan, Montana, New Hampshire, New Jersey, New Mexico, Ohio, Oregon, South Dakota, Texas, Utah, Vermont Wisconsin, Wyoming