Income Inequality:
A complex network analysis of US states

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Abstract

This study performs a long-run, inter-temporal analysis of income inequality in the US spanning the period 1916–2012. We employ both descriptive analysis and the Threshold-Minimum Dominating Set methodology from Graph Theory, to examine the evolution of inequality through time. In doing so, we use two alternative measures of inequality: the Top 1% share of income and the Gini coefficient. This provides new insight on the literature of income inequality across the US states. Several empirical findings emerge. First, a heterogeneous evolution of inequality exists across the four focal sub-periods. Second, the results differ between the inequality measures examined. Finally, we identify groups of similarly behaving states in terms of inequality. The US authorities can use these findings to identify inequality trends and innovations and/or examples to investigate the causes of inequality within the US and implement appropriate policies.

Keywords: Income inequality; Graph theory; US states

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1. Introduction

The distribution of income and/or wealth between the poor and the rich has been a well-debated topic, attracting interest from politicians, researchers, policy makers, and so on. Most studies reach the general conclusion that high income inequality existed during the 20s and the consequent Great Depression, followed by a period of convergence and finally divergence, once again, in more recent years, especially after the latest global financial crisis of 2007-2009.

Piketty (2014) recently conducted a global analysis of income inequality. He concludes *inter alia* that for most of the developed countries, income inequality fell in the period after the two World Wars and re-surged in the 1980s. In related work on the U.S. states, Saez (2013) concludes that 95% of the growth during the recovery from the Great Recession occurred in the Top 1% of the income distribution. Rose (2015) disputes the implication of Saez's claim, arguing that the sample period chosen presents a misleading picture. He uses Piketty's data and argues that the wealthiest 1% of Americans experienced the largest loss of income over 2007-2008 despite the gain in income over 2009-2012. Then using Congressional Budget Office (CBO) data (2014) on a broader measure of income that includes transfer income and excludes taxes paid, Rose (2015) notes that although inequality measured by the Gini coefficient increases for market income between 2007 and 2011, it falls when considering the income measures that adjust for a) transfer payments and b) transfer payments and taxes.

In sum, the relevant literature does not offer a consensus due to the use of different sample periods, different measures of income, and different measures of inequality. This paper considers the movement of inequality in the U.S. states, using annual state-level data from 1916 to 2012 constructed by Frank (2014). Our sample period includes a series of “Great” episodes:

the Great Depression (1929-1944), the Great Compression (1945-1979), the Great Divergence (1980-present), the Great Moderation (1982-2007), and the Great Recession (2007-2009).

Goldin and Margo (1992) popularized the term Great Compression for the period following the Great Depression, an era during which the income inequality between the rich and the poor greatly diminished in relation to prior periods (e.g., the Great Depression). Krugman (2007) called the period following the Great Compression, the Great Divergence, when income inequality began to worsen once again. Piketty and Saez (2003) argue that in the US, the Great Compression ended in the 1970s and then reversed itself.[1]

Our study strays from the classic econometric paths and presents an empirical analysis that evolves in a Graph Theory context. In particular, we apply an optimization technique called the Threshold-Minimum Dominating Set (T-MDS) to describe the evolution of income inequality in the U.S. between 1916 and 2012. By doing this, we gain new insight into the inter-relationships between the 48 U.S. states with respect to income inequality and form groups of closely behaving states.

We organize the paper into the following sections. Section 2 describes the data set and presents the descriptive data analysis. Section 3 outlines the methodological context and explains the use and possible interpretation of the Threshold-Minimum Dominating Set technique. Section 4 provides and discusses the empirical results and Section 5 concludes the paper.

2. Data and Descriptive Analysis

[1] In a recent paper, Kaplan and Rauh (2013) argue that economic factors provide the most logical explanation of rising income inequality. That is, "skill-based technological change, greater scale, and their interaction" (p.53) create the necessary ingredients for demand and supply factors to generate a growing income inequality. They further reject the notion that income inequality reflects the collection of rents by individuals who "distort the economic system to extract resources in excess of their marginal products." (p. 52).

2.1. Data

Frank (2014) constructs inequality measures using data published in the IRS's *Statistics of Income* on the number of returns and adjusted gross income (before taxes) by state and by size of the adjusted gross income. The pre-tax adjusted gross income includes wages and salaries, capital income (dividends, interest, rents, and royalties) and entrepreneurial income (self-employment, small businesses, and partnerships). Interest on state and local bonds and transfer income from federal and state governments do not appear in this measure of income. For more details on the construction of the inequality measures, see Frank (2014, Appendix).

The IRS income data are considered problematic because of the truncation of individuals at the low-end of the income distribution. Frank (2014) notes that the IRS will penalize tax payers for misreporting income, whereas Akhand and Liu (2002) argue that survey-based alternatives to the IRS data introduce bias 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). In our analysis, we use the Top 1% share of the income distribution, which Piketty and Saez (2003) and Piketty (2014) argue is less subject to the omission of individuals at the low end of the income distribution in the IRS data. Moreover, we also perform the same analysis using the Gini coefficient inequality measure to compare the empirical findings. The IRS data possess the advantage of generating annual data by state for 97 years.[2]

2.2. Descriptive Analysis

[2] We performed the same analysis using the Top 10% income share inequality measure as well. This measure yields results that are qualitatively similar to the ones of the Top 1% measure and we exclude them from the paper for brevity.

Based on the existing literature on the Great Depression, Great Compression, and Great Divergence, we identified 1929, 1944, and 1979 as focal points within the sample ranging from 1916 to 2012. Figure 1 plots the average of each state's Top 1% share of income from 1916 to 2012.[3] We also include the maximum and minimum values of the Top 1% in each year. We highlight the years 1929, 1944, 1979 with vertical lines.

Figure 1 suggests that inequality fell during WWI and its immediate aftermath and then rose during the rest of the roaring 20s. Inequality then fell gradually from 1929 through 1979 and began rising through the end of the sample in 2012. Thus, we confirm the observations of the Great Compression and Great Divergence. Delaware experienced the highest inequality across all states from 1924 to 1971, achieving in 1929 the highest income share of the Top 1% that is measured in the sample (namely 0.61).

Figure 2 plots the standard deviation of the Top 1% share of income for each year from 1916 to 2012. Prior to the Great Depression, the inequality dispersion across states first converged (sigma-convergence) and then diverged during the 1920s. Convergence of the standard deviation of inequality among the individual states occurred during the Great Depression and the Great Compression, whereas it diverged, once again, during the Great Divergence era.

Figures 3 and 4 plot the average Gini coefficient and its standard deviation, respectively, over the 1916 to 2012 period. The story for the average Gini coefficient differs significantly from that for the Top 1%. To wit, while the average Gini decreases and then increases in the pre-Great Depression period as it does for the Top 1%, the Gini rises gradually throughout the Great Compression and through the Great Divergence unlike the Top 1%, which decreases during the

[3] We also plotted the median of the Top 1%. The mean and median generally do not differ much from each other, suggesting that the asymmetry imagined from a visual inspection of Figure 1 involves a small number of states. For example, in 1929, the Top 1% in 12 states exceeds 0.2 and in 2 states exceeds 0.3.

Great Compression. On the other hand, the story for the standard deviation of the Gini generally matches that for the Top 1%. That is, prior to the Great Depression, the inequality dispersion across states first converged and then diverged during the roaring 20s. Convergence of inequality dispersion occurred during the Great Depression and the Great Compression, whereas inequality dispersion diverged during the Great Divergence.

3. The Methodology

3.1. Network construction

In representing an economic system as a complex network (more formally a Graph (*G*)), we depict the economic agents as nodes (*N*) and the similarity of the nodes takes the form of edges (*E*) that link these nodes. Mathematically, we define $G=(N,E)$. In this study, the nodes of the network represent the 48 contiguous U.S. states, excluding Alaska and Hawaii due to lack of data availability, while the connecting edges reflect the similarity of the states using two inequality measures –the Top 1% share of the income distribution and the Gini coefficient. We calculate the similarity for both measures using the Pearson correlation coefficient.

For both inequality measures we construct the networks that correspond to the four sub-periods of 1916 to 1929, 1930 to 1944, 1944 to 1979, and 1980 to 2012 and then we identify the T-MDS for each sub-period.[4] The implementation of these four sub-samples introduces a dynamic feature to our analysis.

3.2. Threshold-Minimum Dominating Set

To define the Threshold-Minimum Dominating Set (T-MDS), we must first introduce the simple Dominating Set (DS) and, then, the classic Minimum Dominating Set (MDS).

[4] The Great Compression (Golden and Margo, 1992) refers to the time of wage compression that occurred in the 1940s and 1950s. The reversal of this and the emergence of the Great Divergence did not occur until the late 1970s.

Definition 1: A *Dominating Set* (*DS*) of a graph *G* is a subset of nodes *N* (DS⊆N) such that every node not in DS ($i \notin$ DS) connects to at least one element of the DS ($\forall i \notin DS$, $\exists\, j \in DS : e_{ij} \in E$.).

The DS definition describes a subset of *N,* where every node in the network either lies adjacent to a DS node or is a DS node itself. Thus, since the network is built on the pairwise correlations, the behavior of any non-DS node reflects the behavior of its adjacent DS nodes.

To identify a DS, we start by creating *n* binary variables $x_i, i = 1, \ldots, n$, one for each node of the network, such that:

$$\mathrm{x_i} = \begin{cases} 0, \text{ if } i \notin DS \\ 1, \text{ if } i \in DS \end{cases}$$

to represent each node's membership status in the *DS*. Representing these variables in vector form produces $\mathbf{x} = [x_1, x_2, \ldots, x_n]$.

The DS notion takes the following mathematical form:

$$x_i + \sum_{j \in B(i)} x_j \geq 1, \; i = 1, \ldots, n, \tag{1}$$

where $B(i)$ is the set of neighboring nodes of node i. Equation (1) implies that each network node can either lie a) in the DS (i.e., $x_i = 1$) or b) adjacent to one or more DS nodes (i.e., $\exists\, j \in$ N(i): $x_j = 1$).[5]

We can identify many *DS*s for every network. Nonetheless, our interest focuses on the minimum sized ones. Thus, a Minimum Dominating Set (MDS) is defined as follows:

[5] This does not constitute a mutually exclusive relationship, as we may find nodes that verify both cases.

Definition 2: The *Minimum Dominating Set* (*MDS*) equals the *DS* with the smallest cardinality.

This definition conforms to the following relationship:

$$\min_x f(x) = \sum_{i=1}^{n} x_i \,. \tag{2}$$

Finally, the calculation of the MDS is essentially the minimization of equation (2) under the constraints in equation (1).

The MDS can adequately describe the collective behavior of an entire network by using only a minimum required subset of nodes. By studying these nodes, a researcher can infer knowledge on the topology of their neighboring ones. Nevertheless, in a correlation-based economics network, low correlation edges connect nodes with dissimilar behavior and should not participate in the identification of the MDS, since they may provide false inference and misleading results. For example, if an edge links two states and displays a correlation of p=0.2, we should not consider them as adjacent (in the sense of behavior similarity), since they are, for all practical matters, uncorrelated and none of them can effectively represent the other. We overcome this inadequacy of the classic MDS optimization procedure in an economics network by imposing a threshold on the initial network's correlation values.

Definition 3: A *Threshold-Minimum Dominating Set* (*T-MDS*) is defined as a two-step methodology for identifying the most representative nodes in a network. These steps are defined as follows:

Step 1. Eliminate all edges where the correlation falls below the threshold correlation.

Step 2. Identify the MDS nodes on the remaining network.

The thresholding step may lead to the emergence of *isolated* nodes (i.e., nodes without any edges to connect them to the rest of the network), while Step 2 identifies the nodes that can efficiently represent the collective behavior of the interconnected network. These nodes are called *Dominant*. The T-MDS, by definition, must include every isolated node. Thus, the T-MDS typically equals the union of the isolated and the dominant node sets, T-MDS= $I \cup C$, where I and C are the sets of the isolated and the dominant nodes, respectively. We should not, however, consider this as a cohesive network: we must distinguish the subset of the isolated nodes from the dominant nodes' subset, since the two subsets exhibit entirely different and independent features. The states that correspond to isolated nodes exhibit highly idiosyncratic behavior and, thus, cannot represent (or be represented by) any other state.

In any arbitrary network, the T-MDS size can take values between two extremes. For complete networks, where every node connects to every other node, the T-MDS size equals one and each node can possibly define a unique MDS node. For a totally disconnected network, where all nodes are isolated, the T-MDS size equals the number of the nodes in the network. As described above, smaller T-MDS values indicate a rather dense network and larger T-MDS values indicate a sparser network. A dense network, by definition, exhibits higher correlations between the network's nodes. In our case, a dense network with smaller T-MDS values provides evidence of convergence between the inequality measures in the U.S. states.

We also use the thresholded networks and the identified neighborhoods of the dominating nodes to pin-point strongly connected groups of U.S. states. These groups present highly similar intra-group behavior in terms of the evolution of income inequality and fiscal and monetary authorities can use these groups to examine the causes of these inter-relations and possibly counter inequality in a collective, systemic fashion.

4. Empirical Results

We perform the aforementioned analysis and report the respective empirical results on both the Top 1% and the Gini coefficient measures of inequality for the case of a threshold p=0.90.[6] In the following analysis, we examine two distinct issues with respect to inequality: the degree of inequality synchronization between the 48 U.S. states and the degree of convergence in inequality. Synchronization measures whether inequality in the different states moves to the same direction in time; either towards lower or greater inequality. Convergence measures whether the states come closer together over time in the degree of income inequality. Thus, a high degree of synchronization does not indicate convergence. Two perfectly synchronized states (ρ = 1) will never converge. In that sense, a low degree of synchronization is the prerequisite for convergence. Finally, in the appendix (Tables 3 and 4), we analytically report the dominant and isolated nodes in each sub-period, in terms of the income inequality measure. A thorough examination of the isolated nodes (that correspond to practically uncorrelated U.S. states) and the analysis of the reasons for their appearance inter-temporally may provide policy makers with valuable information in order to successfully address the causes of income inequality within the U.S. We perform this analysis for both measures of inequality: the Top 1% income share and the Gini coefficient.

4.1. Top 1%

In Table 1, we report the empirical results from the Top 1% inequality measure and in Figure 5, we plot the movements of this measure for the dominant states over the four sub-

[6] We perform the analysis for three alternative threshold levels p=0.85, p=0.90 and 0.95 which all seem to yield qualitatively similar results. We do not report these results for the sake of brevity.

periods. Each dominant state captures the behavior of its direct neighbors so that by studying only the dominant states, we can gain insight on the collective behavior of the entire network of 48 U.S. states[7].

In the first period before the Great Depression, the number of dominant states is at its maximum of eight. This signifies the existence of several different group patterns of inequality evolution. Moreover, the number of isolated states (14) is the second highest of the four periods. Thus, the T-MDS set cardinality is high, providing evidence of low synchronization in inequality. Figure 5, Panel A, exhibits the evolution of the inequality measure in the period before the Great Depression for the eight dominant states. We observe a general U-shaped pattern for each state and the eight states maintain their distances throughout this period. Thus, we detect no significant convergence in inequality.

During the Great Depression, the number of dominant states falls to six, but the isolated states rise significantly to 22. As a result, the T-MDS set reaches its maximum cardinality during this period. Inequality, in general, as we discussed earlier, falls during this period, but the patterns of convergence of the 48 U.S. states are quite distinct. This is evident in Figure 5, Panel B as well. The inequality measure (Top 1% share) of the six dominant states appears to be distinct and possibly erratic for the most part of this period. Only after the start of WWII do these 6 series appear to converge.

In the third period of the Great Compression, 5 dominant states emerge and the isolated ones fall significantly to 10. The cardinality of the T-MDS falls almost to half (from 28 to 15), indicating an increased synchronization in the evolution of inequality. From Figure 5, Panel C, we observe that the increased synchronization evidenced from the T-MDS results couples with a

[7] Comprehensive tables with the dominant nodes along with their neighborhoods are contained in the Appendix, see Tables 5 and 6.

high degree of convergence in inequality. All five dominant states move closer together throughout this period.

Finally, in the last period of the Great Divergence, we see from the T-MDS methodology that the dominant states fall to only three. Moreover, we do not see any isolated states so that the T-MDS cardinality is three. We interpret this as strong evidence in support of a high degree of synchronization of inequality within the 48 U.S. states. According to this result, the set of the 48 states divides into 3 neighborhoods and we can represent the evolution of the states by just 3 dominant states. In Figure 5, Panel D, we observe that the three dominant states California, Texas, and Wisconsin (and their respective neighbors) converge closely until1987. Then, the California and Texas neighborhoods continue to converge throughout this period with rising patterns of inequality. On the other hand, the Wisconsin neighborhood diverges significantly in the Top 1% share in total income from 1987 to 2001. From 2002 to 2007, it reverts toward the other two dominant states, But after 2007, the Wisconsin neighborhood diverges again significantly with a distinct trend towards less inequality (i.e., the Top 1% share in total income falls to approximately half of that in the California and Texas neighborhoods).

4.2. Gini Coefficient

Table 2 reports the T-MDS results and Figure 6 plots the Gini coefficient inequality measure over the four sub-periods for the dominant states. Once again, each dominant state captures the behavior of its direct neighbors so that by studying only the dominant states, we can gain insight on the collective behavior of the entire network of 48 U.S. states.

In the first period before the Great Depression, the T-MDS methodology identifies a set of five dominant states and a set of eight isolated states. This indicates that about one in six U.S.

states presents a highly atypical behavior during the era before the Great Depression, while there appear five major neighborhoods around the dominant states. In Figure 6, Panel A, we plot the Gini coefficients of these five dominant states. The U-shape pattern found for the Top 1% measure of inequality also appears here. The state of North Dakota and, consequently, its direct neighborhood exhibits a significantly lower degree of inequality across the whole period. The other four dominant states converge toward each other and achieve near equality during the middle of this period, namely 1920-1924.

During the Great Depression, we observe that the number of isolated states increases sharply to 22. We identify Missouri, Oklahoma and West Virginia as the dominant states and the remaining 26 states belong in their respective neighborhoods. The high number of isolated states provides strong evidence of inequality de-coupling during the Great Depression. From Figure 6, Panel B, we can observe that inequality for the dominant states and their neighborhoods displays a slight downward trend during this period.

For the Great Compression, the number of isolated states remains at a high level (i.e., 21 rather than 22). Additionally, the number of dominant states increases from three to six and the T-MDS set reaches a cardinality of 27, the highest across all four periods. Now, the 48 U.S. states display an even lower degree of inequality synchronization during this third period. These results contrast to the ones for the Top 1% inequality measure. The latter provided evidence of decreasing inequality while the former exhibits a slight upward trend.

Finally, in the Great Divergence, the isolated states fall sharply to only two. Moreover, we also see three dominant states and, consequently, the T-MDS cardinality falls to only five. This provides strong evidence in favor of a high degree of inequality synchronization during the years of floating exchange rates and the financial crisis of 2007. From Figure 6, Panel D, we can observe that the three dominant states show slightly increasing Gini coefficients throughout this sub-sample.

5. Conclusion

This paper studies the changing patterns of inequality in the U.S. using complex network analysis and an optimization technique called the Threshold-Minimum Dominating Set. We use two alternative measures of income inequality, the Top 1% share of income and the Gini coefficient. We perform dynamic analysis over four consecutive periods running from 1916 to 2012. Our findings reveal a heterogeneous pattern of income inequality and economic integration of the U.S. states according to each focal period. Furthermore, the empirical findings differentiate slightly in response to each of the selected inequality measures. Finally, we highlight groups of similarly behaving states in regard to the inequality measure that can be used by policy makers to examine the causes of inequality within the U.S. and exert the appropriate policies to address it.

In a related set of papers, Lin and Huang (2011, 2012a, 2012b) employ a series of unit-root tests to consider the convergence of income inequality measures for the 48 contiguous states using the Frank (2008) annual data from 1916 to 2005.[8] Lin and Huang (2012b) ultimately use the panel unit-root test of Carrion-i-Silvestre et al. (2005), which extends the Hadri (2000) panel unit-root test to include an unknown number of structural breaks and cross-sectional dependence. The more conventional panel unit-root tests that they implement indicate that the inequality

[8] As Lin and Huang (2012b) note, convergence does not necessarily mean convergence to a lower level of inequality. That is, convergence could occur around a rising level of income inequality.

measures do not converge. The Carrion-i-Silvestre (2005) test, however, indicates convergence of the income inequality measures.[9]

While we do not test for β-convergence in this paper, our Figures 2 and 4 do provide information on σ-convergence. For both the Top 1% and the Gini coefficient series, we observe σ-convergence from 1916 through 1980 and then σ-divergence from 1980 through 2012.

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Table 1. T-MDS metrics for the Top 1% inequality measure

	1916-1929	1930-1944	1945-1979	1980-2012
T-MDS cardinality	22	28	15	3
Isolated states	14	22	10	0
Dominant states	8	6	5	3

Table 2. T-MDS metrics for the Gini coefficient

	1916-1929	1930-1944	1945-1979	1980-2012
T-MDS cardinality	13	25	27	5
Isolated states	8	22	21	2
Dominant states	5	3	6	3

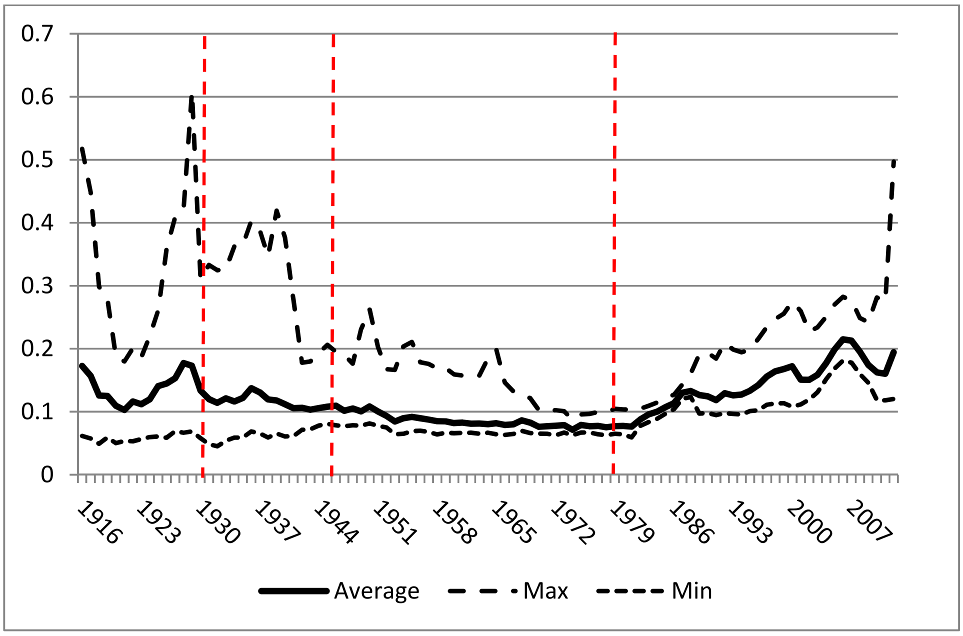


Figure 1. Top 1% share of income

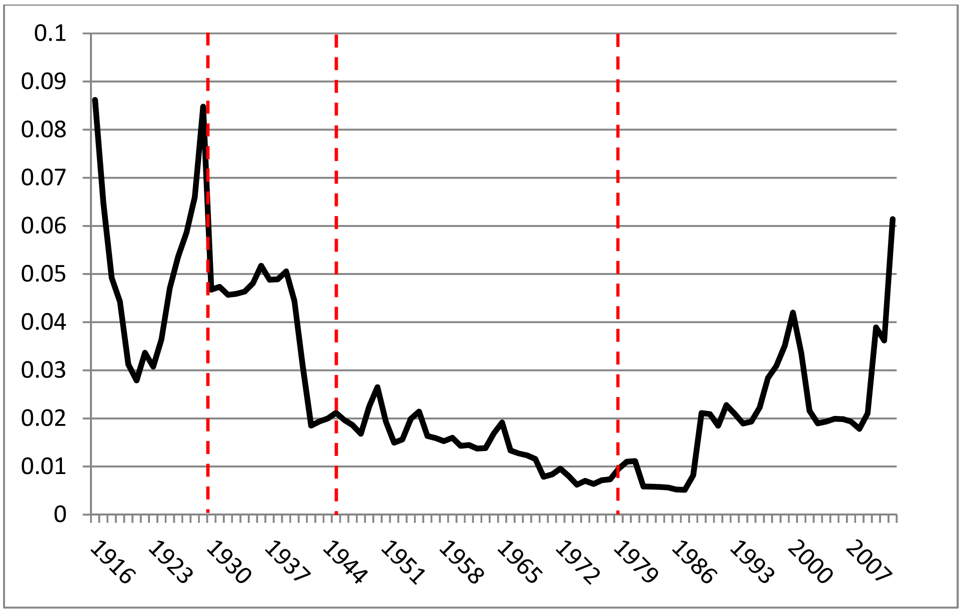


Figure 2. Standard deviation of the Top 1% share of income

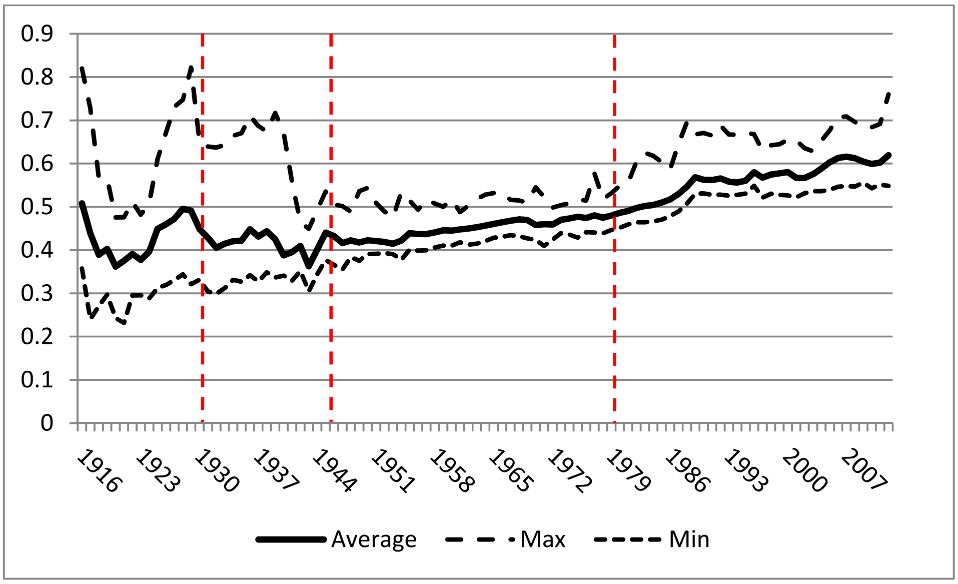


Figure 3. Gini coefficient

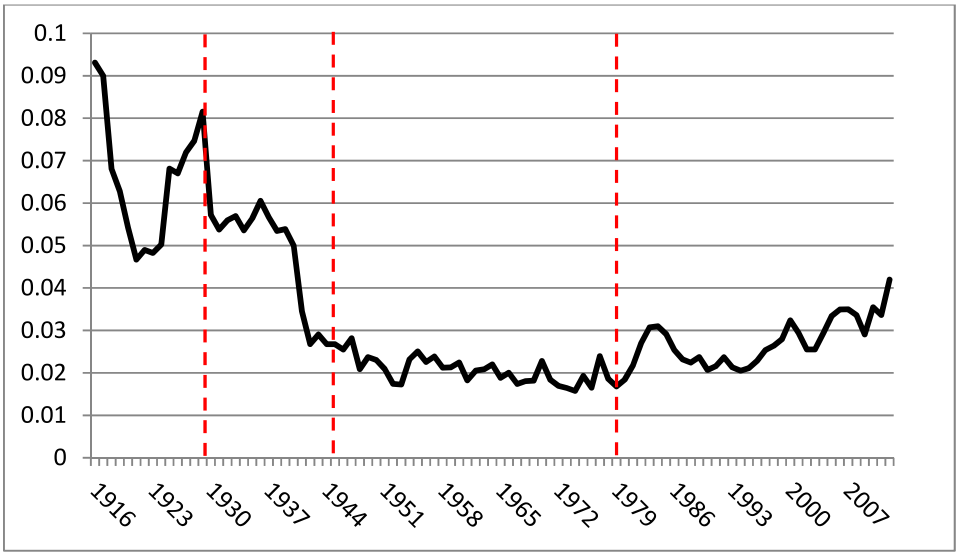


Figure 4. Standard deviation of the Gini coefficient

Figure 5: Dominant States by Sub-Period as measured with the Top 1% measure

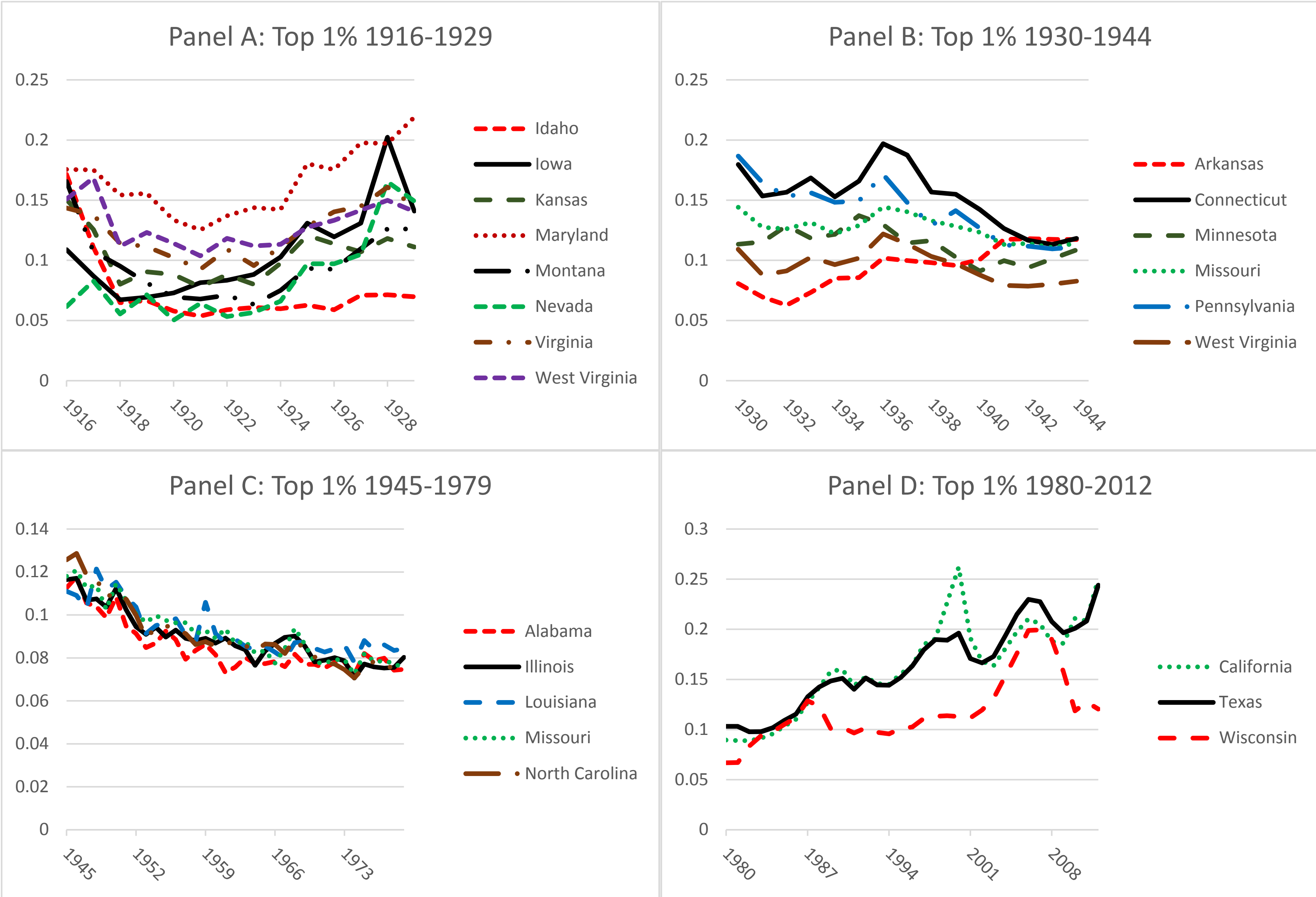
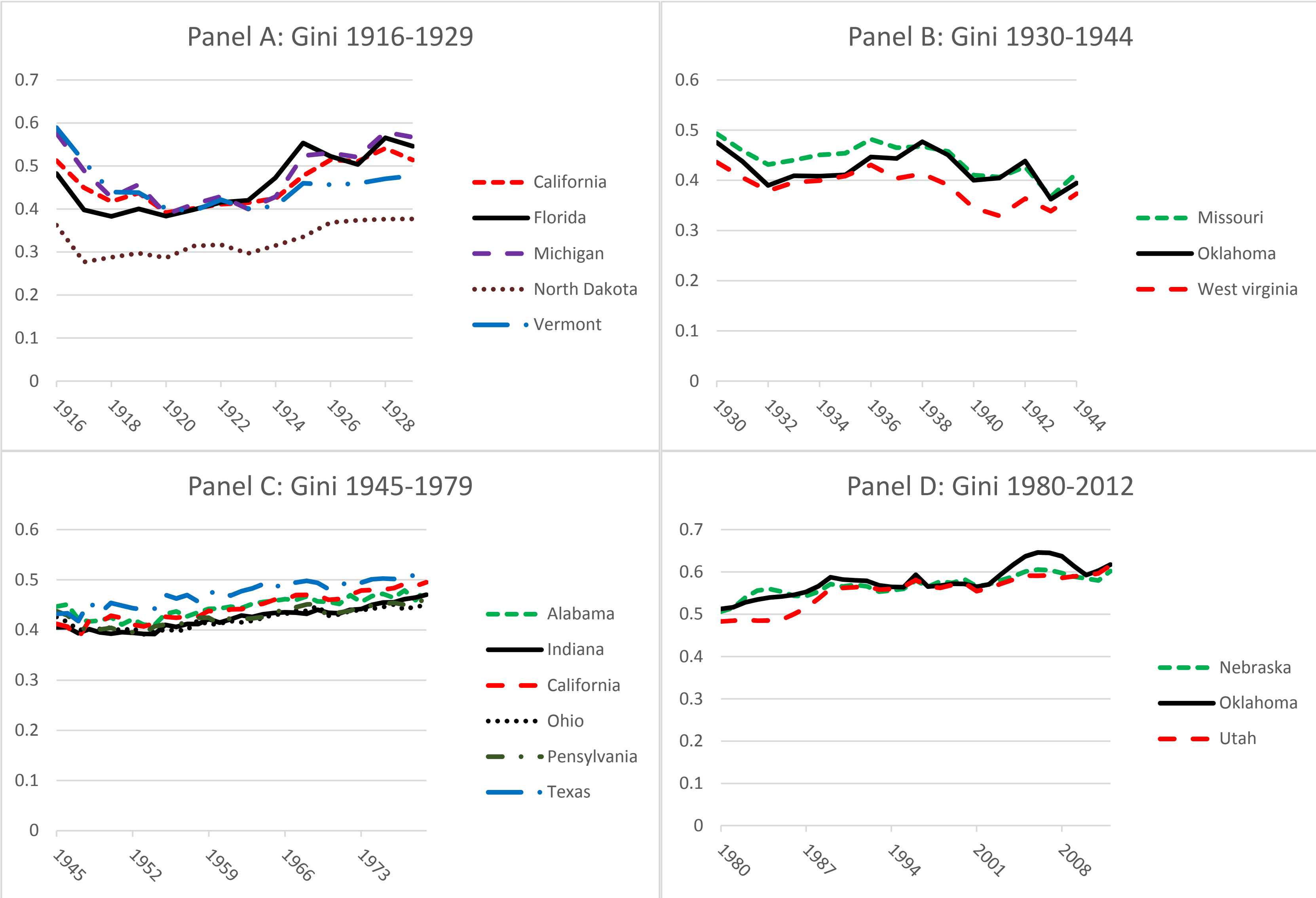


Figure 6: Dominant States by Sub-Period as measured with the Gini coefficient



APPENDIX

Table 3. Dominant and Isolated nodes in each sub-period: Top 1%

Period	Status	State
1916-1929	Dominant	Idaho, Iowa, Kansas, Maryland, Montana, Nevada, Virginia, West Virginia
	Isolated	Alabama, Arkansas, Georgia, Kentucky, Louisiana, Maine, Mississippi, Nebraska, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Wyoming
1930-1944	Dominant	Arkansas, Connecticut, Minnesota, Missouri, Pennsylvania, West Virginia
	Isolated	Alabama, Arizona, Delaware, Florida, Georgia, Idaho, Kansas, Louisiana, Maine, Montana, Nebraska, New Mexico, North Carolina, North Dakota, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Vermont, Washington, Wyoming
1945-1979	Dominant	Alabama, Illinois, Louisiana, Missouri, North Carolina
	Isolated	Delaware, Idaho, Montana, Nevada, North Dakota, Oklahoma, South Dakota, Vermont, West Virginia, Wyoming
1980-2012	Dominant	California, Texas, Wisconsin
	Isolated	-

Table 4. Dominant and Isolated nodes in each sub-period: Gini coefficient

Period	**Status**	**States**
1916-1929	Dominant	California, Florida, Michigan, North Dakota, Vermont
	Isolated	Arkansas, Louisiana, Mississippi, Oklahoma, South Carolina, South Dakota, Washington, Wyoming
1930-1944	Dominant	Missouri, Oklahoma, West Virginia
	Isolated	Alabama, Arizona, Arkansas, Delaware, Florida, Georgia, Idaho, Iowa, Kansas, Louisiana, Maine, Mississippi, Montana, Nebraska, New Mexico, North Dakota, Oregon, South Carolina, South Dakota, Tennessee, Vermont, Wyoming
1945-1979	Dominant	Alabama, California, Indiana, Ohio, Pennsylvania, Texas
	Isolated	Arkansas, Colorado, Delaware, Iowa, Kansas, Kentucky, Maine, Mississippi, Missouri, Nebraska, New Hampshire, New Mexico, North Carolina, North Dakota, Oklahoma, Rhode Island, South Dakota, Tennessee, Vermont, West Virginia, Wyoming
1980-2012	Dominant	Nebraska, Oklahoma, Utah
	Isolated	North Dakota, South Dakota

Table 5. Dominant state neighborhoods: Top 1%

Period	Dominant State	Neighborhood
1916-1929	Idaho	Vermont
	Iowa	Florida, Nevada
	Kansas	Colorado, North Dakota
	Maryland	Connecticut, Delaware, Illinois, Massachusetts, Michigan, Missouri, New Jersey, New York, Pennsylvania, Virginia
	Montana	New York, North Carolina, Ohio, Texas, Washington
	Nevada	Iowa, Michigan, Tennessee
	Virginia	Arizona, California, Connecticut, Illinois, Indiana, Maryland, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Utah, Wisconsin
	West Virginia	Colorado, New Mexico, Ohio, Utah
1930-1944	Arkansas	Mississippi, Oregon
	Connecticut	Indiana, Minnesota, Missouri, New Hampshire, New Jersey, Ohio, Rhode Island, Utah, West Virginia, Wisconsin
	Minnesota	California, Connecticut, Illinois, Indiana, Kentucky, Massachusetts, Missouri, New Hampshire, New Jersey, New York, Ohio, Rhode Island, West Virginia, Wisconsin
	Missouri	Connecticut, Indiana, Minnesota, Nevada, New Hampshire, Ohio, West Virginia, Wisconsin
	Pennsylvania	Illinois, Indiana, Iowa, Maryland, Massachusetts, Michigan, New Jersey, New York, Ohio, Rhode Island, Wisconsin
	West Virginia	Colorado, Connecticut, Minnesota, Missouri, New Hampshire, Virginia
1945-1979	Alabama	Arkansas, California, Colorado, Florida, Georgia, Illinois, Indiana, Kansas, Kentucky, Maryland, Massachusetts, Minnesota, Mississippi, Missouri, New Hampshire, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Utah, Virginia, Washington, Wisconsin
	Illinois	Alabama, California, Colorado, Connecticut, Florida, Georgia, Indiana, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, Tennessee, Virginia, Wisconsin
	Louisiana	Arizona, California, Colorado, Kansas, New Mexico, Ohio, Oregon, Texas, Washington
	Missouri	Alabama, Arkansas, Colorado, Florida, Georgia, Illinois, Indiana, Iowa, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, New York, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, Tennessee, Virginia, Wisconsin
	North Carolina	Alabama, Arkansas, California, Colorado, Florida, Georgia, Illinois, Indiana, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, New Hampshire, New York, Ohio, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Virginia, Wisconsin
1980-2012	California	Colorado, Connecticut, Florida, Illinois, Maryland, Massachusetts, Nevada, New Hampshire, New Jersey, New York, Texas, Virginia, Washington
	Texas	Arizona, California, Colorado, Florida, Georgia, Illinois, Kansas, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New York, Oklahoma, Pennsylvania, Rhode Island, South Dakota, Tennessee, Utah, Virginia, Washington, Wisconsin, Wyoming
	Wisconsin	Alabama, Arizona, Arkansas, Colorado, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Mexico, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina,

		South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, West Virginia

Table 6. Dominant state neighborhoods: Gini coefficient

Period	**Dominant State**	**Neighborhood**
1916-1929	California	Alabama, Colorado, Connecticut, Georgia, Illinois, Indiana, Kentucky, Maine, Maryland, Michigan, Minnesota, Missouri, Montana, Nevada, New Hampshire, New Jersey, North Carolina, Ohio, Tennessee, Utah, Virginia, Wisconsin
	Florida	Alabama, Georgia, Indiana, Iowa, Nevada
	Michigan	Arizona, California, Colorado, Connecticut, Delaware, Georgia, Illinois, Indiana, Kansas, Maine, Maryland, Massachusetts, Minnesota, Missouri, Montana, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Ohio, Oregon, Pennsylvania, Texas, Utah, Virginia, West Virginia, Wisconsin
	North Dakota	Indiana, Nebraska, Nevada
	Vermont	Idaho, Rhode Island
1930-1944	Missouri	California, Colorado, Connecticut, Illinois, Indiana, Kentucky, Massachusetts, Minnesota, Nevada, New Hampshire, New Jersey, New York, North Carolina, Ohio, Rhode Island, Utah, Washington, West Virginia
	Oklahoma	Texas
	West Virginia	Connecticut, Illinois, Indiana, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Utah, Virginia, Wisconsin
1945-1979	Alabama	Georgia, Illinois, Indiana, Massachusetts, Minnesota, New Jersey, Ohio, Pennsylvania, South Carolina, Utah, Virginia, Wisconsin
	California	Arizona, Illinois, Indiana, Louisiana, Massachusetts, Michigan, Nevada, New Jersey, Oregon, Texas, Washington, Wisconsin
	Indiana	Alabama, California, Illinois, Louisiana, Massachusetts, Michigan, Minnesota, Montana, New Jersey, Ohio, Oregon, Texas, Washington, Wisconsin
	Ohio	Alabama, Connecticut, Georgia, Illinois, Indiana, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, Pennsylvania, Utah, Wisconsin
	Pennsylvania	Alabama, Florida, Georgia, Illinois, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New York, Ohio, South Carolina, Wisconsin
	Texas	Arizona, California, Idaho, Indiana, Louisiana, Oregon, Washington
1980-2012	Nebraska	Alabama, Idaho, Iowa, Kansas, Kentucky, Missouri, Montana, Ohio, Oklahoma, South Carolina, Tennessee, Vermont
	Oklahoma	Alabama, Arkansas, Florida, Georgia, Idaho, Indiana, Kansas, Kentucky, Louisiana, Maine, Michigan, Mississippi, Missouri, Montana, Nebraska, New Mexico, North Carolina, Ohio, Oregon, South Carolina, Tennessee, Texas, Vermont, West Virginia, Wisconsin
	Utah	Alabama, Arizona, California, Colorado, Connecticut, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Kansas, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nevada, New Hampshire, New Jersey, New York, North Carolina, Ohio, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Vermont, Virginia, Washington, Wisconsin