Doctor of Philosophy Thesis

ESSAYS ON THE DETERMINANTS OF INCOME AND WEALTH INEQUALITY IN THE UNITED STATES

Presented by

Shinhye Chang, MCom

Major Supervisor

Professor Rangan Gupta

Co-supervisor

Professor Stephen M. Miller

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ABSTRACT

This study investigates the relevant factors that drive income and wealth inequality in the United States with the aim of facilitating a better understanding of the dynamic relationships between inequality and key macroeconomic variables. This can serve as a prerequisite to the ability of policymakers to restrain the negative externalities associated with increasing inequality and implement measures to reduce the unexpected effects.

The thesis consists of five independent papers corresponding to five chapters. As economic growth is a primary goal of every country and widely accepted tool for reducing economic inequality, our study starts with economic growth. The first paper examines the relationship between the U.S. per capita real GDP and income inequality over the period 1917 to 2012. The literature uncovers a complex set of interactions, which depends on the specific research method and sample, between inequality and economic growth and highlights the difficulty of capturing a definitive causal relationship. Inequality either promotes, retards, or does not affect growth. Most existing studies that examine the inequality-growth nexus exclusively utilize time-domain methods. We use wavelet analysis which allows the simultaneous examination of correlation and causality between the two series in both the time and frequency domains. We find robust evidence of positive correlation between the growth and inequality across frequencies. Yet, directions of causality vary across frequencies and evolve with time. In the time-domain, the time-varying nature of long-run causalities implies structural changes in the two series. These findings provide a more thorough picture of the relationship between the U.S. per capita real GDP and

inequality measures over time and frequency, suggesting important implications for policy makers.

Inflation targeting is a monetary policy where the central bank sets a specific inflation rate as its goal. The federal government spurs economic growth by adding liquidity, credit, and jobs to the economy and inflation stimulate the demand needed to drive economic growth. The second paper investigates the effects of the inflation rate on income inequality to see whether monetary policy and the resulting inflation rate can affect income inequality and improve the well-being of individuals. Our analysis relies on a cross-state panel for the United States over the 1976 to 2007 period to assess the relationship between income inequality and the inflation rate, employing a semiparametric instrument variable (IV) estimator. By using cross-state panel data, we minimize the problems associated with data comparability often encountered in cross-country studies related to income inequality. We find that the relationship depends on the level of the inflation rate. A positive relationship occurs only if the states exceed a threshold level of the inflation rate. Below this value, inflation rate lowers income inequality. The results suggest that a nonlinear relationship exists between income inequality and the inflation rate.

The researchers also examine the relationship between income inequality and growth in personal income, since personal income exerts a large effect on consumer consumption, and since consumer spending drives much of the economy. The third paper investigates the causal relationship between personal income and income inequality in a panel data of 48 states for the period of 1929-2012. Although inequality rose almost everywhere between 1980 to present, some states and regions experienced substantially greater increases in inequality than did others. The decentralization allows different state level of policies, however, there is also a cross-state consistency in how those policies respond to the main economic shocks. Since U.S. states are subject to significant spatial effects given their high level of integration, ignoring cross-sectional dependency may lead to substantial bias and size distortions. We employ a causality methodology proposed by Emirmahmutoglu and Kose (2011), as it takes into account possible slope heterogeneity and cross-sectional dependency 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.

The level of development of the United States is related to the sophistication of the financial structure which influences the ability to hedge against shocks and to loosen spending constraints. It leads us to investigate if the financial development affects income inequality in the U.S. In the fourth paper, we look into the role of financial development on U.S. state-level income inequality in a panel data of 50 states from 1976 to 2011. To our knowledge, this paper is the first regarding examining the role of financial development on U.S. state-level inequality. We analyze the data using Fixed Effect and Dynamic Fixed Effect regression. We also divide 50 states into two groups-states, with higher inequality measure and states with lower inequality measures than average of the cross-state average of the inequality, to examine the possible nonlinear impact of financial development on income inequality. We find robust results whereby financial development linearly increases income inequality for the 50 states. When we divide 50 states into two separate groups of higher and lower inequality states than the cross-state average inequality, the effect of financial development on income inequality appears non-linear. When financial development improves, the effect increases at an increasing rate for high income inequality states, whereas an inverted U-shaped relationship exists for low-income inequality states.

Finally, literature mostly discovers that the volatility increases income inequality. However, researchers also find that income inequality may intensify the output volatility and inflation rate. This shows that possible bi-directional causality between economic volatility and inequality. In light of these considerations, the fifth paper explores the relationship between the U.S. economic growth volatility, and income and wealth inequality measures over the period 1917 to 2015 and 1962 to 2014. We consider the relationship between output volatility during positive and negative growth scenarios. Our findings provide evidence of positive correlation between the volatility and inequality across high (short-run) and low-frequencies (long-run). The direction of causality varies across frequencies and time. Strong evidence exists that volatilities lead inequality at low-frequencies across income inequality measures from 1917 to 1997. After 1997, however, the direction of causality changes. These findings provide a more thorough picture of the relationship between the U.S. growth volatility and inequality measures over time and frequency domains. Also, the causalities can be linked to the U.S. business cycles for further investigation.

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ETHICS STATEMENT

The author, whose name appears on the title page of this thesis, has obtained, for the research described in this work, the applicable research ethics approval. The author declares that he/she has observed the ethical standards required in terms of the University of Pretoria's Code of ethics for researchers and the Policy guidelines for responsible research.

Chapter 1
Introduction

1.1 Background and motivations

Increasing income and wealth inequality is a worldwide trend. We know that income inequality may lower the level of human capital by restricting education opportunities for lower income groups, may cause additional social cost by increasing rent-seeking, and may trigger social turmoil. The United States experienced a relatively low level of income inequality for about 30 years after the World War II. Since then U.S. income inequality has increased consistently. In 1963, John F. Kennedy could say that “a rising tide lifts all boats” as the average annual income for the bottom 90 percent kept pace with productivity growth between the 1950s and the 1970s. This trend, however, did not last forever and turned around in the 1980s. Income inequality began to increase and has continued to increase ever since.

Income inequality has increased over the last three decades and a high tide lifts only a few boats. Despite average annual growth in U.S. output of around 3 percent in the 1980s and the 1990s, and around 2 percent since 2001, the average real income of the bottom 90 percent of the U.S. has stagnated. This prompts the question of whether income inequality may negatively affect the growth prospects of a country.

The issue of income inequality has drawn great interest from researchers, politicians, and policy makers, since the well-being of many individuals often depends on the distribution of income. Consequently, the determinants of income inequality and the political and/or economic solutions to reduce inequality have become important discussions. Some policy makers assume that inequality is a natural and necessary result of growth and economic growth focused policy would resolve the income inequality problem. Since the financial crisis, the Federal Reserve has used monetary policy aggressively to promote economic growth and regain economic stability. When the Federal Reserve conducted such aggressive monetary policy, such as cutting the federal funds rate to zero and purchasing large amount of

U.S. Treasury securities and mortgage-backed securities, the possible redistributive results of monetary policy can play an important role. In spite of their effort, inequality continues to worsen.

A number of researchers point out skill biased technological change as a reason for increasing inequality during the period of technological innovation. When we look at only this determinant, however, it personalizes the income inequality issue. We need to consider both individual determinants and macroeconomic factors, which policy makers' control. Thus, understanding the determinants and consequences of income inequality is central to macroeconomics.

1.2 Organization and summary of the study

The thesis consists of five independent papers corresponding to five chapters. As economic growth is a primary goal of every country and widely accepted tool for reducing economic inequality, our study starts with economic growth. The first paper examines the relationship between the U.S. per capita real GDP and income inequality over the period 1917 to 2012. The literature uncovers a complex set of interactions, which depends on the specific research method and sample, between inequality and economic growth and highlights the difficulty of capturing a definitive causal relationship. Inequality either promotes, retards, or does not affect growth. Most existing studies that examine the inequality-growth nexus exclusively utilize time-domain methods. We use wavelet analysis which allows the simultaneous examination of correlation and causality between the two series in both the time and frequency domains.

Inflation targeting is a monetary policy where the central bank sets a specific inflation rate as its goal. The federal government spurs economic growth by adding liquidity, credit, and jobs to the economy and inflation stimulate the demand needed to drive economic growth. The second paper investigates the effects of the inflation rate on income inequality to see whether monetary policy and the resulting inflation rate can affect income inequality and improve the well-being of individuals. Our analysis relies on a cross-state panel for the United States over the 1976 to 2007 period to assess the relationship between income inequality and the inflation rate, employing a semiparametric instrument variable (IV) estimator. By using cross-state panel data, we minimize the problems associated with data comparability often encountered in cross-country studies related to income inequality.

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U.S. state-level inequality. We analyze the data using Fixed Effect and Dynamic Fixed Effect regression. We also divide 50 states into two groups-states, with higher inequality measure and states with lower inequality measures than average of the cross-state average of the inequality, to examine the possible nonlinear impact of financial development on income inequality.

Finally, literature mostly discovers that the volatility increases income inequality. However, researchers also find that income inequality may intensify the output volatility and inflation rate. This shows that possible bi-directional causality between economic volatility and inequality. In light of these considerations, the fifth paper explores the relationship between the U.S. economic growth volatility, and income and wealth inequality measures over the period 1917 to 2015 and 1962 to 2014. We consider the relationship between output volatility during positive and negative growth scenarios.

In sum, this study looks at trends in the United States income and/or wealth inequality at the aggregate and state levels and examines its relationships with macroeconomic variables, such as output, inflation, level of financial development, and economic volatility. This study facilitates a better understanding of the dynamic relationship between inequality and key macroeconomic variables. This can serve as a prerequisite to the ability of policymakers to restrain the negative externalities associated with increasing inequality and implement measures to reduce the unexpected effects. Each contribution represents a different chapter.

Chapter 2

Causality between Per Capita Real GDP and Income Inequality in the U.S.: Evidence from a Wavelet Analysis[1]

2.1 Introduction

Kuznets (1955) and Kaldor (1955) posed the issue of the relationship, if any, between income inequality and economic growth. Since then, researchers explore whether a country's inequality in the distribution of income increases or decreases in concert with its economic growth. Studies provide evidence that supports the view that inequality slows growth over the medium and long terms (Alesina and Perotti 1996; Alesina and Rodrik 1994; Persson and Tabellini 1992; Birdsall et al. 1995; Clarke 1995; Deininger and Squire 1996; Easterly 2007; Wilkinson and Pickett 2007; Berg et al. 2012). These researchers suggest several channels for a negative influence, such as inequality prevents the poor from accumulating human capital by delaying the timing of investment in human capital (Galor and Zeira 1993; Perotti 1996; Galor and Moav 2004; Aghion et al. 1999), and/or inequality generates political and economic instability that reduces investment (Persson and Tabellini 1992, 1994; Alesina and Perotti 1996) and obstructs the social consensus required to mitigate shocks and maintain growth (Rodrik 1999; Woo 2005). In contrast, a number of studies provide evidence of a positive relationship between inequality and growth. According to these researchers, inequality affects growth positively by providing incentives for entrepreneurship (Lazear and Rosen 1981; Hassler and Mora 2000), and/or by boosting saving and investment (Kaldor 1955; Bourguignon 1981), by developing human capital (Saint-Paul and Verdier 1993; Barro 2000).

In addition to the studies that consider the long-term relationship between inequality and growth, other studies focus on the ambiguous short-term relationship (Stiglitz 1969; Loury

[1] Published in Social Indicators Research

1981; Tamura 1991; Perotti 1993; Benabou 1996; Galor and Tsiddon 1996, 1997; Aghion and Bolton 1997; Li and Zou 1998; Aghion et al. 1999; Maoz and Moav 1999; Fishman and Simhon 2002; Zilcha 2003; Galor et al. 2009; Forbes 2000; Banerjee and Duflo 2003; Halter et al. 2014). This literature uncovers a complex set of interactions, which depends on the specific research method and sample, between inequality and economic growth and highlights the difficulty of capturing a definitive causal relationship. Inequality either promotes, retards, or does not affect growth.

Most existing studies that examine the inequality growth nexus exclusively utilize time-domain methods. Few studies consider the frequency-domain relationships. The time- and frequency-varying relationships can provide significant implications for macroeconomic policymakers. The time-varying relationships indicate that the variables influence each other differently at different points in the business cycle (time) (Li et al. 2015). Frequency-varying relationships reveal short- versus long-term linkages between variables. Forbes (2000) emphasizes that a temporary relationship between inequality and growth does not directly contradict a permanent relationship and suggests a careful re-examination of the numerous linkages between inequality and growth.

Our paper explores these short- and long-term relationships between inequality and growth from the perspective of macroeconomic policy makers who undertake policies that could simultaneously improve growth and equality. We employ wavelet coherency analysis to examine the relationships between the U.S. per capita real GDP and inequality measures in the time and frequency domains. Wavelet coherency and phase differences simultaneously evaluate how causalities between U.S. per capita real GDP and the inequality measures fluctuate across frequencies and vary over time. This allows us to obtain short-term (high-frequency) and long-term (low-frequency) relationships between the two series–per capita real GDP and each of our income inequality measures–as well as potential structural breaks and time-varying relationships.

Wavelet analysis can extract time- and frequency-localized information not only from stationary series but also from non-stationary and locally stationary series as well as series with structural changes (Roueff and Sachs 2011). Economic processes emerge as outcomes of the actions of numerous agents at different frequencies, which implies that a macroeconomic time series incorporates information that operates at different time domains. Wavelet analysis separates the time series into several sub-series, which may associate with a particular time domain and which narrows the focus to provide fruitful insights on economic phenomena (Ramsey and Zhang 1996, 1997). By considering time series at different frequencies, we may obtain new insights about the series, which may allow isolation of interesting aspects of economic time series not observable in the time-domain.

2.2 Methodology: wavelet theory and methods

The wavelet transform is a method to decompose an input signal into a set of simple waveforms, called "wavelets". Wavelet analysis conducts the estimation of spectral characteristics of a time series as a function of time (Aguiar-Conraria et al. 2008). By extracting localized information in both time and frequency domains, wavelets helps researchers uncover interactions which are hard to see using only time or frequency focused econometric method. In addition, the wavelet analysis is a nonparametric spectral method that eliminate the need of parametric modelling, encountering facilities such as certainty in model parameters and the ability to fit data with complex spectral contents (Dhamala et al. 2008).

2.2.1 Mother wavelet

The wavelet transform decomposes a time series into dilated and translated versions of a given "mother wavelet". In other words, wavelets are constructed by simply translating and dilating the given "mother wavelet" and wavelets are able to localize behavior in both time (via translation) and frequency (via dilation). In this manner, the series is expanded into a time–frequency space where its oscillations appear in an intuitive way. There are several wavelet functions available, such as Morlet, Mexican hat, Daubechies, etc. In this study, a complex morlet wavelet[2] is used as it brings in information on the amplitude and phase which both are essential to study synchronism between different time-series.

2.2.2 Continuous wavelet transform

Two kinds of wavelet transforms exist: discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT). The DWT reduces noise and compresses data whereas the CWT extracts features and detects data self-similarities (Grinsted et al. 2004; Loh 2013).

The CWT, with respect to the wavelet ψ, is a function

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-\tau}{s}\right)dt,$$

where $*$ denoted complex conjugation. The parameter s is scaling factor that controls the length of the wavelet and τ is a location parameter that indicates where the wavelet is centered. Scaling a wavelet simply means stretching it (if $|s| > 1$), or compressing it (if $|s| < 1$).

If the wavelet function $\psi(t)$ is complex, the wavelet transform W_x will also be complex. The transform can then be divided into the real part ($\mathcal{R}\{W_x\}$) and imaginary part ($I\{W_x\}$), or amplitude, $|W_x|$, and phase, $tan^{-1}(\frac{I\{W_x\}}{\mathcal{R}\{W_x\}})$. The phase of a given time series $x(t)$ is parameterized in radians, ranging from $-\pi$ to π. In order to separate the phase and amplitude information of a time series, it is important to make use of complex wavelets.

[2] See Goupillaud et al. (1984) and Aguiar-Conraria et al. (2008) for detailed information of the Morlet wavelet.

2.2.3 Wavelet coherency and phase difference

Hudgins et al. (1993) and Torrence and Compo (1998) develop methodologies of the cross-wavelet power, the cross-wavelet coherency, and the phase difference. While wavelet analysis closely relates to Fourier analysis, wavelet analysis, however, possesses certain advantages. Wavelet analysis conserves information in both time and frequency domains by conducting the estimation of spectral characteristics of a time series as a function of time (Aguiar-Conraria et al. 2008). Also, wavelet analysis applies for non-stationary or locally stationary series (Roueff and Sachs 2011). Wavelet coherency allows for a three-dimensional analysis, which considers the time and frequency elements at the same time, as well as the strength of the correlation between the time-series elements (Loh 2013). In this way, we can observe both the time- and frequency-variations of the correlation between two series in a time-frequency domain. Consequently, wavelet coherency provides a much better measure of co-movement between variables, U.S. per capita real GDP and our various income inequality measures, in comparison to conventional causality and correlation analysis. Following the approach of Li et al. (2015), we estimate wavelet coherency by using the cross-wavelet and auto-wavelet power spectrums as follow:

$$R_{xy}^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau,s))|^2}{S(s^{-1}|W_x(\tau,s)|^2)S(s^{-1}|W_y(\tau,x)|^2},$$

where complex argument $\arg W_{xy}(\tau, s)$ represents the local relative phase between x_t and y_t, $|W_x(\tau, s)|^2$ is the wavelet power, $\arg W_x(\tau, s)$ represents local phase, and S is a smoothing operator.[3] The ratio of the cross-wavelet spectrum to the product of the spectrum of each series equals the local correlation of the two series. This formula gives a quantity between 0 and 1 in a time-frequency window. Zero coherency indicates no co-movement between per capita real GDP and an income inequality measure, while the highest coherency implies the

[3] Without smoothing, the squared wavelet coherency is always equal to 1 at any frequency and time. Torrence and Compo (1998) show that smoothing in time or frequency increases the degrees of freedom of each point and increases the confidence of the wavelet spectrum.

strongest co-movement between the two series. On the wavelet coherency plots, red colors correspond to strong co-movement whereas blue colors correspond to weak co-movement.

We cannot easily distinguish between positive and negative co-movements as the wavelet coherency is squared. Thus, we use the phase difference to provide information on positive and negative co-movements as well as the leading relationships between the two series.[4] Bloomfield et al. (2004) characterizes the phase difference relationship between $x(t)$ and $y(t)$ such that:

$$\phi_{xy} = tan^{-1}\left(\frac{\mathcal{I}\{S(s^{-1}W_{xy}(\tau,s))\}}{\Re\{S(s^{-1}W_{xy}(\tau,s))\}}\right), with\ \phi_{xy} \in [-\Pi, \Pi] ,$$

where $\mathcal{I}$ and $\Re$ equal the imaginary and real parts of the smoothed cross-wavelet transform, respectively.

A phase difference of zero reveals that the two underlying series move together, while a phase difference of $\pi(-\pi)$ indicates that two series move in the opposite directions. If $\phi_{xy} \in (0, \pi/2)$, then the series move in phase (positively co-move) with $y(t)$ preceding $x(t)$. If $\phi_{xy} \in (\pi/2, \pi)$, then the series move out of phase (negatively co-move) with $x(t)$ preceding $y(t)$. If $\phi_{xy} \in (-\pi, -\pi/2)$, then the series move out of phase with $y(t)$ preceding $x(t)$. Finally, if $\phi_{xy} \in (-\pi/2,0)$, then the series move in phase with $x(t)$ preceding $y(t)$. Also, the phase difference can imply causality between $x(t)$ and $y(t)$ in both the time and frequency domains. In sum, wavelet analysis permits deeper understanding than the conventional Granger causality test, which assumes that a single causal link holds for the whole sample period as well as at each frequency (Grinsted et al. 2004; Tiwari et al. 2013). For example, in wavelet analysis, if $x(t)$ precedes $y(t)$, then a causal relationship runs from $x(t)$ to $y(t)$ at a particular time and frequency (Li et al. 2015).

[4] The term phase means the position in the pseudo-cycle of the series as a function of frequency.

2.3 Data

Our analysis relies on the natural logarithm of U.S. per capita real GDP and the four income inequality measures[5] - Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil's entropy Index,– as well as Top 10%, and Top 1% income shares as useful proxies for inequality across the income distribution (Leigh 2007) over the period 1917 – 2012. Income inequality measures as well as income share measures come from the online data segment of Professor Mark W. Frank's website.[6] Real GDP (at constant 2009 prices) comes from the Global Financial Database, which we divide by population from the data segment of Shiller website[7], to derive the real per capita GDP. We conduct the analysis considering two frequency cycles. The 1-2-year cycle associates with the short-term (high-frequency) and the 2-4-year cycle associates with the long-term analysis (low-frequency)[8].

2.4 Preliminary analysis

Though our focus considers wavelets, we initially do a preliminary analysis, involving standard causality tests. To start, we first test the data series for unit roots, using the standard augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests (see Dickey and Fuller 1979; Phillips and Perron 1988). Table 2.1 shows that these tests fail to reject the null hypothesis of non-stationarity for the six income inequality measures as well as per capita real GDP at the 5-percent level. These tests further indicate that the first differences of the series do reject the

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[5] We take natural logarithms to correct for potential heteroskedasticity and dimensional differences between the series. Also, taking natural logarithms is standard practice, since it implies that we can interpret the coefficients as elasticities.

[6] See http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed dataset based on the Internal Revenue Service (IRS) information, which has a limitation of omission of some individual earning less than a threshold level of gross income. For this reason, we focus more on 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.

[7] See http://www.econ.yale.edu/~shiller/data.htm.

[8] Given that for per capita real GDP and income inequality the most coherent regions are between the 1-4 years band, we focus our phase difference analysis on two frequency bands: 1-2 and 2-4 years.

null of a unit root. Therefore, the unit-root tests indicate that the data conform to I(1) processes.

The presence of unit roots makes the traditional asymptotic inference invalid by violating asymptotic normality. Toda and Yamamoto (1995) propose an interesting, yet simple, procedure requiring the estimation of an augmented VAR that guarantees the asymptotic distribution of the Wald statistics (an asymptotic Chi square distribution), since the testing procedure proves robust to the integration and cointegration[9] properties of the processes. In other words, the result holds no matter whether series are I(0) or I(1) and/or whether cointegration does or does not exist. Table 2.2 shows that the Toda-Yamamoto causality tests indicate that one-way causality exists from the inequality measures to per capita real GDP for Atkin05, Rmeandev and Theil, whereas one-way causality exists from per capita real GDP to the Top 10%. Also, it shows two-way causality exists between the Gini coefficient and per capita real GDP and no causality between the Top 1% and per capita real GDP. The Toda-Yamamoto test, however, cannot distinguish between short- and long-run causality. Thus, we should test for cointegration and causality jointly across the frequency domain.

To examine the short- and long-run stability of the coefficients of the VAR model formed by each one of the six income inequality measures and per capita real GDP, we apply the Lc tests of Nyblom (1989) and Hansen (1990), which test the null hypothesis of constant parameters against the alternative hypothesis that the parameters follow a random-walk process (Gardner 1969). When the series are I(1), the Lc test can also serve as a test of cointegration, which indicates stability of the implied long-run relationship. According to Andrew (1993) and Andrew and Ploberger (1994), the F-statistics test the null hypothesis of

[9] Cointegration is the long-term, or equilibrium, relationship between two series. To ascertain long-run stability of the parameters, we perform the Johansen (1988, 1991) cointegration tests to determine whether the per capita real GDP and each of six income inequality measures cointegrate with each other. The test results show that no cointegration exists between per capita real GDP and each inequality measure, implying that per capita real GDP and the income inequality measures do not maintain a long-term relationship.

no structural break against the alternative hypothesis of a single shift of unknown change point. We also apply these tests for stability of the short-run parameters, using the three different test statistics: Sup-F, Ave-F, and Exp-F. Contrary to the Lc test, the F-tests require trimming from the ends of the sample. The *p* values and critical values for all stability tests come from parametric bootstrapping, which avoids the use of asymptotic distribution.

Tables 2.3 and 2.4, report the results of the parameter stability tests for the per capita real GDP and the six income inequality measures. Andrew and Ploberger (1994) suggest that the use of the Sup-F, Mean-F, and Exp-F tests, which test the same null hypothesis but differ in the alternative hypotheses, depends on the purpose of the test. The Sup-F statistic tests parameter constancy against a one-time sharp shift in parameters, so that the alternative hypothesis for the Sup-F test is an immediate shift in the regime. If the system shift gradually, however, then the Mean-F and Exp-F statistics, which assume that parameters follow a martingale process, are suitable. Both statistics test the global constancy of the parameters, implying that the Mean-F and Exp-F tests are appropriate to investigate whether the underlying relationship among the variables stays stable over time. Table 2.3A, B, D, F show that the Sup-F, Mean-F, and Exp-F tests reject the null hypothesis of parameter constancy, implying parameter non-constancy in the per capita real GDP equations as well as Atkin 05, Gini, and Theil index equations. Table 2.3C reports significant evidence of parameter non-constancy in the per capita real GDP equation but not in the null of overall stability of the VAR (2) model. Table 2.3E reports significant evidence of parameter non-constancy in the Top 10% equation but not in the null of overall stability of the VAR (2) model.

Investigating the causal relationship between the variables, using short-run parameters of the differenced or cointegrated VAR can lead to meaningless results with biased inference and inaccurate forecasts and Granger causality tests will show sensitivity to changes in the sample period. Overall, the parameter stability test show that the cointegrated VAR model possesses unstable short- and long-run parameters, suggesting the existence of structural changes.[10]

To check for the robustness of long-run stability of the parameters, we also estimate the cointegration equation between the variables based on the FM-OLS estimator.

Table 2.4 reports the results of the Lc tests. For all six FM-OLS estimators, the Nyblom-Hansen Lc test rejects the null hypothesis of cointegration at the 5-percent level. Thus, we observe both short- and long-run instability, motivating wavelet coherency analysis. When the frequency components exhibit nonstationarity, the traditional approach may miss such frequency components. Wavelet analysis provides localized information to deal with the time-varying characteristics found in most economic time series. Thus, we can avoid the assumption of stationarity (Fan and Gençay 2010). Furthermore, wavelet analysis allows us to examine the time- and frequency-localized information with structural breaks.[11]

2.5 Main analysis

From 1983 to 2012, the U.S. per capita real GDP and Atkin05 show a statistically significant high coherency across 1-2 year frequency band in Fig. 2.1. Figure 2.1 also shows positive correlations between the U.S. per capita real GDP and Atkin05 over the short and long term.

Across the 2-4 year frequency band in Table 2.5, U.S. per capita real GDP leads the Atkin05 inequality measure in 1917-1948 and 1977-2012, while the Atkin05 inequality measure leads U.S. per capita real GDP in 1949-1976. The change of direction of the causality, from per capita real GDP leads to inequality leads in the late 1940s probably relates

[10] We examine the existence of structural breaks in VAR. Results of the Bai and Perron (1998) tests show that there are structural breaks. Also, given the existence of structural breaks in the series, we test for unit roots with one or two structural breaks using methodologies for endogenising dates, including Zivot and Andrews (2002), Lumsdaine and Papell (1997) and Lee and Strazicich (2003). See appendix 2.2 for the results of unit root test with structural breaks. As the unit root test of Lee and Strazicich (2003) only allows breaks under both null and the alternative hypothesis, we put more weight on the results of two-break minimum LM unit root test by Lee and Strazicich (2003). According to the LM test, series are I(1) with possible structural breaks.

[11] The results of the cointegration test motivate our focus on a time-varying approach. One way to implement time-varying cointegration uses a rolling causality analysis. We choose not to follow this method for the following reasons. First, the results may depend on the optimal window length. Second, rolling causality analysis only works in the time domain.

to a democratization of wealth in the post-war period. Also, stagnating real wages for the majority of the population despite increasing productivity. Across the 1-2 year frequency band, we see the causal link running from per capita real GDP to the Atkin05 inequality measure for several periods – 1965-1973, 1978-1987, and 2011-2012 (see Table 2.5). The 1970s saw couple of oil price spikes as OPEC began affecting prices. After the 1973 oil shocks, productivity growth suddenly slowed and the oil price shocks led to higher unemployment and inflation.

The Gini coefficient exhibits a positive and statistically significant correlation with U.S. per capita real GDP from 1917 to 1930 and from 1970 to 2012 in Fig. 2.2. Figure 2.2 also shows causality between U.S. per capita real GDP and the Gini coefficient. Over the short and long term, the two series show positive correlation.

U.S. per capita real GDP leads the Gini coefficient from 1967-1972 at high frequency in Table 2.6, while the Gini coefficient leads per capita real GDP from 1917-1970 to 1983-2012 at low frequency. The Vietnam War covered the 1967-1972 period which in turn productivity growth slowed. Also, as a consequence of fiscal and monetary policies during this War, the U.S. experienced rising inflation and unemployment during most of the 1960s into the early 1980s. Moreover, OPEC oil price shocks also occurred during the 1970s, as noted above. We can see the temporary causality does not determine long-run causality (see Table 2.6).

From 1980 to 2012, U.S. per capita real GDP and the Rmeandev inequality measure show a statistically significant high coherency across the 1-2 year frequency band (see Fig. 2.3) with an in-phase relation (see Table 2.7).

We observe across the 1-2 year frequency band in Table 2.7 an in-phase relationship in 1966-1975 with per capita real GDP leading. At low frequencies, we see the causal link running from per capita real GDP to Rmeandev from 1917 to 1948 and Rmeandev leads per capita real GDP from 1949 to 2012, which relates to compression in wages during the 1940s.

Theil index exhibits a strong positive correlation with U.S. per capita real GDP from 1980 to 2012 across the 1-2 year frequency band in Fig. 2.4.

The phase difference shows causality between the U.S. per capita real GDP and the Theil index in Table 2.8. Throughout the period from 1917 to 2012, per capita real GDP leads the Theil index at low frequency. This indicates that per capita real GDP positively affects income inequality (Theil). At high frequencies, per capita real GDP leads Theil index repeatedly from 1963 to 1972 (see Table 2.8), which also corresponds to the Vietnam War period.

Across the 1-2 years frequency band, two significant islands exist of high coherency between U.S. per capita real GDP and the Top 10% around 1955 and from 1985 to 2012 in Fig. 2.5. Across the 2-3 years frequency band, we observe a significant island from 1945 to 1957 (see Fig. 2.5), which is related to the World War II as the Top 10% income share fell substantially during the World War II (Goldin and Margo 1992). We observe the consistent strong positive correlation between U.S. per capita real GDP and inequality measures at the 1-2 years frequency at the recent sample years (see Fig. 2.5). This may relate to the Tax Reform Act of 1986, which lowered the top tax rate and raised the bottom tax rate. As a result, income inequality leads U.S. per capita real GDP in the recent sample years.

Table 2.9 shows causality between the U.S. per capita real GDP and the Top 10%. At high frequency, per capita real GDP leads the Top 10% from 1917 to 1988. At low frequency, per capita real GDP leads the Top 10% from 1917 to 1973 to 1979-1984 (see Table 2.9).

In Fig. 2.6, we observe a statistically positive correlation from the 1926 to the 1949 between per capita real GDP and the Top 1 % across the 2-3 year frequency band as during the Great Depression the top 1% declined extensively.

At high frequency, per capita real GDP leads the Top 1% from 1917-1993 to 2003-2012 in Table 2.10. At low frequency, per capita real GDP leads the Top 1% from 1917-1983 to 1986-2012 (see Table 2.10).

We also consider a Maximal Overlap Discrete Wavelet Transform (MODWT), non-decimated form of the discrete wavelet transform, to decompose the time-series. Then we analyze the causality in different frequencies and see whether the underlying driver lies in low or high frequency domain using Granger causality test.[12] Table 2.11 reports the results of Granger causality tests in the different frequency domain. In low frequency domain, the causality tests reject the null of no-causality from all six inequality measures to real per capita GDP whereas the null of no-causal relationship from real per capital GDP to income measures-Atkin05, Gini, Rmeandev and Theil- are rejected in high frequency domain. Also, in high frequency domain, there is no causality between Top income shares and real per capita GDP, and no causality between income measures-Atkin05, Gini, Rmeandev and Theil- and real per capita GDP in medium frequency. We do not find any stable causality holding for the whole sample period. Rather, the causality findings exhibit substantial time- and frequency-dependence.

Overall, we observe a positive correlation between per capita real GDP and income inequality. Also, we observe that the directions of short- and long-term causality vary.[13] If we restrict our analysis to classical time series, we cannot find any information about frequency differences. To develop a deeper understanding of the relationships between U.S. per capita real GDP and our measures of income inequality requires wavelet analysis.

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[12] Testing causality in frequency domain collapses the time dimension into a single point in time, and therefore information is lost on the time variation in causality.

[13] The wavelet coherency and phase difference for the levels of per capita real GDP and income inequality measures still show very similar correlation and causalities.

2.6 Conclusion

Policy makers attempt to reduce inequality and to sustain and/or boost economic growth. The relationship between inequality and growth received much analysis in the existing literature. Unfortunately, numerous variables affect these variables simultaneously or at different points of time, rendering net causality and correlation results difficult to document. This paper investigates the causal relationship between U.S. per capita real GDP and six measures of income inequality. We use wavelet coherency analysis, which allows the causal relationship between the two series to vary over time and frequency. Wavelet analysis is robust to lag length (Fan and Gençay 2010), stationarity (Roueff and Sachs 2011), model specification (Percival and Walden 2006) and cointegration as wavelet analysis allows time- and frequency-varying approach. Furthermore, it permits to measure local co-movement between two time series in the time-frequency domain and discover the lead-lag relationship between two time series. We use annual time-series data from 1917 to 2012 from the U.S., which covers numerous economic expansions and recessions.

This paper addresses the possible presence of structural breaks. We employ tests for parameter constancy to examine the stability of the estimated VAR model and to test for both short- and long-term instability. Also, we test the existence of structural breaks in each series. Observed instability and structural change, therefore, make the traditional Granger causality test inappropriate. We apply the time- and frequency-varying wavelet coherency analysis to assess the causal relationship between the U.S. per capita real GDP and our six income inequality measures.

Results show that the periods and directions of short- and long-term causality vary. Also, short-term relationships do not necessarily coincide with long-term relationships. Causality changes direction – from inequality leading to per capita real GDP leading. We find different directions of causality for our six income inequality measures – especially during periods of volatility such as World War II (1939-1945), the OPEC oil shocks (1973-1979), the early 1980s recession, the transitory recession in the 1990s, and the recent financial crisis and Great Recession. An exception is that per capita real GDP mainly leads the Top 1 and 10% inequality measures at both high- and low-frequencies.

This paper began with a mass of mutually conflicting findings on how inequality affects growth. Our findings support the view that inequality and growth are positively correlated in the short and long term, which implies that the benefits of economic growth do not trickle down across society. In addition, we find not only inequality matters for growth but also growth matters for inequality, especially the Top 1 and 10% income shares.

The most used and direct policy to reduce inequality redistributes income through government spending, taxes, and transfer payments. Yet, rapid and forced redistribution from rich to poor may not provide the best solution. In particular, significant adjustments to fiscal policy to achieve a lower level of income inequality may cause slower economic growth. For example, higher transfer payments to low income families may lead to a higher budget deficit, absent other fiscal actions. A higher budget deficit, then, may lead to higher interest rates and, thus, to reduced investment, net exports, and consumption, leading to reduced growth in real GDP. In this case, policies that help to reduce inequality may undermine growth.

As another strategy, policy makers use taxes to redistribute income from the rich to the poor. Such tax induced redistribution may not work because it takes away incentives and may produce rent-seeking (Lazear and Rosen 1981; Hassler and Mora 2000). This paper finds that inequality and growth are positively correlated. While the literature on this topic remains contentious, the view of a trade-off between inequality and growth seems embedded in policy makers' choice. In this example, we see once again that policies that help to reduce inequality may undermine growth.

Future research could consider the relationship between fiscal policy adjustments and income inequality. That is, how do changes in different fiscal controls to address income inequality affect economic growth and how significant a change in fiscal policy can occur without impinging on economic growth?

Table 2.1. Unit root tests

	Level					
	ADF			PP		
	C	C+T	N	C	C+T	N
Per capita real GDP	-0.519	-2.885	2.129	-0.731	-2.665	3.653
Atkin05	-1.22	-2.037	-0.924	-1.495	-2.795	-0.494
Gini	-0.832	-2.578	-0.751	-0.943	-2.787	-0.733
Rmeandev	-0.26	-2.3	-1.032	-1.632	-3.183	-0.818
Theil	-0.884	-0.942	-1.005	-1.318	-2.098	-0.816
Top 10%	-0.694	-0.794	-0.698	-0.756	-0.788	-0.698
Top 1%	-1.141	-1.162	-0.451	-1.078	-1.022	-0.457
	First difference					
	ADF			PP		
	C	C+T	N	C	C+T	N
Per capita real GDP	-6.655***	-6.612***	-6.172***	-6.773***	-6.733***	-6.172***
Atkin05	-8.781***	-6.033***	-8.786***	-8.781***	-8.77***	-8.787***
Gini	-9.638***	-6.361***	-9.589***	-9.63***	-9.608***	-9.575***
Rmeandev	-6.578***	-6.72***	-6.502***	-9.165***	-9.125***	-9.169***
Theil	-8.392***	-5.736***	-8.412***	-8.381***	-8.491***	-8.402***
Top 10%	-8.788***	-8.894***	-8.801***	-8.747***	-8.856***	-8.761***
Top 1%	-9.748***	-9.882***	-9.787***	-9.809***	-10.14***	-9.848***

Note: The Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test corresponds to Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests; *** indicates the rejection of the null hypothesis at 1% level of significance.

Table 2.2. Toda-Yamamoto causality modified WALD test

Null Hypothesis	Chi-sq	Prob.	Granger Causality
per capita real GDP does not granger cause Atkin05	3.345	0.188	One-way directional Causality
Atkin05 does not granger cause per capita real GDP	10.268	0.006	Atkin05 -> per capita real GDP
per capita real GDP does not granger cause Gini	8.04	0.045	Two-way directional Causality
Gini does not granger cause per capita real GDP	13.736	0.003	Gini <-> per capita real GDP
per capita real GDP does not granger cause Rmeandev	4.346	0.114	One-way directional Causality
Rmeandev does not granger cause per capita real GDP	6.291	0.043	Rmeandev -> per capita real GDP
per capita real GDP does not granger cause Theil	3.009	0.222	One-way directional Causality
Theil does not granger cause per capita real GDP	8.598	0.014	Theil -> per capita real GDP
per capita real GDP does not granger cause Top10 percent	10.705	0.005	One-way directional Causality
Top10 percent does not granger cause per capita real GDP	1.455	0.483	Per capita real GDP -> Top 10%
per capita real GDP does not granger cause Top1 percent	3.036	0.219	No causality
Top1 percent does not granger cause per capita real GDP	3.86	0.145	

Table 2.3. Parameter stability tests in VAR(2) model

A	Per capita real GDP Equation		Atkin05 Equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	44.57	<0.01	31.8	<0.01	54.13	<0.01
Mean-F	6.69	0.03	12.11	<0.01	11.87	0.020
Exp-F	18.07	<0.01	12.3	<0.01	23.56	<0.01
B	Per capita real GDP Equation		Gini Equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	44.54	<0.01	16.27	0.020	50.05	<0.01
Mean-F	7.84	0.01	6.11	0.020	11.23	0.030
Exp-F	18.07	<0.01	4.71	0.030	20.98	<0.01
C	Per capita real GDP Equation		Rmeandev equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	37.87	<0.01	27.57	<0.01	51.62	<0.01
Mean-F	7.62	0.02	5.33	0.090	11.37	0.030
Exp-F	14.84	<0.01	9.59	<0.01	21.73	<0.01
D	Per capita real GDP Equation		Theil Equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	62.55	<0.01	54.57	<0.01	56.42	<0.01
Mean-F	11.11	<0.01	10.83	<0.01	13.87	0.010
Exp-F	27.35	0.01	23.07	<0.01	25.42	<0.01
E	Per capita real GDP Equation		Top 10 Equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	260.95	<0.01	21.33	<0.01	42.85	<0.01
Mean-F	11.65	<0.01	12.48	<0.01	17.45	<0.01
Exp-F	126.25	1	7.81	<0.01	17.62	<0.01
F	Per capita real GDP Equation		Top 1 Equation		VAR(2) System	
	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value	Statistics	Bootstrap p-value
Sup-F	45.64	<0.01	33.84	<0.01	46.69	<0.01
Mean-F	6.84	0.03	18.34	<0.01	18.94	<0.01
Exp-F	19.1	<0.01	13.51	<0.01	20.28	<0.01

Note: The parameter stability tests exhibit non-standard asymptotic distributions. Using the parametric bootstrap procedure, Andrews (1993) and Andrews and Ploberger (1994) report the critical values and *p* values for the non-standard asymptotic distributions of these tests. We obtain the critical values and *p* values using asymptotic distribution constructed by means of Monte Carlo simulations using 10,000 samples generated from a VAR model with constant parameters. Besides, according to Andrews (1993), 15-percent trimming from both ends of the sample is required for the Sup-F, Mean-F and Exp-F. Hence, we apply the tests to the fraction of the sample in (0.15, 0.85).

Table 2.4 Parameter stability tests in long-run relationship FM-OLS

	Atkin05		Gini		Rmeandev		Theil		Top 10%		Top 1%	
	Stats	Bootstrap p-value	Stats	Bootstrap p-value	Stats	Bootstrap p-value	Stats	Bootstrap p-value	Stats	Bootstrap p-value	Stats	Bootstrap p-value
Lc	14.59	<0.01	11.48	<0.01	14.08	<0.01	16.92	<0.01	15.71	<0.01	15.47	<0.01

Note: We apply the Lc test proposed by Nyblom (1989) and Hansen (1992) to investigate the long-run parameter stability with the long-run relationship estimated using the Fully Modified ordinary least squares (FM-OLS) estimator of Phillips and Hansen (1990). When the underlying series are I(1), it also serves as a test of cointegration. We calculate p-value using 10,000 bootstrap repetitions.

Table 2.5. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Atkinson index)**

High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1964	$(0,\frac{\pi}{2})$, In-phase	+	Atkin05 -> U.S. per capita real GDP
	1965-1973	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP-> Atkin05
	1974-1977	$(0,\frac{\pi}{2})$, In-phase	+	Atkin05 -> U.S. per capita real GDP
	1978-1987	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP-> Atkin05
	1988-2010	$(0,\frac{\pi}{2})$, In-phase	+	Atkin05 -> U.S. per capita real GDP
	2011-2012	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP-> Atkin05
Low frequency	1917-1948	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP-> Atkin05
	1949-1976	$(0,\frac{\pi}{2})$, In-phase	+	Atkin05 -> U.S. per capita real GDP
	1977-2012	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP-> Atkin05

Table 2.6. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Gini coefficient)**

High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1966	$(0,\frac{\pi}{2})$, In-phase	+	Gini -> U.S. per capita real GDP
	1967-1972	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP -> Gini
	1973-2012	$(0,\frac{\pi}{2})$, In-phase	+	Gini -> U.S. per capita real GDP
Low frequency	1917-1970	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP -> Gini
	1971-1982	$(0,\frac{\pi}{2})$, In-phase	+	Gini -> U.S. per capita real GDP
	1983-2012	$(\frac{-\pi}{2},0)$, In-phase	+	U.S. per capita real GDP -> Gini

Table 2.7. Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Rmeandev)

High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1965	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev -> U.S. per capita real GDP
	1966-1975	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Rmeandev
	1976-2012	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev -> U.S. per capita real GDP
Low frequency	1917-1948	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Rmeandev
	1949-2012	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev -> U.S. per capita real GDP

Table 2.8. Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Theil index)

High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1962	$(0, \frac{\pi}{2})$, In-phase	+	Theil -> U.S. per capita real GDP
	1963-1972	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Theil
	1973-2012	$(0, \frac{\pi}{2})$, In-phase	+	Theil -> U.S. per capita real GDP
Low frequency	1917-2012	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Theil

Table 2.9. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Top 10%)**

High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1988	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top10%
	1989-2012	$(0, \frac{\pi}{2})$, In-phase	+	Top10% -> U.S. per capita real GDP
Low frequency	1917-1973	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top10%
	1974-1978	$(0, \frac{\pi}{2})$, In-phase	+	Top10% -> U.S. per capita real GDP
	1979-1984	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top10%
	1985-2012	$(0, \frac{\pi}{2})$, In-phase	+	Top10% -> U.S. per capita real GDP

Table 2.10. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Top 1%)**

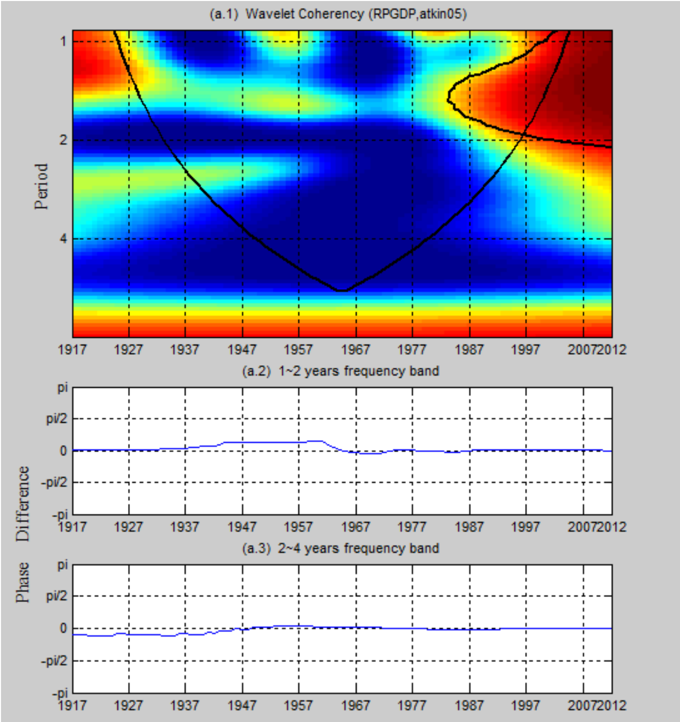
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1993	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top1%
	1994-2002	$(0, \frac{\pi}{2})$, In-phase	+	Top1% -> U.S. per capita real GDP
	2003-2012	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top1%
Low frequency	1917-1983	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top1%
	1984-1985	$(0, \frac{\pi}{2})$, In-phase	+	Top1% -> U.S. per capita real GDP
	1986-2012	$(\frac{-\pi}{2}, 0)$, In-phase	+	U.S. per capita real GDP -> Top1%

Table 2.11. Results of Granger causality in different frequencies

	Frequencies decomposed by the MODWT						Granger causality	
Frequency	Short term		Medium term		Long term		Whole sample period	
Null Hypothesis	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.
Atkin05 does not Granger Cause per capita real GDP	1.992		1.328		21.006	***	5.134	***
per capita real GDP does not Granger Cause Atkin05	7.081	***	0.856		1.263		1.671	
Gini does not Granger Cause per capita real GDP	3.466	**	1.410		57.379	***	4.789	**
per capita real GDP does not Granger Cause Gini	2.765	*	0.493		5.697	***	1.885	
Rmeandev does not Granger Cause per capita real GDP	2.781	*	0.797		25.808	***	3.146	**
per capita real GDP does not Granger Cause Rmeandev	6.872	***	0.561		1.455		2.173	
Theil does not Granger Cause per capita real GDP	1.509		1.390		106.472	***	4.299	**
per capita real GDP does not Granger Cause Theil	9.045	***	0.642		6.111	***	1.505	
Top10 does not Granger Cause per capita real GDP	0.356		9.851	***	86.045	***	0.727	
per capita real GDP does not Granger Cause Top10	0.694		8.756	***	2.081		5.352	***
Top1 does not Granger Cause per capita real GDP	0.033		16.094	***	119.145	***	1.930	
per capita real GDP does not Granger Cause Top1	1.474		10.729	***	7.575	***	1.518	

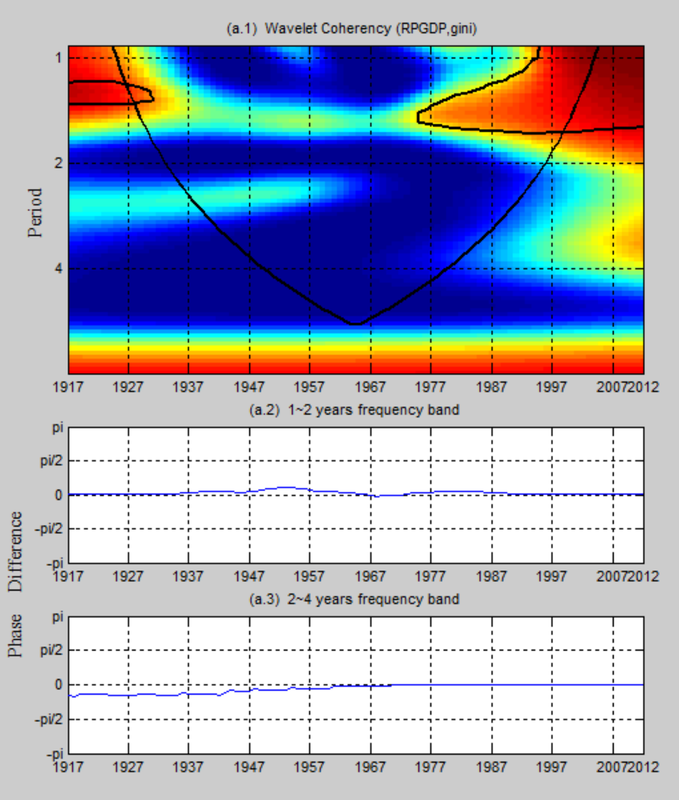
Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. We use the MODWT based on the Daubechies and decompose our data up to level 8.

Figure 2.1. Causal relationship between per capita real GDP and Atkinson index



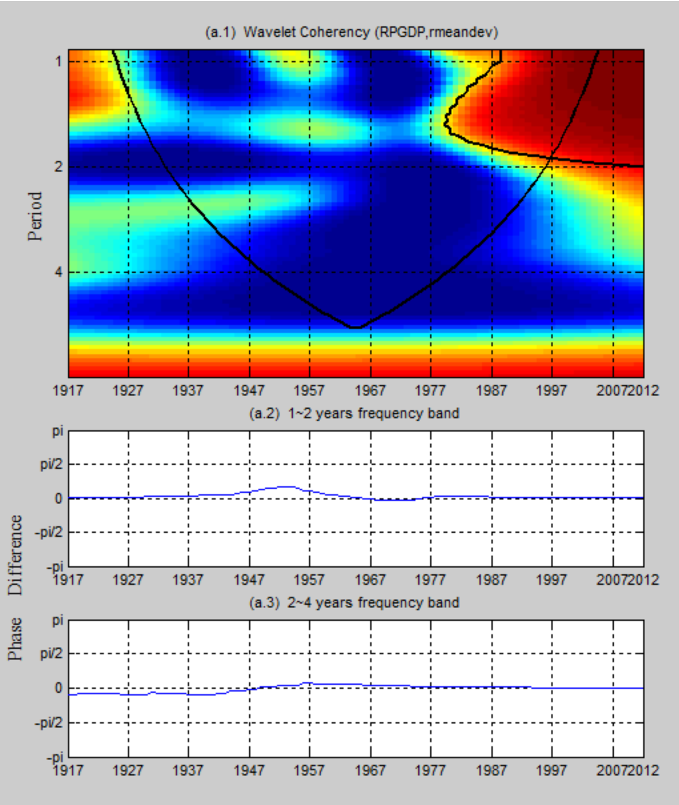
Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and Atkin05. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Figure 2.2. Causal relationship between per capita real GDP and Gini coefficient



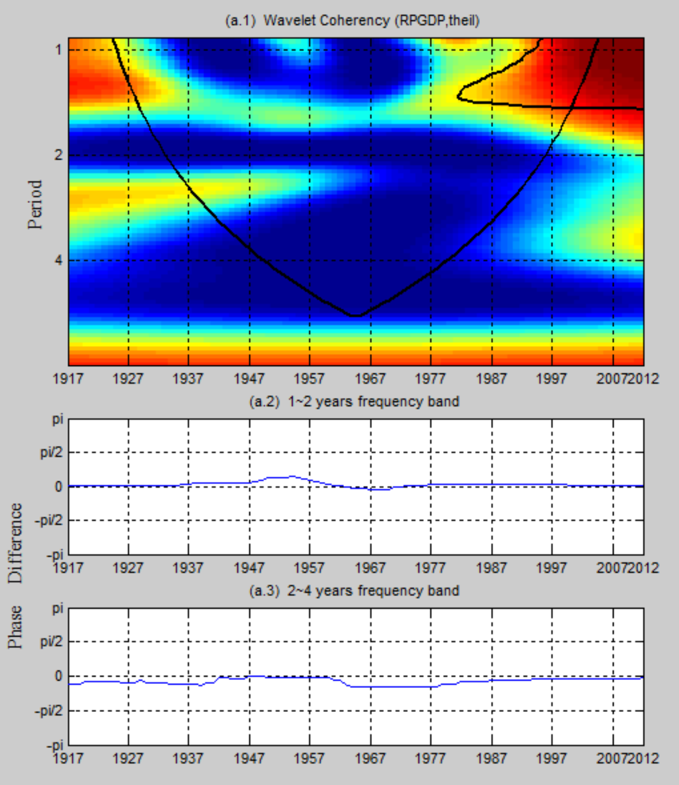
Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and Gini coefficient. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Figure 2.3. Causal relationship between per capita real GDP and the Relative Mean Deviation



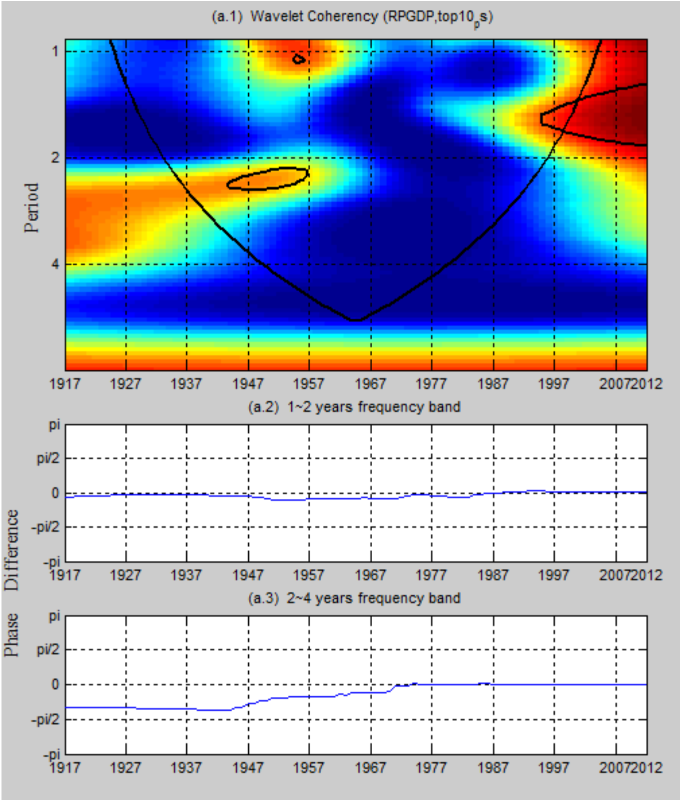
Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and the relative mean deviation. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Figure 2.4. Causal relationship between per capita real GDP and Theil's entropy index



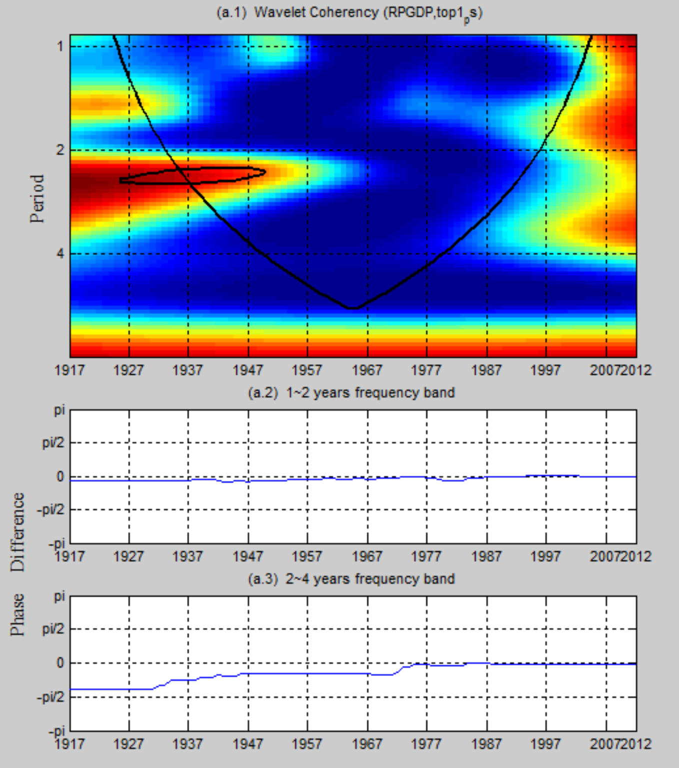
Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and Theil's entropy index. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Figure 2.5. Causal relationship between per capita real GDP and Top 10% income share



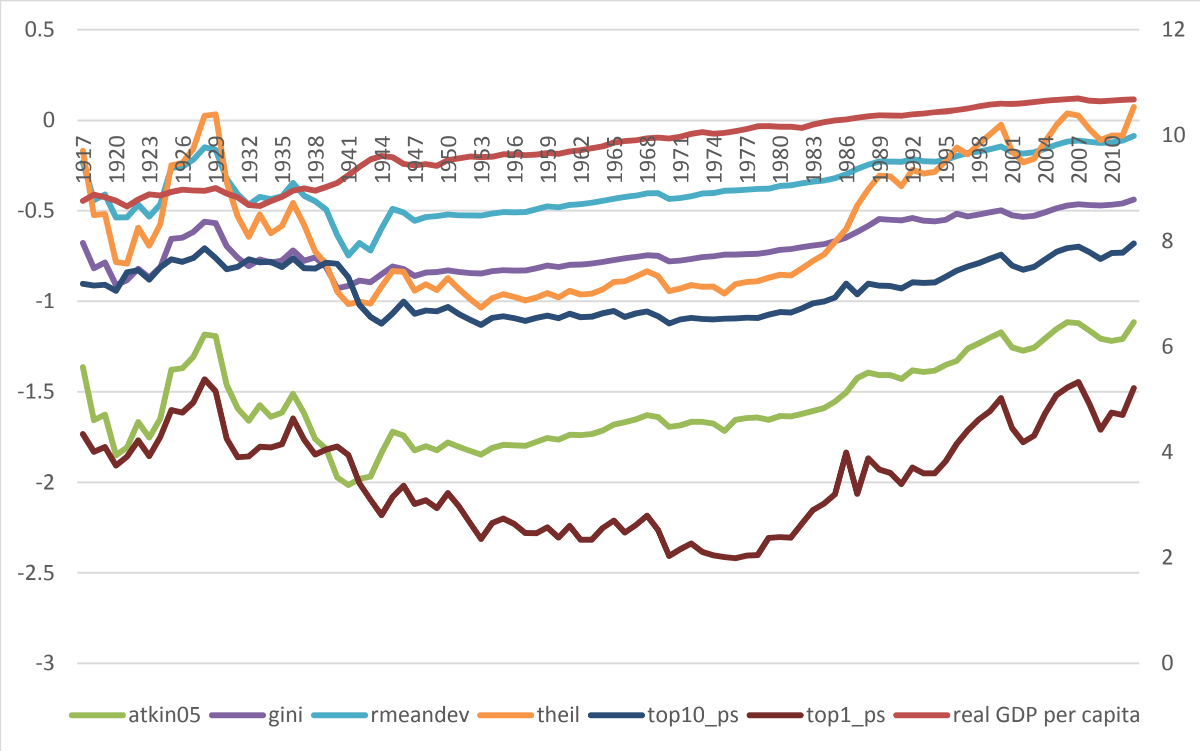
Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and Top 10% income share. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Figure 2.6. Causal relationship between per capita real GDP and Top 1% income share



Note: The wavelet coherency (a.1) and phase difference (a.2 , a.3) between the per capita real GDP and Top 1% income share. The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2012. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.

Appendix 2.1. Graph of per capita real GDP and income inequality measures



Note: Variables are in natural logarithms.

Appendix 2.2. Unit root tests with structural breaks

Zivot and Anderews (1992)*	Endogenous with one break
Real GDP per capita	-6.018 ***
Atkin05	-6.312 ***
Gini	-6.480 ***
Rmeandev	-8.104 ***
Theil	-4.896 ***
Top 10 percent	-4.916 ***
Top 1 percent	-4.681 ***
Lumsdaine and Papell (1997)*	Endogenous with two breaks
Real GDP per capita	-6.523
Atkin05	-8.059 **
Gini	-8.306 **
Rmeandev	-8.588 **
Theil	-6.320
Top 10 percent	-7.520 **
Top 1 percent	-5.371
Lee and Strazicich (2003)**	Endogenous with two breaks
Real GDP per capita	-3.559
Atkin05	-3.523
Gini	-3.708
Rmeandev	-3.563
Theil	-3.419
Top 10 percent	-5.113
Top 1 percent	-4.780

Note: * Assume no break(s) under the null hypothesis of unit root.

**Assume break(s) under both the null and the alternative hypothesis.

Chapter 3

The Relationship between the Inflation Rate and Inequality across US States: A Semiparametric approach[14]

3.1 Introduction

Over the last 30 years, the U.S. economy has experienced an increasing income inequality. Researchers consider many possible explanations for this trend, yet no political/economic instrument seems to explain this long-run trend. In this paper, we investigate the effects of the inflation rate on income inequality to see whether monetary policy and the resulting inflation rate can affect income inequality and improve well-being of individuals. In the political economy arguments, the redistribution of income commonly reflects changes in fiscal policy by government spending, taxation, or transfer payments. Monetary policy and its effect on the inflation rate can also redistribute income as households differ in many dimensions. First, the inflation rate affects different sources of income differently. Different prices change at different rates. For example, the prices of commodities change every day and others, such as wages, adjust much more slowly. Second, each households' income source differs. For instance, income can come from capital or labor, or both. Thus, the effect of the inflation rate on the total household income is heterogeneous. By affecting each household's income in a different way, the inflation rate affects the income distribution (Da Costa and Werning 2008).

Theoretically, monetary policy affects income inequality both in the short and long run. In short-run, a lower inflation rate slows down the relative loss in purchasing power of non-indexed nominal fixed incomes, such as pensions and transfers, relative to indexed nominal incomes, such as capital income. Because the poor receive a larger proportion of their income from transfers than the rich, lower inflation slows the rise in income inequality (Albanesi 2007; Erosa and Ventura 2002; Easterly and Fischer 2001). Therefore, in the short-run, the

[14] Published in Quality & Quantity

inflation rate affects income inequality through the cycle in economic activity generated by the policy change (Romer and Romer 1999).

In long-run, through various channels, inflation can affect income inequality (See for example, Jin 2009; Camera and Chien 2014; Areosa and Areosa 2016). Rising inflation can decrease the real value of nominal, non-indexed assets and the real value of non-indexed transfers. The poor probably cannot protect themselves from rising inflation due to the existence of entry barriers in markets for real, indexed financial assets (Easterly and Fischer 2001). In this case, rising inflation enhances income inequality (Cysne et al. 2005). On the other hand, rising inflation can decrease the real value of private debt, which can reduce income inequality. In the long-run, the relationship between inflation and income inequality can depend on the initial level of inflation.[15] For instance, lower long-run inflation positively affects growth for countries with initially high inflation (Fischer 1993; Funk and Kromen 2010; Vaona and Schiavo 2007). In low and moderate inflation economics, however, inflation does not affect economic instability which can discourage investment and restrain long-run growth (Pindyck and Solimano 1993). The trade-off between inflation and unemployment provides another example of the relationship between inflation and income inequality, which depends on the initial level of inflation. Downward rigidities in nominal wages imply that reducing inflation from low to lower levels could lead to a larger increase in unemployment (Ribba 2003).

The plan of the paper is as follows. In section 2, we look at the literature. We discuss the methodology for empirical analysis in section 3. Discussion of data and results are presented in section 4. Conclusions appear in section 5.

[15] For non-linear effect of inflation on economic growth, see Hess and Morris (1996), Barro (1996), Fischer (1993), Sarel (1996), and Kremer et al. (2013).

3.2 Literature review

Da Costa and Werning (2008) look at the optimality of the Friedman rule in an economy with heterogeneous agents subject to nonlinear taxation of labor income. The authors find that the Friedman rule is Pareto efficient when an increasing income tax is combined with zero inflation. As zero inflation is always on the Pareto optimal frontier, non-linearity in the labor incomes is vital for inflation as a redistributive instrument.

Jin (2009) shows that inflation and inequality can exhibit a positive or negative relationship. By incorporating inflation, growth, and income inequality in a consistently specified framework and introducing two types of heterogeneity -- skill endowments and initial capital holdings -- across households, the author shows that along the balanced growth path wealthier households that experience higher capital shares tend to work less, whereas more skilled households that exhibit higher skill shares tend to work more. Consequently, the relative income share of each household represents a convex combination of its relative capital and skill shares (Jin 2009).

Areosa and Areosa (2016) examine optimal monetary policy in the presence of inequality by introducing unskilled labor with no access to the financial system into a DSGE model with sticky prices. The authors find a contractionary interest rate shock increases inequality, while inflation and the output gap decrease. Also, they find that a higher proportion of unskilled labor weakens monetary policy while fiscal policy produces a more relevant effect on the economy.

Menna and Tirelli (2017) re-examine the issue of the inflation-tax burden and show that a combination of higher inflation and lower income taxes moderates inequality. Also, the authors obtain optimal inflation rate which is above 4%. These findings strengthened in which the Planner can levy distinct labor and capital income taxes.

Thus, these studies suggest that the net long-run effect of inflation on income inequality depends on the initial rate of inflation. When a country experiences low inflation, no clear relationship exists between inflation and income inequality. Whereas when a country experiences high inflation, higher inflation leads to higher income inequality.

A number of empirical studies examine the relationship between inflation and inequality, yielding inconsistent results. Some authors find a positive or negative relationship between inflation and income inequality, while others find no relationship. Thus, the pre-2000 literature generates an inflation-inequality puzzle. Galli and van der Hoeven (2001) provide a review of the empirical literature. Post-2000 empirical studies also add to this inconsistency. Scully (2002), Albanesi (2007), and Beck et al. (2007) find a positive relationship between inflation and the income inequality. Erosa and Ventura (2002) find inflation acts like a regressive tax in the United States, implying that inflation increases income inequality as lower-income households hold a larger fraction of their assets in cash. Heer and Maußner (2005), Sun (2011, 2014), Maestri and Roventini (2012), and Coibion et al. (2017) find that inflation decreases income inequality. Whereas these empirical studies focus on linear relationship between inflation and inequality, Romer and Romer (1999) find that the slope of income distribution varies with inflation. Bulir (2001) finds a non-linear relationship between inflation and inequality. By dividing the dataset into low, middle, and high inflation sections, the author shows that inflation and inequality exhibit a negative relationship from low to middle inflation and exhibit a positive relationship from middle to high inflation sections. That is, the initial decline in inflation from a hyperinflation situation reduces inequality, whereas further declines in lower levels of inflation increases inequality. Bulir (2001) finds a threshold of five percent inflation, where below the threshold reducing inflation causes income inequality to rise and above the threshold reducing inflation causes income inequality to fall. Galli and van der Hoeven (2001) also find a non-linear relationship between inflation and income inequality and estimate the inequality minimizing rate of inflation at around six percent in the United States. The authors show that increasing inflation reduces inequality with low initial inflation and boosts inequality with high initial inflation rate.

In this paper, we use a semiparametric instrument variable (IV) estimator to assess the relationship between the inflation rate and income inequality. The semiparametric estimator proves extremely sensitive to outliers. By using cross-state panel data, we minimize the problems associated with data comparability often encountered in cross-country studies related to income inequality. That is, cross-state data are more comparable than those for different countries. Also, states form a group of observations with minimal differences in institutions and political regimes.

Analysts generally agree that economic policies aimed at stimulating growth need to consider effects on inequality and poverty, emphasizing equitable growth policies and explicit redistributive policies (Gali and van der Hoeven 2001). The use of monetary policy, as an instrument of economic policy, is important not only for growth but also for reducing inequality.

3.3 Methodology and data

3.3.1 Methodology

A semiparametric estimator proves useful for situations when the researcher expects a nonlinear relationship between two variable and controls for the effect of other covariates. Also, the semiparametric model allows the data to uncover a more realistic functional form. By employing the semiparametric IV estimator of Park (2003), we also can account for the potential endogeneity of the inflation rate.

In the first stage, we determine the validity of the instrumental variable. We use a F-test to decide whether the instrument should enter the first-stage regression. The auxiliary instrumental variable regressions take the following form:

$$\pi_t = \mu + \theta z_t + \varepsilon_t, \text{ t=1,2, … T} \quad (1)$$

where π_t is the inflation rate, $z_t = \pi_{t-1}$ (instrumental variable), and $\varepsilon_t \sim iid(0, \sigma^2)$ is the error term.

The semiparametric specification can be expressed as follow:

$$g_{it} = \phi x_{it} + f(\pi_{it}) + \varepsilon_{it}, \text{ i=1,2,… N, t=1,2, … T} \quad (2)$$

where $f(\pi_{it})$ is a nonlinear function and x_{it} is a set of exogenous variables. We account for the possibility that $E[\varepsilon_{it}|\pi_{it}] \neq 0$ by estimating (2) using the model with a valid instrumental variable. Following Vaona and Schiavo (2007) and Balcilar et al. (2014), we estimate the model in equation (2) using the semiparametric IV estimation approach of Park (2003)[16].

We determine the bandwidth, using the least-square cross-validation method of Li et al. (2013). We use a Gaussian kernel for semiparametric model.

3.3.2 Data

The analysis relies on a cross-state panel from 1976 to 2007, which includes the U.S. state Consumer Price Index, U.S. per capita income, human capital attainment measures, unemployment, and six income inequality measures - Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil's entropy Index, as well as the Top 10%, and the Top 1% income shares.[17] The income inequality measures, income share measures, and human capital attainment measures come from the online data segment of Professor Mark W. Frank's website.[18] We employ the revised 2009 version of the Berry-Fording-Hanson state cost of living index of Berry et al. (2000), who construct a panel from 1960 to 2009.[19] U.S. per capita income is from the Bureau of Economic Analysis (BEA). Unemployment rate is from the Federal Reserve Economic Data (FRED). We create a dummy variable that equals one for

[16] Please see appendix 3.1

[17] Leigh (2007) finds that these measures are useful proxies for inequality across the income distribution.

[18] See http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed his dataset based on the Internal Revenue Service (IRS), which has a limitation of omission of some individual earning less than a threshold level of gross income. For this reason, we focus more on top income shares as primary indicators of inequality measures.

[19] See http://dvn.iq.harvard.edu/dvn/.

less than 6 percent of inflation and zero otherwise to avoid the bias results as the semiparametric estimator is sensitive to outliers.

3.4 Empirical results

3.4.1 Preliminary results

Since our approach requires the use of mean reverting data, we ensure that all variables are stationary. Hence, before considering the empirical link between inflation and income inequality, we examine the stationarity properties of the variables. For this, we perform the Im, Pesaran, and Shin (2003, IPS) unit-root test, which assumes individual unit roots across each cross-section. The IPS test has the null hypothesis of a unit root. Table 3.1 presents the results. The results show that all variables used are I(1), but the growth rate (first-difference of the natural logarithm) of all the variables are stationary, which, in turn, are what we use in the model specifications. Since we use growth rates of the variables, we lose the observations corresponding to 1976.

We use the first lag of inflation as our instrumental variable. Table 3.2 reports results indicating that the instrumental variable is valid and should enter the first stage regression.

3.4.2 Main results

We choose variables that previous studies use (e.g., Johnson and Shipp 1999; Romer and Romer 1999; Cutler and Katz 1992; Bulir 2001; Easterly and Fischer 2001; Chu, Davoodi, and Gupta 2000). The dependent variable is the growth of inequality measures. We control for the growth rates of human capital attainment, of real per capita income, and of the unemployment rate. The inflation rate is instrumented by its first lag.

Figure 3.1 plot the results for the semiparametric IV estimator, which we estimate without dummy variables[20], and show the functional relationships between income inequality and

[20] Initially, we tested semiparametirc IV regression without accounting a structural break and results showed threshold around 6 percent inflation. However as there is the structural break in the dataset, we create dummy variable. Following years and states with greater than 6 percent inflation:

inflation. This relationship is nonlinear, mostly U-shaped, for the six inequality measures. Figure 3.2 plots the results when we include dummy variables, since the semiparametric estimator proves sensitive to outliers and the inflation is mostly high in the oil shock periods.[21]

We find that increasing inflation coincides with decreasing income inequality for low inflation levels and that increasing inflation coincides with increasing income inequality for high inflation levels (i.e., negative relationship between inequality and inflation below the threshold; positive relationship above the threshold). Figures 3.2.a, 2.c, 2.e show that the threshold level falls around 0.035. That is, below 3.5 percent, inflation exerts a negative relationship on income inequality, while the relationship becomes positive above the threshold. Figures 3.2.b and 2.d show that the threshold level falls around 0.02, or 2 percent. The threshold level falls around 0.056, or 5.6 percent, in Figure 3.2.f[22]. In the United States, the dynamics of income inequality mostly reflects variation in the upper end of income distribution since the early 1980's. Thus, the estimated effect of monetary policy could depend on the inequality measure used in the empirical analysis. That is, the estimated effects can differ if it does not represent the whole income share of the population, particularly the top 1-percent income share. Our results fall in line with Bulir (2001) and Galli and van der Hoeven (2001) who find a U-shaped relationship between inflation and income inequality with a threshold of around five and six percent, respectively, in the United States.

Our finding, the existence of the threshold, implies that inflation affects the income distribution due to its effect on economic growth, wage income, and the debtor-creditor

(i) From 1977-1981 50 states had higher inflation than 6 percent, except in 1980 Mississippi where inflation rate was below 6 percent. (ii) From 1988-1990 to 2004-2005, inflation rate in California and Hawaii were above 6%. The inflation rates were mostly high during the oil shock and Volcker's disinflationary periods. Since the semiparametric estimator is sensitive to outliers, we created a dummy variable that equals one when the inflation rate was less than 6 percent and zero otherwise to avoid biasing the results.

[21] Given possible endogeneity issues, we also use the first lag of the control variables in the model – the growth rates of real per capita income, of high school attainment, of college attainment, and of the unemployment rate. Our results here are qualitatively similar to the model that does not address possible endogeneity issues.

[22] For robustness, we also estimate threshold using the method suggested by Hansen (1999) and the results are presented in appendix 2. We find the results are similar to the results from the semiparametric approach.

relationship. When inflation falls below the threshold, reducing inflation could lead to a larger increase in the unemployment rate as downward rigidities hold for the nominal wage rate (Ribba 2003) and, consequently, this effect increases income inequality. When inflation is above the threshold of 2 percent, it negatively affects economic growth and increases inequality (Balcilar et al. 2014). Also, when inflation is above the threshold of 2.8 percent, it affects relative prices and increases income inequality (Kremer et al. 2013). Furthermore, when inflation is adjusted, the speed of adjustment differs as wages usually lag behind inflation. In addition, our results relate to skill-biased technological transition, which affects income inequality in the United States (Autor et al. 2008). The Federal Reserve wants to stimulate employment. When the Federal Reserve tries to maximize employment, it may affect different segments of the population differently, as the risk of unemployment differs. Also, our results relate to the level of development of the United States and the sophistication of the financial structure (Bulir and Gulde 1995; Bulir 2001; and Doepke and Schneider 2006). Financial structure influences the ability to hedge against shocks and to loosen spending constraints. Higher inflation lowers the consumption of those who experience a tight budget and who cannot borrow. The continuance of the shock positively affects inequality.

3.5 Conclusion

One important, ongoing political issue in the United States is income inequality, which has increased over the past 30 years. In the political economy argument, the redistribution of income typically comes through fiscal policy. Yet, economic activity responds to both fiscal and monetary policy. Though fiscal and monetary policies are used for comparatively different macroeconomic objectives, both policies can affect the income distribution. Fiscal policy can affect income inequality through taxes, public sector employment, government spending, and other fiscal policy instruments. Monetary policy can affect income inequality through its effect on inflation, which then can affect income distribution through the inflation rate's heterogeneous effect on sources of income.

In this study, we analyze the relationship between the inflation and income inequality for the United States Empirically, the results show that a non-linear relationship exists between inflation and income inequality for the 50 U.S. states over 1976 to 2007. This result matches Bulir and Gulde (1995), where they conclude that the inflation rate affects the inequality relationship in a non-monotonic manner. Also, Easterly and Fischer (2001) find that the well-being of the poor negatively correlates with inflation and higher inflation reduces the well-being of the poor with a non-linear factor. Bulir (2001) and Galli and van der Hoeven (2001) find that the inflation rate and inequality relationship is nonlinear and that pushing inflation below a certain threshold reverses the correlation.

Since the financial crisis, the Federal Reserve has used monetary policy aggressively to promote economic growth and regain economic stability. When the Federal Reserve conducted such aggressive monetary policy, such as cutting the federal funds rate to zero and purchasing large amount of U.S. Treasury securities and mortgage-backed securities, the possible redistributive results of monetary policy can play an important role. In spite of their effort, inequality has worsened in recent years.

In our sample period, inequality has widened and became a long-term trend relationship. Unfortunately, in current monetary system, a tendency exists for income to flow to the rich.

Each household owns different combinations of assets/debts, which makes it almost impossible to avoid the redistributive effects of monetary policy. Policymakers should explicitly consider the possible redistributive effects of monetary policy. Also, more research can determine the optimal average level of inflation as well as the redistribution effects of unconventional monetary policy, such as forward guidance and quantitative easing.

As discussed in Bulir and Gulde (1995) and Bulir (2001), the results pertain to the United States and may not extend to an international analysis.

Table 3.1. Panel unit root tests

IPS	Test Statistics	
	Level	First difference
Atkinson Index	7.972	-29.302***
Gini Coefficient	4.594	-26.935***
the Relative Mean Deviation	4.804	-26.276***
Theil's entropy Index	4.532	-21.193***
Top 10% income shares	7.390	-38.905***
Top 1% income shares	5.920	-33.431***
Consumer Price Index	-0.654	-2.597***
Real per capita income	4.373	-8.759***
High school attainment	7.281	-31.931***
College attainment	4.193	-33.234***
Unemployment rate	0.475	-20.838***

Note: Variables are in natural logarithms. *, ** and *** denote rejection of the null hypothesis of unit root at the 10%, 5% and 1% significance levels. IPS test assume asymptotic normality.

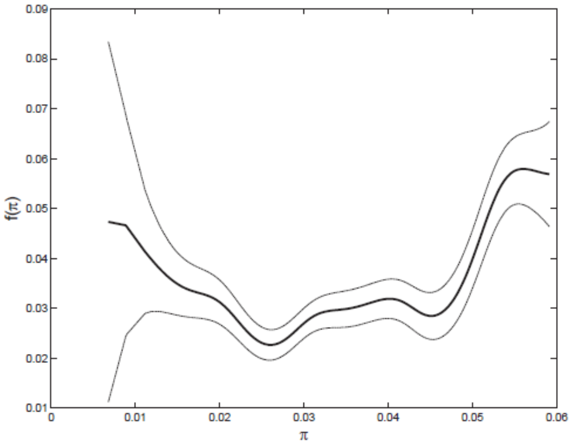
Table 3.2. Linear relationship between income inequality and inflation by OLS regression and IV estimates

Atkin05	Intercept[α]	Inflation[β]
OLS regression	0.0235*** (0.0021)	-0.1976*** (0.0418)
OLS regression on lagged inflation	0.0280*** (0.0020)	-0.3021*** (0.0413)
IV Model	0.0310*** (0.0020)	-0.3700*** (0.0510)
Gini	Intercept[α]	Inflation[β]
OLS regression	0.0068*** (0.0011)	0.0343 (0.0222)
OLS regression on lagged inflation	0.0095*** (0.0011)	-0.0280 (0.0221)
IV Model	0.0100*** (0.0010)	-0.0340 (0.0270)
Rmeandev	Intercept[α]	Inflation[β]
OLS regression	0.0075*** (0.0009)	0.0024 (0.0191)
OLS regression on lagged inflation	0.0082*** (0.0009)	-0.0155 (0.0191)
IV Model	0.0080*** (0.0010)	-0.0190 (0.0230)
Theil	Intercept[α]	Inflation[β]
OLS regression	0.0278*** (0.0037)	-0.0464 (0.0751)
OLS regression on lagged inflation	0.0469*** (0.0036)	-0.4972*** (0.0739)
IV Model	0.0520*** (0.0040)	-0.6090*** (0.0930)
Top 10%	Intercept[α]	Inflation[β]
OLS regression	0.0124*** (0.0015)	-0.0294 (0.0309)
OLS regression on lagged inflation	0.0132*** (0.0015)	-0.0480 (0.0308)
IV Model	0.0140*** (0.0020)	-0.0590 (0.0380)
Top 1%	Intercept[α]	Inflation[β]
OLS regression	0.0498*** (0.0052)	-0.4310*** (0.1063)
OLS regression on lagged inflation	0.0349*** (0.0052)	-0.0786 (0.1065)
IV Model	0.0360*** (0.0060)	-0.0960 (0.1300)
F-statistics		
3128.0347***		

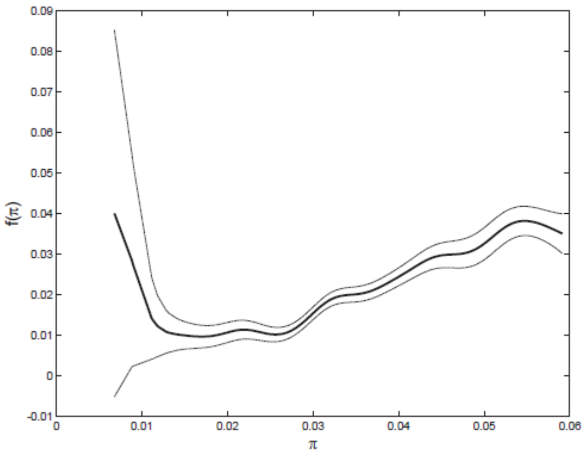
Note: OLS model is the estimate of $g_t = \alpha + \beta\pi_t + \varepsilon_t$ while OLS-lagged estimates $g_t = \alpha + \beta\pi_{t-1} + \varepsilon_t$ using non-instrumental OLS estimation. IV models are estimated by two stage least squares using the first lag of inflation as an instrument. F-statistic is from the estimates of the IV auxiliary regression and indicates that the first lag of inflation is valid as an instrument. *, ** and *** denote significance at the 10%, 5% and 1%, respectively.

Figure 3.1. Semiparametric IV estimates (without dummy variable)

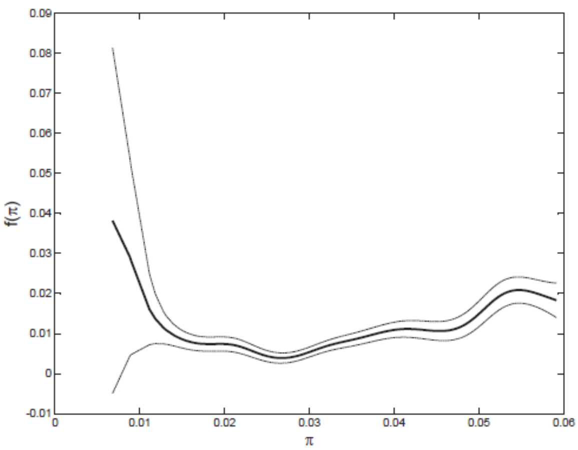
(a) Atkinson Index



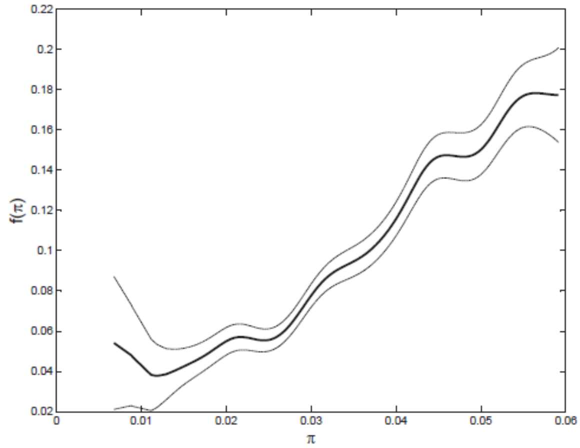
(b) Gini Coefficient



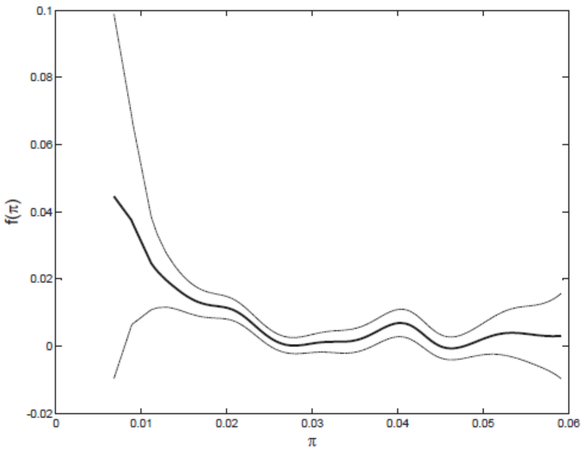
(c) The Relative Mean Deviation



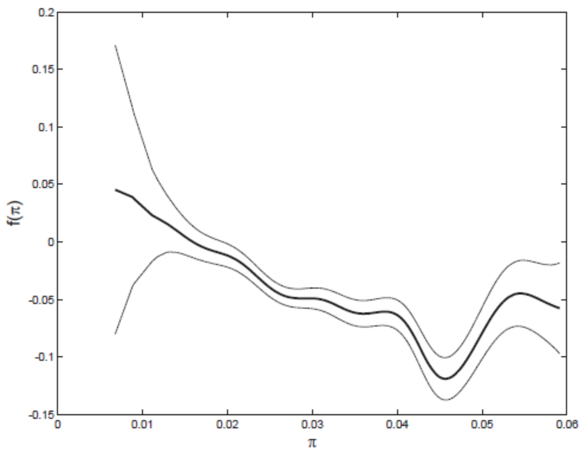
(d) Theil's entropy Index



(e) Top 10% income share



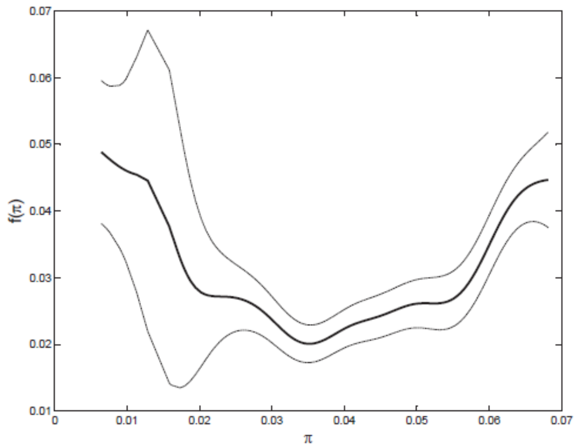
(f) Top1% income share



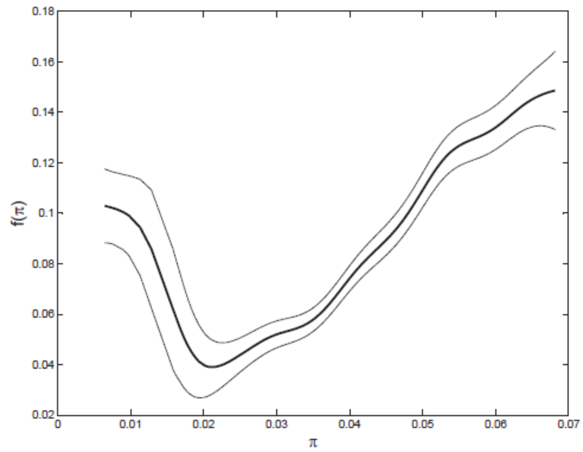
Note: As all variables used are in growth form, slope of figures indicate the relationship between the inequality measures, which is y-axis, and the inflation, which is x-axis. The estimation method is suggested by Park (2003).

Figure 3.2. Semiparametric IV estimates (with dummy variable)

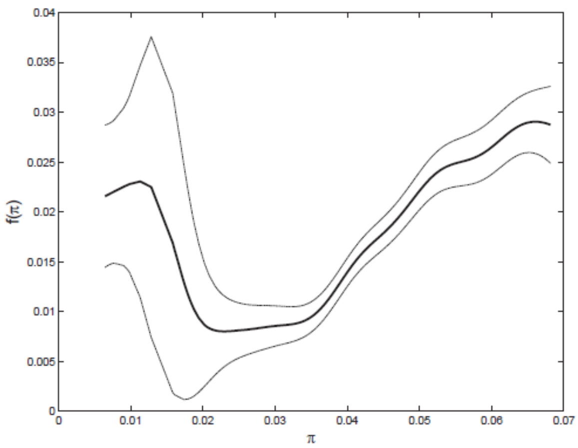
(a) Atkinson Index



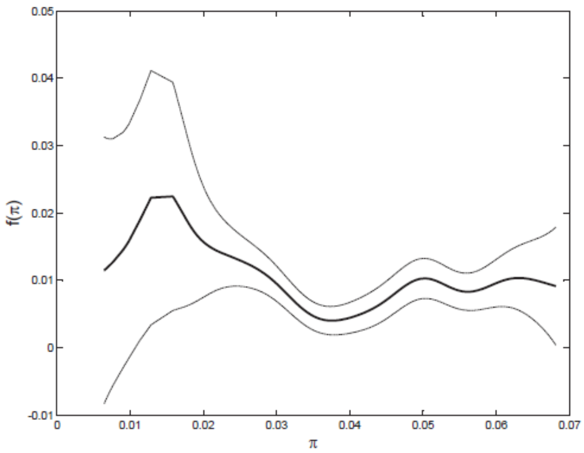
(d) Theil's entropy Index



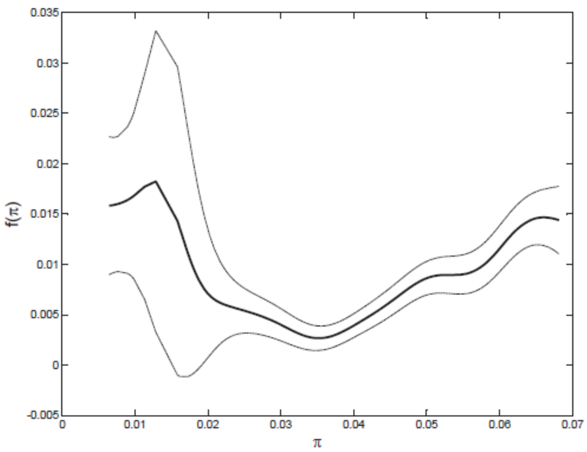
(b) Gini Coefficient



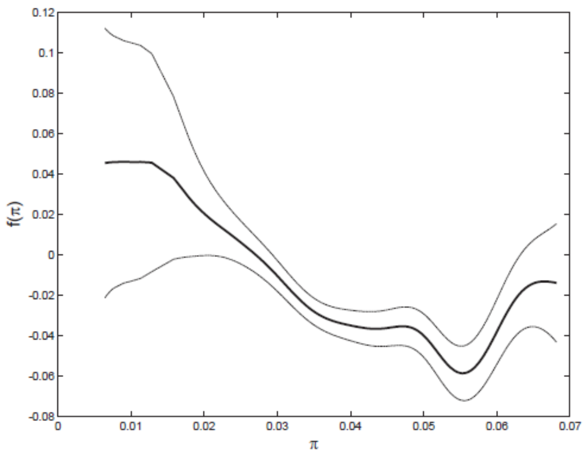
(e) Top 10% income share



(c) The Relative Mean Deviation



(f) Top1% income share



Note: As all variables used are in growth form, slope of figures indicate the relationship between the inequality measures, which is y-axis, and the inflation, which is x-axis. The estimation method is suggested by Park (2003).

Appendix 3.1. Semiparametric regression model by Park (2003)

Park (2003) considers a semiparametric regression model in which the error term is correlated with the nonparametric part. Although they cannot eliminate the nonparametric part in the two-step estimation procedure, they can still obtain a semiparametric estimator with consistency and asymptotic normality with two existing sets of instrumental variables which meet an orthogonality conditions.

The regression model takes the form

$$g_t = \phi x_t + f(\pi_t) + \varepsilon_t \text{ , } t = 1, \dots, T$$

with

$$E[\varepsilon_t | \pi_t] \neq 0$$

The author considers a case in which an error term, $\varepsilon_t \in R,$ is correlated with a nonparametric part, say $f(\pi_t)$, where π is an unknown function from $R^1$to R.

Appendix 3.2. Results of Hansen (1999) threshold method

Estimate of threshold **with dummy**	Estimate	95% confidence interval
Atkinson Index	0.0240	[0.0223 0.0240]
Gini Coefficient	0.0291	[0.0287 0.0292]
the Relative Mean Deviation	0.0327	[0.0308 0.0328]
Theil's entropy Index	0.0286	[0.0281 0.0287]
Top 10% income shares	0.0240	[0.0238 0.0242]
Top 1% income shares	0.0476	[0.0473 0.0478]
Estimate of threshold **without dummy**	Estimate	95% confidence interval
Atkinson Index	0.0240	[0.0240 0.0240]
Gini Coefficient	0.0291	[0.0287 0.0292]
the Relative Mean Deviation	0.0661	[0.0634 0.0676]
Theil's entropy Index	0.0661	[0.0623 0.0676]
Top 10% income shares	0.0240	[0.0238 0.0242]
Top 1% income shares	0.0476	[0.0472 0.0478]

Note: The estimation method is suggested by Hansen (1999).

Chapter 4

Causality between Personal Income and Income Inequality: A Heterogeneous Mixed Panel approach[23]

4.1 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 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; Persson 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.

[23] Accepted in Journal of Income Distribution

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 decentralization 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 analyze 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 analyze 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 analyze 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 (1992) 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[24].

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

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

4.2 Data

Our analysis relies on the natural logarithm of U.S. per capita real personal income and the six income inequality measures[25] - 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 online data segment of Professor Mark W. Frank's website.[26] 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.

4.3 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.

4.3.1 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

[25] 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.

[26] 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.

following panel-data estimation:

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

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 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

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

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.

4.3.2 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 $(N, T) \to \infty$ 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)[27]:

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

where $\breve{\beta}_i$ is the pooled OLS estimatoer, $\tilde{\beta}_{WFE}$ is the weighted fixed effect pooled estimator,

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

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:

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

Under the null hypothesis with the condition of $(N,T) \to \infty$ (as long as $\sqrt{N}/T \to \infty$) 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 the following bias-adjusted version:

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

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 4.1 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 4.1 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.

4.3.3 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:

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

$$y_{i,t} = \mu_i^y + \sum_{j=1}^{k_i+d\max_i} A_{21,ij}\, x_{i,t-j} + \sum_{j=1}^{k_i+d\max_i} A_{22,ij}\, y_{i,t-j} + u_{i,t}^y, \tag{8}$$

where i $(i = 1, \dots, N)$ denotes individual cross-sectional units; t $(t = 1, \dots, T)$ 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.

4.4 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 4.1, 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 4.1 (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 4.2 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 4.2 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 4.3 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 4.4 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 4.5 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 4.6 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 4.7 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).

4.5 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 labor 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.

Table 4.1. 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 4.2. 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 4.3. 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 4.4. 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 4.5. 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 4.6. 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 4.7. 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 4.8. 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

Chapter 5

Does Financial development affect Income Inequality in the U.S. states? A panel data analysis

5.1 Introduction

Conventional wisdom identifies the United States as a land of opportunity, where those who work hard can succeed. The past three-and-a-half decades, however, witnessed growing income inequality (Owyang and Shell 2016; Thompson and Leight 2012). Some argue that inequality results from individual effort and represents a constructive factor in society. Others argue that inequality emerges from an unfair system, which lifts only a few boats at high tide and, thus, creates a disincentive to hard work (Bivens et al. 2014; Stiglitz 2012; Levy and Temin 2011).

The current trend in U.S. inequality creates a number of problems. For instance, low-income groups experience much difficulty in accessing financial and credit markets, and these market imperfections can influence occupational outcomes of low-income individuals. The poor more likely become salary earners and the rich, entrepreneurs. Also, we observe that economic mobility has diminished in recent decades. The children of wealthy parents more likely remain wealthy, and the children of the poor, remain poor (Galor and Zeira 1993; Corak 2016). This reduction in mobility across the income distribution can undermine the confidence in the principles of market economies.

A most potent force driving the increase in U.S. income inequality from the 1970s through the early 2000s reflects the trend strength of the stock market (Favilukis 2013; Hungerford 2013). Hungerford (2013) shows that capital gains and dividends contributed to a near doubling of income inequality between 1991 and 2006. As stock and other asset prices rise, the gains disproportionately accrue to the rich, since the wealth is more unequally distributed than income. That is, the low-income group holds minuscule wealth and cannot participate in wealth accumulation in any significant way. During the 2001 and 2007 recessions and financial turmoil, top income fell significantly as stock and other asset prices experienced significant declines, but the recovery of losses did occur.

Many studies consider the possible factors influencing changes in the income distribution.[28] This paper considers the effect of financial development. The focus of much of financial development theory explores how financial institutions fund new investment. Theoretically and empirically, the research leads to ambiguous findings.

Theoretically, more finance makes it easier for the poor to borrow for viable projects/business, which, in turn, can reduce income inequality (Galor and Moav 2004). Financial imperfections, such as asymmetric information and moral hazard, can hinder the poor who lack collateral and credit histories, and, therefore, relaxation of credit constraints may benefit the poor (Beck et al. 2007). Demirgüç-Kunt and Levine (2009) show that finance affects income inequality (i.e., income distribution) in two ways -- the extensive and intensive margins. The extensive margin affects the number of individuals using financial services, adding individuals from the lower end of the income distribution. Thus, the extensive margin effects reduce inequality. The intensive margin refers to the improvements in the quality and range of financial services. The intensive margin does not broaden access to financial service, but benefits those already using financial services (Demirgüç-Kunt and Levine 2009). In other words, the benefit of intensive margin effects will likely widen the distribution of income.

Other modeling approaches support a nonlinear relationship between finance and income distribution.[29] Greenwood and Jovanovic (1990) find an inverted U-shaped curve of income inequality and financial intermediary development. At early stages of financial development, only a few wealthy individuals can access financial markets. With economic growth, however,

[28] See Claessens and Perotti (2007) and Demirgüç-Kunt and Levine (2009) for broad reviews of the literature.
[29] See Greenwood and Jovanovic (1990), Greenwood and Smith (1997), Deidda (2006), and Townsend and Ueda (2006).

more people can join the financial system and more individuals can enjoy the benefits. Thus, income inequality increases initially. As the economy matures, however, income inequality falls.

Clarke et al. (2006) also suggest a non-linear relationship that more (less) developed financial systems tend to associate with less (more) income inequality. That is, a well-functioning financial system more likely reinforces low inequality, while an underdeveloped financial system reinforces high inequality. Moreover, various combinations of financial development and inequality may produce a non-linear relationship.

Empirical evidence on the relationship between financial development and income inequality gives mixed results. Rajan and Zingales (2003) argue that in weak institutional environments, established interests have privileged access to finance. Thus, financial development induced by captured direct controls likely hurts the poor. Haber (2005) maintains that primarily the well-off and politically connected benefit from improvements in the financial system. Van der Weide and Milanovic (2014) discover that high levels of inequality reduce income growth of the poor and boost the income growth of the rich. De Haan and Sturm (2016, 2017) examine how financial development, financial liberalization[30], and banking crises affect within-country income inequality, using cross-country panel data from 1975-2005. The authors find robust results that all financial variables increase income inequality. Also, de Haan et al. (2017) demonstrate that financial development strengthens the inequality-raising effects of financial liberalization. Jaumotte et al. (2013) use panel data of 51 countries over 1981-2003 and report that financial globalization, especially foreign direct investment, is associated with an increase in inequality. Gozgor and Ranjan (2017) also look at if globalization increases in the distribution of income and show the positive

[30] Financial liberalization refers to a reduction in the role of government and an increase in the role of financial markets and financial development refers to an increase in the volume of financial activity (Abiad et al. 2008).

relationship between globalisation and inequality as well as between globalization[31] and that redistribution is much stronger for OECD countries than for non-OECD countries.

On the other hand, Bulir (2001), Honohan (2004), Beck et al. (2007), and Naceur and Zhang (2016) show that financial development alleviates inequality and poverty. Dollar and Kraay (2002) report that more access to financial and credit markets helps to reduce inequality. Law et al. (2014) say that in the presence of strong institutions, financial development can reduce inequality, allowing the poor to invest in human and physical capital.

U.S. policy has focused more on growth than inequality, since economic growth may ease the inequality problem. Productivity growth, however, has not trickled down to the bottom of the income distribution, and income inequality has not necessarily moved with the business cycle. Furthermore, many studies suggested that too much income inequality might itself be detrimental to long-run economic growth (Alesina and Rodrik 1994; Birdsall et al. 1995; Deininger and Squire 1996; Persson and Tabellini 1992; Sylwester 2000; Easterly and Fischer 2001; Easterly 2007).

With growing size of the stock market, the financial crises have challenged traditional financial sector policies and leave little doubt that financial development indeed matters for income inequality. Given this theoretical background, we conduct an empirical analysis of the role of financial development on inequality.

Inequality has increased throughout almost every U.S. state between 1970 and the present. For example, New York and Connecticut experienced substantially greater increases in inequality than other states (Partridge et al. 1996; Partridge et al. 1998; Morrill 2000; Dvorkin and Shell 2015). Our contribution lies with the usage of cross-state data of the US for the first time in this line of literature dealing with financial development and inequality. We consider

[31] Globalization is considered to stimulate global economic growth and enhance social progress, however, it can also raise income inequality and labor-supply competition. There are studies focus on the impact of financial globalization on the income inequality since financial globalization is substantively changing where firms and households access capital and financial services. See, for example, Gozgor and Ranjan (2017) for theoretical and empirical implications of globalization for inequality and redistribution.

the effect of financial development on income inequality across all states and in states with higher and lower inequality than the cross-sectional average of inequality. Even though the U.S. states differ from each other, using cross-state panel data minimizes not only the differences in institutions and political regimes, but also problems associated with data comparability involving the measurement of inequality, and the various variables that drive inequality across countries.

Our analysis employs the fixed-effects model, given the panel data and research purposes. Nevertheless, to check the robustness of the results to the estimation technique, we also employ the dynamic fixed-effects and system-GMM models.

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

5.2 Data

The analysis relies on a cross-state panel from 1976 to 2011, which includes the U.S. stock market wealth, human capital measures, the unemployment rate, and three income inequality measures, the Gini coefficient as well as the Top 10%, and the Top 1% income shares (Leigh 2007).[32] The income inequality measures and human capital measures come from the online data of Professor Mark W. Frank's website.[33] Annual and quarterly per capita nominal state personal income comes from the Bureau of Economic Analysis (BEA). The unemployment rate comes from the Federal Reserve Economic Data (FRED). U.S. (aggregate) Consumer Price Index comes from Bureau of Labour Statistics (Index 1982-84=100), which we use to deflate the per capita nominal state personal income. As a measure of volatility, we calculate

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[32] For robustness, we also employ other inequality measures such as Atkinson Index, the Relative Mean Deviation, Theil's entropy Index, the Top 5% income share, the Top 0.1% income share and the Top 0.01% income share. We report these results in the Appendix.

[33] See http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed his dataset based on the Internal Revenue Service (IRS), which has a limitation of omission of some individual earning less than a threshold level of gross income. For this reason, we focus more on top income shares as primary indicators of inequality measures.

the annual realized volatility by summing the squared quarterly growth rates of real personal per capita state income.

We need a good measure of financial development to answer our question of the effect of financial development on inequality. A poor measure leads to a poor answer. It is difficult to measure financial development, since the financial sector comprises a mixture of financial markets, institutions, and banks. In this paper, we adopt the ratio of nominal per capita stock market wealth to nominal per capita personal income as our measure of financial development[34]. It captures a component of financial development that relates more closely with production. Quarterly state-level U.S. stock market wealth data come from calculations by Case et al. (2013). We convert quarterly observations to annual data by taking an average. This is virtually the only data set that has financial wealth (and housing wealth) disaggregated to the state level (including District of Columbia). This dataset approximates per capita consumption at the state level by total retail sales. Further note that Case et al. (2013) restricted the growth rate in household financial wealth solely to the growth rate in households' holdings of mutual funds due to data availability.[35]

Since the U.S. stock market wealth data ends in 2012:Q2, the data range runs from 1976 to 2011 based on data-availability of all the variables under consideration at an annual frequency. Except for the unemployment rate and the measure of volatility, we express the variables as growth rates taking logarithmic differences, which, in turn, ensures stationarity of the variables under investigation, as suggested by standard panel data-based unit-root

[34] According to Gimet and Lagoarde-Segot (2011), who examine specific channels linking banks, capital markets, and income inequality, the effect of financial sector development on income inequality seems to run primarily via the banking sector. We also examine two other ratios: bank deposits to personal income and bank deposits plus saving institutions deposits to personal income from 1976 to 2013 as alternative measures of financial development. With these measures, however, we do not find any significant role for financial development on inequality. The increase in U.S. income inequality from the 1970s was accompanied by strong gains in the stock market (Owyang and Shell, 2016). In addition, stock market participation has increased, irrespective of investor's risk tolerance and financial sophistication. Given this, stock market movements may capture the financial sector better through bigger effects on income than those tracked by deposits and, hence, possibly explaining the insignificant results.

[35] Bampinas et al. (2017) recently use this data set to analyze wealth effects controlling for inequality and demographic factors.

tests.[36] As noted above, the use of cross-state panel data minimizes the problems associated with data comparability often encountered in cross-country studies related to income inequality. In addition, it must be pointed out that the choice of the various predictors of inequality is in line with the extant literature (see Balcilar et al. (2017) for a detailed discussion in this regard).

5.3 Methodology and model specification

The models are specified as follows:

$$Ineq_{it} = \alpha_i + \beta_{it}FD_{it} + \gamma_{it}FD^2{}_{it} + u_{it} \tag{1}$$

$$Ineq_{it} = \alpha_i + \beta_{it}FD_{it} + \gamma_{it}FD^2{}_{it} + \delta_{it}PI_{it} + \eta_{it}PI^2{}_{it} + \kappa_{it}UE_{it} + \mu_{it}HS_{it} + \nu_{it}CL_{it} + \rho_{it}V_{it} + u_{it} \tag{2}$$

$$Ineq_{it} = \alpha_i + \beta_{it}FD_{it-1} + \gamma_{it}FD^2{}_{it-1} + u_{it} \tag{3}$$

$$Ineq_{it} = \alpha_i + \beta_{it}FD_{it-1} + \gamma_{it}FD^2{}_{it-1} + \delta_{it}PI_{it-1} + \eta_{it}PI^2{}_{it-1} + \kappa_{it}UE_{it-1} + \mu_{it}HS_{it-1} + \nu_{it}CL_{it-1} + \rho_{it}V_{it-1} + u_{it} \tag{4}$$

for $i = 1,2,\dots,N\,;\, t = 1,2,\dots,T$,

where *Ineq* = Income inequality

FD = Financial development

FD^2 = Squared financial development

PI = Real per capita personal income

PI^2 = Squared real per capita personal income

UE = Unemployment rate

HS = High school attainment

CL = College attainment

[36] Complete details of the unit-root tests are available on request from the authors. To ensure that our econometric framework is not misspecified when estimated using stationary variables and, hence possibly ignoring a long-run relationship between (the various measures) of inequality and its drivers in their non-stationary form, we also tested for cointegration. Using Westerlund's (2007) test, however, we were unable to detect any evidence of cointegration, which, in turn, suggests that our models in first differences are not misspecified by omitting an error-correction term. In addition, inclusion of time-effects in our econometric models produces qualitatively similar results. Complete details of these additional analyzes are available on request from the authors.

RV = Volatility measure

We include squared variables to capture non-linearities, if any. We also include the measure of volatility according to the study by Fang et al. (2015), where the authors found that larger growth volatility positively and significantly associates with higher income inequality. We note that the explanatory variables can suffer from endogeneity and, therefore, we employ lagged values of the explanatory variables (as instruments) to address the endogeneity issue. As lagged variables do not appear in the respective estimation equation and they sufficiently correlate with the explanatory variables, this approach can prove effective.

5.4 Empirical analysis

Table 5.1 shows the results of the fixed-effect regression of the Top 10%, Top 1%, and Gini coefficient for all states. The overall results show that financial development exerts a positive effect on income inequality with no evidence of non-linearity.[37] Higher real per capita personal income contributes to the rise in income inequality, especially for the Top 1% income group. Volatility also makes the distribution of income more unequal, which supports the findings in Fang et al. (2015). We do not find that the unemployment rate and the level of education significantly affect income inequality.

To control for endogeneity, we include lagged values of the explanatory variables in the regressions. We do not use second and higher lags to avoid autocorrelation with the current error term. Table 5.2 reports the results. Our findings of the effect of financial development on income inequality are robust.

Tables 5.3 and 5.4 show the results of the fixed-effect regression of the Gini coefficient, the Top 10%, and the Top 1% income inequality measures, when we divide the data into two

[37] Our results remain robust to alternative specifications, which incorporates the first lag of the growth of inequality to capture possible persistence (see Table 5.1 in the Appendix). We also applied system-GMM, which deals with issues of endogeneity and reverse causality. The regression results (see Table 5.5 in the Appendix) indicate that the fixed-effects and system-GMM estimates are generally similar.

sets -- states with higher and lower inequality than the cross-sectional average.[38] We list the low and high inequality states in Appendix 5.6 and also plotted in Appendix 5.1 in the map of the U.S. The results not only show the positive relationship between financial development and income inequality, but also indicate the existence of non-linearity between the two variables, except for the Top 0.5%, 0.1% and 0.01% measures of income inequality, which show a linear relationship.[39] These results indicate that the effect of financial development increases inequality at an increasing rate for those states above the average income inequality. The threshold level of financial development ($-\beta/2\gamma$) is -0.013 (see Table 5.3), and, hence, the reduction of inequality can only occur at negative growth rates (contraction) of the financial sector

For states with lower income inequality, the results indicate an inverted U-shaped non-linear relationship between two variables with threshold level of financial development ($-\beta/2\gamma$) around 0.015 (see Table 5.4). This implies that gap of income distribution increases up to financial development reaches its threshold. After the threshold level, financial development reduces income inequality. Results of fixed effect regressions with other inequality measures - Atkinson Index, the Relative Mean Deviation (Rmeandev), Theil's entropy Index and Top 5, 0.5, 0.1 and 0.01 % income shares – indicate the same results of the role of financial development (See Appendix 5.2, 5.3 and 5.4). We can see volatility matters for inequality. For Top 0.5%, 0.1% and 0.01%, interesting results emerge with contemporaneous variables (see Appendix 5.2). The results indicate an inverted U-shaped non-linear relationship between income inequality and real per capita personal income, which proxies for economic growth. This finding supports Kuznets curve (Kuznets 1955).

[38] We first compute average cross-sectional inequality for each year and then take the average of the cross-sectional average. We then compare the average of the cross-sectional average with the average inequality for each state.

[39] Please see Appendix 5.3 in the appendix for the results of the Atkinson Index, the Relative Mean Deviation, Theil's entropy Index, and the Top 5, 0.5, 0.1 and 0.01 % income inequality measures.

5.5 Conclusion

The rising income inequality in the United States for the past three-and-a-half decades portrays more than a story of New York City, the hub of the financial sector. While many of the high-income earners live in states such as New York and Connecticut, IRS data confirm that rising income inequality (e.g., increases in the Top 1% share) affects every state.

In this paper, we implemented the fixed-effect panel regression to test for the existence of causal relationships between financial development and income inequality, using annual data for the 50 U.S. states from 1976-2011.

We find that financial development positively affects income inequality, which supports the findings of van der Weide and Milanovic (2014) and de Haan et al. (2017). A linear relationship exists in 50 U.S. states between financial development and income inequality. Also, the unemployment rate does not significantly affect income inequality.

A general discussion exists about income inequality in the United States across generations. That is, investment in education and human capital, using current generations' resources, will bear fruit in next generation. For instance, giving children good education will equip them to succeed and achieve higher incomes (Heinrich and Smeedling 2014). Although more higher education leads to higher lifetime earnings, our paper finds no evidence of a significant effect on income inequality.

When we divide the states into two group based on their position relative to the average income inequality, a non-linear relationship exists between financial development and income inequality, except for the Top 0.5%, 0.1% and 0.01% income shares. For higher income states, income inequality decreases up to the percentage where financial development reaches its threshold. After the threshold level, a growing financial sector increases income inequality at an increasing rate. For lower income states, a growing financial sector increases income inequality at a slower rate until financial development reaches its threshold level.

Once financial development passes the threshold level, income inequality begins to fall. This finding supports the inverted U-shaped relationship suggested by Greenwood and Jovanovic (1990), but only for lower income inequality states.

A number of cross-country studies examine the role of financial development on income inequality. Denk and Cournède (2015), using data from OECD/developed countries over the past three decades, analyze the relationship between finance and income inequality. The authors found that more finance associate with higher income inequality (see also Rodriguez-Pose and Tselios 2009; Fournier and Koske 2013). Some of cross-country studies also find non-linear relationships. Nikoloski (2013) and Kim and Lin (2011) analyze income inequality data for developed and developing countries, the authors find robust empirical evidence for the existence of an inverted U-curve relationship between financial sector development and income inequality. Based on our results as well as the existing cross-country studies, whether financial development effect depends on the initial level of income inequality proves an interesting topic for future research.

Table 5.1. Results of fixed-effect regression for 50 U.S. states

Contemporaneous variables	Baseline						Baseline+Controls					
	Top10% Coefficient		Top1% Coefficient		Gini Coefficient		Top10% Coefficient		Top1% Coefficient		Gini Coefficient	
Financial development	0.0472	***	0.1225	***	0.0269	***	0.0491	***	0.1218	***	0.0277	***
Financial development^2	-0.0004		-0.0088		-0.0007		-0.0003		-0.0082		-0.0005	
Income							0.2117		1.3525	***	0.1102	***
Income^2							0.6890		-6.5033	***	0.2390	
Unemployment rate							-0.0002		0.0028	**	-0.0002	
High school attainment							0.0394		0.1081		-0.0225	
College attainment							-0.0107		-0.0515		0.0210	**
Volatility							1.2894	***	4.6205	***	0.6394	
Constant	0.0076	***	0.0149	***	0.0058	***	0.0023		-0.0246	**	0.0039	***

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. “Income” is real per capita personal income and “Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Table 5.2. Results of fixed-effect regression for 50 U.S. states

Lagged variables	Baseline						Baseline + Controls					
	Top10% Coefficient		Top1% Coefficient		Gini Coefficient		Top10% Coefficient		Top1% Coefficient		Gini Coefficient	
Financial development	0.0275	***	0.1032	***	0.0158	**	0.0278	***	0.1059	***	0.0164	**
Financial development^2	0.0006		-0.0036		-0.0014		0.0009		-0.0029		-0.0013	
Income							-0.0098		0.0255		-0.0224	
Income^2							-2.5824	*	-3.2191	*	0.6411	
Unemployment rate							-0.0005		0.0003		-0.0004	
High school attainment							0.0578		0.2316	**	-0.0152	
College attainment							-0.0075		-0.0513		0.0217	**
Volatility							1.1165	*	1.1151		0.3539	**
Constant	0.0083	***	0.0158	***	0.0063	***	0.0107	**	0.0125		0.0073	***

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. “Income” is real per capita personal income and “Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Table 5.3. Results of fixed-effect regression for states with high inequality

Baseline + Controls	Contemporaneous						Lagged					
	Top10% Coefficient		Top1% Coefficient		Gini Coefficient		Top10% Coefficient		Top1% Coefficient		Gini Coefficient	
Financial development	0.0671	***	0.2082	***	0.0420	***	0.0408	**	0.1330	***	0.0216	**
Financial development^2	0.0264	***	0.0751	***	0.0160	***	0.0136	**	0.0447	***	0.0067	**
Income	0.5890	***	1.4007	**	0.1670	***	-0.2050		0.0134		-0.0027	
Income^2	1.3714		-6.5202	***	1.4176	***	2.4989		-2.1272		1.2813	**
Unemployment rate	0.0024	***	0.0022		0.0000		-0.0005		-0.0006		-0.0002	
High school attainment	-0.0059		0.1249		-0.0442		0.0370		0.0984		-0.0431	
College attainment	0.0260		0.0287		0.0283	**	0.0125		0.0791		0.0316	**
Volatility	1.3879	***	5.3900	***	0.7776	***	-0.6158	**	1.7656	*	0.2280	
Constant	-0.0177	***	-0.0239		0.0017		0.0145	*	0.0182		0.0071	***
Threshold level of development $(-\beta/2\gamma)$ (%)	-1.2724		-1.3861		-1.3107		-1.4976		-1.4858		-1.6012	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Table 5.4. Results of fixed-effect regression for states with low inequality

Baseline + Controls	Contemporaneous						Lagged					
	Top10% Coefficient		Top1% Coefficient		Gini Coefficient		Top10% Coefficient		Top1% Coefficient		Gini Coefficient	
Financial development	0.0706	***	0.1615	***	0.0401	***	0.0372	***	0.1830	***	0.0271	***
Financial development^2	-0.0217	***	-0.0589	***	-0.0128	***	-0.0083	**	-0.0588	***	-0.0094	***
Income	-0.0406		1.3099	***	0.0578		0.0862		0.1657		-0.0314	
Income^2	1.3660		-7.1706	**	0.1452		-4.2044	***	-8.8489	***	0.4438	
Unemployment rate	-0.0018	**	0.0028	***	-0.0005		-0.0008		0.0024	**	-0.0003	
High school attainment	0.0774		0.1338		0.0001		0.0865		0.3871	***	0.0172	
College attainment	-0.0251		-0.0996	**	0.0156		-0.0210		-0.1256	**	0.0137	
Volatility	0.8962	***	3.4529	***	0.5603	*	1.6740	***	0.1597		0.4258	**
Constant	0.0126	*	-0.0256	***	0.0043		0.0091	*	-0.0034		0.0048	
Threshold level of development $(-\beta/2\gamma)$ (%)	1.6302		1.3707		1.5641		2.2448		1.5559		1.4385	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.1. Results of dynamic fixed-effect regression for 50 U.S. states

Contemporaneous variables	Baseline + Controls																			
	Top10%		Top1%		Gini		Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Dynamic variable	-0.2981	***	-0.4264	***	0.1057	**	-0.0527		0.0057		0.1723	***	-0.3648	***	-0.4369	***	-0.4423	***	-0.4593	***
Financial development	0.0601	***	0.1926	***	0.0263	***	0.0873	***	0.0280	***	0.1242	***	0.0950	***	0.2005	***	0.2597	***	0.2828	***
Financial development^2	-0.0010		-0.0099		-0.0006		-0.0040		-0.0001		-0.0073		-0.0032		-0.0127		-0.0149		-0.0241	
Income	0.3184	**	1.8201	***	0.1052	***	0.4997	***	0.1020	**	0.8873	***	0.7652	***	2.1357	***	2.9519	***	3.5810	***
Income^2	1.4840	*	-5.5854	***	0.1986		-2.0970	**	0.1170		-0.8711		0.5418		-7.2540	***	-12.6313	***	-21.3001	***
Unemployment rate	-0.0009		-0.0002		-0.0001		-0.0015	**	0.0001		0.0000		-0.0006		0.0010		0.0034	*	0.0042	
High school attainment	0.0372		0.0967		-0.0174		0.0344		-0.0191		0.0430		0.1063	*	0.0896		-0.0055		-0.0273	
College attainment	-0.0154		-0.0555	*	0.0207	**	-0.0084		0.0110	**	0.0011		-0.0454	**	-0.0336		-0.0397		-0.0908	
Volatility	1.3662	***	5.7141	***	0.6046	***	0.9779	***	0.4700	**	1.2803	***	1.3669	***	7.8246	***	12.9289	***	20.2393	***
Constant	0.0069		-0.0091		0.0026		0.0106	**	0.0021		-0.0013		0.0030		-0.0189		-0.0379	**	-0.0410	*
Lagged variables	Baseline + Controls																			
	Top10%		Top1%		Gini		Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Dynamic variable	-0.2449	***	-0.3188	***	0.1125	***	-0.0220		0.0182		0.2263	***	-0.2762	***	-0.3379	***	-0.3496	***	-0.4039	***
Financial development	0.0384	***	0.1433	***	0.0136	**	0.0642	***	0.0199	***	0.0503	***	0.0735	***	0.1560	***	0.1904	***	0.1933	***
Financial development^2	0.0006		-0.0063		-0.0011		-0.0019		-0.0012		0.0016		0.0001		-0.0063		-0.0021		0.0029	
Income	-0.0037		0.3021	**	-0.0285		0.1448	***	-0.0392	***	-0.0822		0.1744	**	0.2347	*	0.2725	*	0.7062	***
Income^2	-1.9330		-3.6201	**	0.5393		-0.8272		0.6302		0.9484		-2.4985	*	-4.3877	***	-4.0461	**	-4.3397	
Unemployment rate	-0.0012	*	-0.0009		-0.0003		-0.0009	*	0.0000		-0.0015	*	-0.0004		-0.0011		-0.0002		0.0012	
High school attainment	0.0608		0.2288	**	-0.0102		0.0689		-0.0087		0.1054		0.1476	**	0.2594	**	0.2393		0.2523	
College attainment	-0.0114		-0.0516		0.0213	**	-0.0040		0.0118	*	0.0019		-0.0381		-0.0316		-0.0409	*	-0.0958	
Volatility	1.0122	**	1.3206	**	0.3292	**	-0.2851	*	0.1893		-0.9653	***	0.0485		2.5364	***	4.9557	***	9.7231	***
Constant	0.0165	***	0.0212	**	0.0063	***	0.0137	***	0.0054	***	0.0241	***	0.0143	**	0.0252	**	0.0265	**	0.0215	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.2. Results of fixed-effect regression for 50 U.S. states

Contemporaneous variables	Baseline + Controls													
	Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Financial development	0.0853	***	0.0281	***	0.1325	***	0.0665	***	0.1148	***	0.1412	***	0.1194	***
Financial development^2	-0.0039		-0.0001		-0.0081		-0.0016		-0.0099		-0.0130		-0.0194	
Income	0.4782	***	0.1028	**	0.9796	***	0.5531	***	1.6250	***	2.2891	***	2.8774	***
Income^2	-2.2099	**	0.1202		-0.9825		-0.3923		-7.7652	***	-12.6429	***	-20.4211	***
Unemployment rate	-0.0012	**	0.0001		-0.0019	*	0.0010		0.0040	***	0.0064	***	0.0075	***
High school attainment	0.0346		-0.0194		0.0220		0.0735		0.1176		0.0685		0.1402	
College attainment	-0.0079		0.0110	**	-0.0025		-0.0306		-0.0289		-0.0329		-0.0858	
Volatility	0.9527	***	0.4717	**	1.5110	***	1.2424	***	6.3388	***	10.1771	***	14.8796	***
Constant	0.0086	*	0.0021		0.0118		-0.0063		-0.0344	**	-0.0535	***	-0.0595	***
Lagged variables	Baseline + Controls													
	Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Financial development	0.0625	***	0.0204	***	0.0772	***	0.0571	***	0.1172	***	0.1390	***	0.1403	***
Financial development^2	-0.0018		-0.0012		-0.0006		0.0009		-0.0020		0.0040		0.0128	
Income	0.1386	***	-0.0384	***	0.0774		0.0827		-0.1202		-0.2642		-0.1038	
Income^2	-0.8058		0.6438		1.1734		-2.9709	**	-4.1195	**	-3.0806		-0.6130	
Unemployment rate	-0.0008		-0.0001		-0.0030	***	0.0005		-0.0003		-0.0003		0.0000	
High school attainment	0.0684		-0.0095		0.0822		0.1196	*	0.2802	**	0.2997	*	0.4199	*
College attainment	-0.0039		0.0119	*	-0.0012		-0.0277		-0.0312		-0.0405		-0.1005	
Volatility	-0.2860	*	0.1899		-0.9136	***	0.2497		2.1440	***	3.7875	***	6.0735	***
Constant	0.0129	***	0.0056	***	0.0353	***	0.0072		0.0187	*	0.0245		0.0238	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. “Income” is real per capita personal income and “Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.3. Results of fixed-effect regression for states with high inequality

Contemporaneous variables	Baseline + Controls													
	Atkinson Coefficient		Rmeandev Coefficient		Theil Coefficient		Top5% Coefficient		Top0.5% Coefficient		Top0.1% Coefficient		Top0.01% Coefficient	
Financial development	0.1303	***	0.0438	***	0.1918	***	0.1036	***	0.1055	**	0.1256	**	0.1093	**
Financial development^2	0.0475	***	0.0168	***	0.0688	***	0.0385	***	-0.0077		-0.0095		-0.0154	
Income	0.5957	***	0.2075	***	1.1830	***	1.1071	***	1.7041	***	2.3449	***	3.2226	***
Income^2	-1.4846		0.8767		-1.0505		-0.6211		-7.3616	***	-12.6749	***	-19.7251	***
Unemployment rate	-0.0018	**	-0.0001		-0.0003		0.0034	***	0.0037		0.0056	*	0.0068	
High school attainment	0.1109	**	0.0075		0.0686		0.0408		0.1294		0.0300		0.2646	
College attainment	-0.0139		-0.0006		0.0467		0.0165		0.0347		0.0880		0.0410	
Volatility	1.4844	***	0.8168	***	2.1459	***	1.9678	***	6.5829	***	10.6301	***	16.5490	***
Constant	0.0074		0.0014		-0.0031		-0.0279	***	-0.0303		-0.0465	*	-0.0588	*
Lagged variables	Baseline + Controls													
	Atkinson Coefficient		Rmeandev Coefficient		Theil Coefficient		Top5% Coefficient		Top0.5% Coefficient		Top0.1% Coefficient		Top0.01% Coefficient	
Financial development	0.0773	***	0.0302	***	0.0956	**	0.0809	**	0.0972	**	0.1176	**	0.1107	**
Financial development^2	0.0261	***	0.0101	***	0.0305	**	0.0279	***	0.0004		0.0072		0.0171	
Income	0.1526	*	-0.0243		0.0910		-0.2568		-0.0761		-0.2194		-0.1788	
Income^2	-2.6582	***	-0.1405		-1.3146		2.6982		-3.3065		-2.4222		0.4155	
Unemployment rate	-0.0016		-0.0004		-0.0028	*	-0.0019		-0.0018		-0.0023		-0.0050	
High school attainment	0.1245	*	0.0206		0.0848		0.0870		0.1713		0.1073		0.4108	
College attainment	-0.0009		0.0026		0.0764		0.0243		0.0664		0.1127		0.0506	
Volatility	-0.0192		0.2468	*	-0.7112	**	-1.0213	**	2.1645	**	4.0180	***	7.2189	***
Constant	0.0189	**	0.0090	***	0.0364	***	0.0255	**	0.0310	*	0.0393		0.0562	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.4. Results of fixed-effect regression for states with low inequality

Contemporaneous variables	Baseline + Controls													
	Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Financial development	0.1312	***	0.0382	***	0.2091	***	0.0814	***	0.1258	***	0.1693	***	0.1168	
Financial development^2	-0.0449	***	-0.0115	***	-0.0739	***	-0.0248	***	-0.9151	***	-1.4813	***	-1.9427	***
Income	0.3597	**	0.0101		0.8174	***	0.1106		1.5377	***	2.2283	***	2.3545	***
Income^2	-1.6506	*	0.2594		0.3660		1.2080		-10.9231	**	-15.9180	**	-26.6249	***
Unemployment rate	-0.0012		0.0004		-0.0031	**	-0.0001		0.0045	***	0.0078	***	0.0085	**
High school attainment	0.0214		-0.0397		0.0422		0.1251		0.0825		0.0856		0.0565	
College attainment	-0.0066		0.0198	**	-0.0308		-0.0540	*	-0.0797		-0.1485		-0.2070	
Volatility	0.5020		0.2280		0.9516		0.2008		5.3746	***	8.2706	***	11.2385	***
Constant	0.0079		0.0004		0.0179		0.0041		-0.0270	**	-0.0439	**	-0.0306	
Lagged variables	Baseline + Controls													
	Atkinson		Rmeandev		Theil		Top5%		Top0.5%		Top0.1%		Top0.01%	
	Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient		Coefficient	
Financial development	0.1054	***	0.0296	***	0.1219	***	0.0859	***	0.1775	***	0.2159	***	0.2236	***
Financial development^2	-0.0332	***	-0.0097	***	-0.0344	***	-0.0232	***	-0.8326	***	-1.3660	***	-1.5527	***
Income	0.1482	***	-0.0318	*	0.0975		0.2607	***	-0.1155		-0.2620		0.0007	
Income^2	0.4679		0.8791	*	2.6115	**	-4.7574	***	-8.1571	**	-7.8895	*	-7.1531	
Unemployment rate	0.0003		0.0008		-0.0026	*	0.0017	**	0.0020	*	0.0032	**	0.0050	
High school attainment	0.0701		-0.0260		0.1210		0.1649	*	0.3881	**	0.5258	**	0.4878	
College attainment	-0.0102		0.0196	**	-0.0447		-0.0554	*	-0.0781		-0.1512	*	-0.2098	
Volatility	-0.5533	**	0.1580		-1.1744	***	0.7748		1.4883		2.1650	**	3.0766	**
Constant	0.0029		-0.0012		0.0286	***	-0.0057		0.0101		0.0155		0.0117	

Note: ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.5. Results of system-GMM for 50 U.S. states

sys-GMM	Gini		Top10%		Top1%	
	Coefficient		Coefficient		Coefficient	
Dynamic variable	0.2318	***	-0.3484	***	-0.5230	***
Financial development	0.0384	***	0.1567	***	0.3531	***
Financial development^2	-0.0666		-0.0573		-0.0777	
Income	0.1822	**	0.6501	***	3.7458	***
Income^2	-0.5312		2.6788		-25.8610	*
Unemployment rate	-0.0008	**	-0.0005		0.0034	
College attainment	0.1363	***	-0.0413		-0.1799	
Volatility	0.6886		1.7102	**	12.5126	***
Constant	0.0037		-0.0019		-0.0519	***
P-value						
AR(1)	0.003		0		0	
AR(2)	0.748		0.509		0.796	
Hansen	0.237		0.225		0.22	

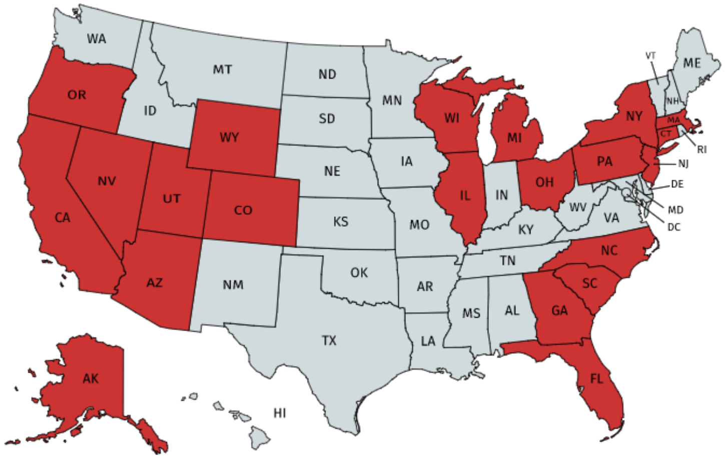
Note: As the estimation is two-step sys-GMM, Hansen J statistic is reported (Roodman 2009). The test statistic has a $\chi2$ distribution under the null hypothesis that the instruments are valid. ***, **, and * indicate significance at the 1-, 5-, and 10-percent levels, respectively. "Income" is real per capita personal income and "Income^2 is squared term of real per capita personal income. Except unemployment rate and measure of volatility, the variables are in growth form by taking the difference of its natural logarithm value.

Appendix 5.6. List of high and low inequality states

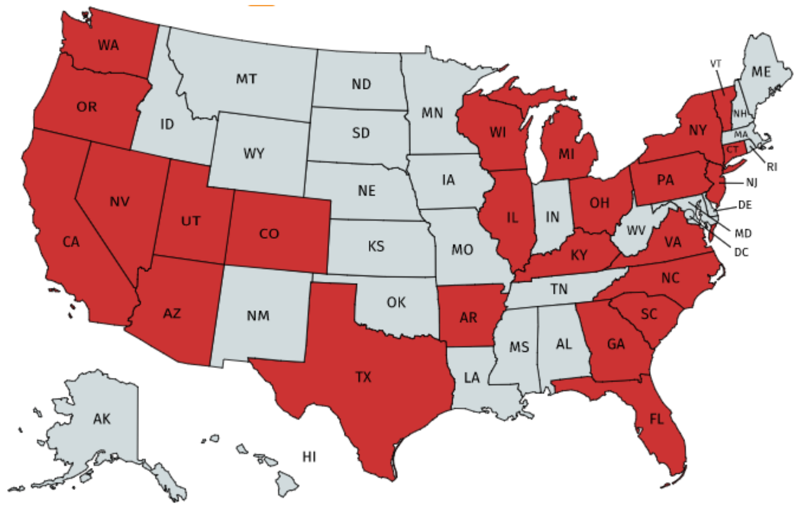
Top 10%	High	AK, AZ,CA, CO, CT, FL, GA, IL, MA, MI, NV, NJ, NY, NC, OH, OR, PA, SC, UT, WI, WY
	Low	AL, AR, DE, HI, ID, IN, IA, KS, KY, LA, ME, MD, MN, MS, MO, MT, NE, NH, NM, ND, OK, RI, SD, TN, TX, VT, VA, WA, WV
Top 1%	High	AK, AZ, CA, CO, CT, FL, IL, MD, MA, MI, MN, NV, NH, NJ, NY, ND, PA, SD, TX, VA, WA, WI, WY
	Low	AL, AR, DE, GA, HI, ID, IN, IA, KS, KY, LA, ME, MS, MO, MT, NE, NM, NC, OH, OK, OR, RI, SC, TN, UT, VT, WV
Gini coefficient	High	AZ, AR, CA, CO, CT, FL, GA, IL, KY, MA, MI, NV, NJ, NY, NC, OH, OR, PA, SC, TX, UT, VT, VA, WA, WY
	low	AL, AK, DE, HI, ID, IN, IA, KS, LA, ME, MD, MN, MS, MO, MT, NE, NH, NM, ND, OK, RI, SD, TN, WV, WI

Appendix 5.7. Low (in grey) and high (in red) inequality states

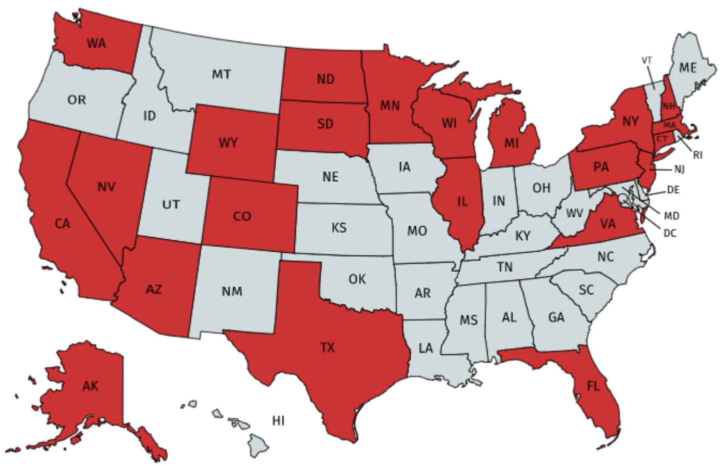
Top10



Gini



Top1



Chapter 6

Growth Volatility and Inequality in the U.S.: A Wavelet analysis

6.1 Introduction

Does growth volatility affect income/wealth inequality? Ramey and Ramey (1995) examine the relationship between output growth and its volatility. They find an inverse relationship between output volatility and the output growth rate. Their results raise the question of whether volatility also affects other macroeconomic variables. Hausmann and Gavin (1996) investigate the relationship between volatility and inequality, finding adverse effects of income volatility on the distribution of income. How does volatility affect the inequality?

Theory suggests several channels to explain how growth volatility affects the distribution of income. Volatility can affect the income distribution as individuals possess different levels of risk tolerance and the channels of influence on inequality relate to risk. First, entrepreneurs exhibit higher levels of risk tolerance than salary earners. Also, bearing risk enables entrepreneurs to capture the resulting higher risk premium that contributes to their income and wealth. Caroli and García-Peñalosa (2002), focusing on this wage channel, consider an economy where random shocks affect output and, in turn, wages fluctuate. They argue that the share of output captured by entrepreneurs becomes larger the more volatile the output because salaried workers will take a decreased salary to get a constant wage.

Second, Checchi and García-Peñalosa (2004), considering the human capital channel, examine the effects of wage volatility on wage differentials between low and high skilled workers. They find that high wage volatility causes a high degree of educational inequality and, as a result, income inequality rises.

Third, volatility makes economic growth less favourable to the poor. Low-income groups do not experience good access to financial and credit markets. These market imperfections can influence occupational outcomes of low-income individuals. Also, they depend more on state grants and social services (Jeanneney and Kpodar 2011). The poor receive less diversified sources of income, possess inferior qualifications, and exhibit less mobility than the rich (Galor and Zeira 1993; Agénor 2004; Laursen and Mahajan 2005; Corak et al. 2014).

How can we explain the divergence in the patterns of output volatility and income inequality that the data support? Eksi (2017) shows that an increase in the time-series variance of micro income shocks lead to increases in both output and income inequality. Moreover, a decrease in the cross-sectional correlation of these shocks across individuals leads to a decrease in output volatility, but to an increase in income inequality. In other words, one variable is an increasing function of the correlation parameter, while the other is a decreasing function of it. Eksi (2017) argues that the simultaneity of the changes in output volatility and income inequality during the Great Moderation period is not a coincidence, but reflects the fact that the variables depend on the same parameters of the underlying income microdata.

Many empirical studies find that higher volatility associates with higher income inequality. Hausmann and Gavin (1996) find that Latin American countries display higher income inequality and much more volatile economic growth rates. Laursen and Mahajan (2005) find that output volatility negatively influences the equality of the income distribution of the bottom 20% income group. With the cross-sectional data of the Gini coefficient and the income share of the top quintile of developing and developed countries, Breen and García-Peñalosa (2005) show that higher growth volatility links to higher income inequality.

Numerous empirical studies exist that use panel data. Using a panel data set of 70 countries from 1960 to 2002, Konya and Mouratidis (2006) find that volatility affects inequality, but that inequality does not exert a direct effect on volatility. They also find that low growth volatility reduces inequality, whereas high growth volatility leads to more unequal income distribution. In other words, growth volatility reduces inequality in countries with low volatility, while it increases income inequality in countries with high volatility. Calderón and Yeyati (2009) use a panel data set of 75 countries over 1970-2005 and also find that output volatility increases income inequality, especially with extremely high volatility, such as macroeconomic crises. They conclude that volatility increases the income share of the highest quintiles at the expense of the middle 40%. Using annual data from the 48 U.S. states over 1945-2004, Huang et al. (2015) find robust results that larger growth volatility positively and significantly associates with higher income inequality. Chauvet et al. (2017) also examine the relationship between income volatility and inequality, considering aid and remittances. The authors employ a panel of 142 countries over 1973-2012 and find that volatility increases inequality, where lower income groups are most exposed to the volatility. They also find robust evidence suggesting that aid helps to reduce the negative effects of volatility on the distribution of income.

The effect of output volatility on inequality is well-documented in the literature and most of the studies find that volatility produces an unfavourable effect on the distribution of income. Studies also suggest, however, a possibility of income inequality intensifying macroeconomic volatility. Alesina and Perotti (1996) argue that income inequality exerts an indirect effect on macroeconomic volatility via increased political instability. Aghion, et al. (1997) and Aghion, et al. (1999) argue that inequality in the form of unequal access to investment opportunities combined with a high level of capital market imperfection may generate persistent credit cycles, resulting in output and investment volatility. Levy (2002) uses an AS-AD model and theoretically shows income inequality may influence macro-economic variables by affecting the money multiplier and the trade-off between inflation and output.

One study considers the short- and long-run effects of income volatility on inequality. Bahmani-Oskooee and Motavallizadeh-Ardakani (2018) employ linear and nonlinear ARDL approaches on annual U.S. state panel data from 1945 to 2013 and discover short-run asymmetric effects of income volatility on a measure of inequality in many states. The short-run effects translate to long-run asymmetric effects, however, in nineteen states. Only one state, South Dakota, shows long-run symmetric effect wherein increased volatility worsens inequality and decreased volatility improves it. The authors also find that both increased volatility and decreased volatility can create unequalizing effects on income distribution in only Indiana, Michigan and Wyoming and conclude overall that, in the United States, reducing income or output volatility will not help to reduce income inequality.

Given the conclusions in the existing literature, our paper provides three main contributions. First, we extend the existing literature on the effects of income and wealth inequality on output volatility, combining time-series and frequency-domain analyzes. Wavelet analysis allows us to examine the time-frequency historical effects of volatility on U.S. income and wealth inequality. Using wavelet coherency, we can assess the role of income and wealth inequality on growth volatility dynamics at different frequencies and specific moments in time. At the same time, we can indicate the direction of the causality between inequality and volatility at different moments in time. The time- and frequency-varying relationships can provide significant implications for macroeconomic policymakers. The time-varying relationships indicate that the variables influence each other differently at different points in the business cycle (Li et al. 2015). Frequency-varying relationships reveal short- versus long-term linkages between two variables. In addition, unlike standard tests of Granger causality that require pre-testing for unit roots and cointegration, wavelet analysis provides robust evidence in favour of or against causal relationships between variables under consideration without accounting for issues associated with stationary or non-stationary data and the existence or non-existence of long-run relationships. In other words, we can work with the raw data and do not need to transform the data, which, in turn, often tends to change the definition of the original variables for which we are trying to detect causal relationships.

Second, in contrast to the bulk of the literature that uses output volatility defined as the standard deviation of the rate of output growth, we use the realized volatility calculated by taking the sum over the squared quarterly GNP growth rates. Realized volatility is a nonparametric, ex-post estimate of the return (growth) variation and it provides empirical content to the latent variance variable (Andersen and Teräsvirta 2009). Therefore, this approach proves useful for specification testing of the restrictions imposed on volatility by parametric models previously estimated with low-frequency data. Further, realized volatility measures facilitate direct estimation of parametric models.[40]

Finally, we not only examine the aggregate growth volatility but also investigate the volatility related to positive growth (i.e. good volatility) and the volatility connected to negative growth (i.e. bad volatility), which allows deeper examination on the different aspects of volatilities.

The rest of the paper is organized as follows. Section 2 presents the methodology. Sections 3 and 4 present the data and the empirical results, respectively. Section 5 concludes the paper.

6.2 Methodology

Wavelet analysis can extract time- and frequency-localized information not only from stationary series but also from non-stationary and locally stationary series as well as series with structural changes (Roueff and Sachs 2011). Economic processes emerge as outcomes of the actions of numerous agents at different frequencies, which implies that a macroeconomic time series incorporates information that operates at different time domains. Wavelet analysis separates the time series into several sub-series, which may associate with a particular time

[40] Please see Andersen and Teräsvirta, 2009 for detailed discussion on realized volatility

domain and which narrows the focus to provide fruitful insights on economic phenomena (Ramsey and Zhang 1996, 1997).

6.2.1 Continuous wavelet transform

There are two kinds of wavelet transforms exist: discrete wavelet transforms (DWT) and continuous wavelet transforms (CWT). The DWT reduces noise and compresses data whereas the CWT extracts features and detects data self-similarities (Grinsted et al. 2004; Loh, 2013).

The continuous wavelet transforms, with respect to the wavelet ψ, is a function

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-\tau}{s}\right)dt,$$

where $*$ denoted complex conjugation. The parameter s is scaling factor that controls the length of the wavelet and τ is a location parameter that indicates where the wavelet is centered. Scaling a wavelet simply means stretching it (if $|s| > 1$), or compressing it (if $|s| < 1$).

If the wavelet function $\psi(t)$ is complex[41], the wavelet transform W_x will also be complex. The transform can then be divided into the real part ($\mathcal{R}\{W_x\}$) and imaginary part ($I\{W_x\}$), or amplitude, $|W_x|$, and phase, $tan^{-1}(\frac{I\{W_x\}}{\mathcal{R}\{W_x\}})$. The phase of a given time series $x(t)$ is parameterized in radians, ranging from $-\pi$ to π. In order to separate the phase and amplitude information of a time series, it is important to make use of complex wavelets.

6.2.2 Wavelet coherency and phase difference

[41] The wavelet transform is a method to decompose an input signal into wavelets via "mother wavelet" function. In this study, a morlet wavelet - a complex valued wavelet with optimal joint time-frequency concentration- is used as "mother wavelet" as it brings in information on the amplitude and phase which both are essential to study synchronism between different time-series. See Goupillaud et al. (1984) and Aguiar-Conraria et al. (2008) for detailed information of the mother wavelet and Morlet wavelet.

Hudgins et al. (1993) and Torrence and Compo (1998) develop methodologies of the cross-wavelet power, the cross-wavelet coherency, and the phase difference. Wavelet analysis closely links to Fourier analysis; but, it possesses certain advantages. Wavelet analysis conserves information in both time and frequency domains by conducting the estimation of spectral characteristics of a time series as a function of time (Aguiar-Conraria et al. 2008). Also, wavelet analysis applies to non-stationary or locally stationary series (Roueff and Sachs 2011). Wavelet coherency involves a three-dimensional analysis, which counts the time and frequency elements at the same time as well as the strength of the correlation between the time-series elements (Loh 2013). Thus, we can observe both the time- and frequency-variations of the correlation between two series in a time-frequency domain. When the frequency components exhibit non-stationarity, the traditional approach may miss such frequency components. Wavelet analysis provides the time- and frequency-localized information with structural breaks. Thus, we can avoid the need to assume stationarity (Fan and Gençay 2010).

As a result, wavelet coherency delivers a better measure of the co-movement between variables, U.S. income and wealth inequality and output volatility, in comparison to conventional causality and correlation analysis. Following the approach of Li et al. (2015), we estimate wavelet coherency by using the cross-wavelet and auto-wavelet power spectrums as follow:

$$R_{xy}^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau,s))|^2}{S(s^{-1}|W_x(\tau,s)|^2)S(s^{-1}|W_y(\tau,x)|^2},$$

where complex argument $\arg W_{xy}(\tau, s)$ is the local relative phase between x_t and y_t, $|W_x(\tau, s)|^2$ represents the wavelet power, $\arg W_x(\tau, s)$ is local phase, and S represents a smoothing operator.[42] The ratio of the cross-wavelet spectrum to the product of the spectrum of each series equals the local correlation of the two series. This formula gives a quantity between 0 and 1 in a time-frequency window. Zero coherency indicates that no co-movement occurs between the volatility, and the income and wealth inequality measures, while the highest coherency implies the strongest co-movement between the two series. On the wavelet coherency plots, red and blue colours correspond to strong and weak co-movements, respectively.

As the wavelet coherency is squared, we cannot easily distinguish between positive and negative co-movements. Rather, we use the phase difference to provide information on positive and negative co-movements as well as the lead-lag relationships between the two series.[43] Bloomfield et al. (2004) characterize the phase difference relationship between $x(t)$ and $y(t)$ such that:

$$\phi_{xy} = tan^{-1}\left(\frac{\mathcal{J}\left\{S\left(s^{-1}W_{xy}(\tau,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(\tau,s)\right)\right\}}\right), with\ \phi_{xy}\ \in [-\Pi, \Pi],$$

where $\mathcal{J}$ is the imaginary part of the smoothed cross-wavelet transform and $\Re$ represents the real part of the smoothed cross-wavelet transform.

A phase difference of zero reveals that the two underlying series move together, while a phase difference of $\pi(-\pi)$ indicates that the two series move in the opposite directions. If $\phi_{xy}\ \in (0, \pi/2)$, then the series move in phase (positively co-move) with $y(t)$ leading $x(t)$. If $\phi_{xy} \in\ (\pi/2, \pi)$, then the series move out of phase (negatively co-move) with $x(t)$ leading $y(t)$. If $\phi_{xy}\ \in (-\pi, -\pi/2)$, then the series move out of phase with $y(t)$ leading $x(t)$. Finally, if $\phi_{xy} \in\ (-\pi/2, 0)$, then the series move in phase with $x(t)$ leading $y(t)$. Also, the phase difference indicates causality between $x(t)$ and $y(t)$ in both the time and frequency

[42] Without smoothing, the squared wavelet coherency is always equal to 1 at any frequency and time. Torrence and Compo (1998) show that smoothing in time or frequency increases the degrees of freedom of each point and increases the confidence of the wavelet spectrum.
[43] The term phase means the position in the pseudo-cycle of the series as a function of frequency.

domains. Overall, wavelet analysis enables a deeper understanding than the conventional causality test, which assumes that a single causal link holds for the whole sample period as well as at each frequency (Grinsted et al. 2004; Tiwari et al. 2013). For instance, in wavelet analysis, if $x(t)$ leads $y(t)$, then a causal relationship runs from $x(t)$ to $y(t)$ at a particular time and frequency (Li et al. 2015).

6.3 Data

The U.S. economy experienced several episodes of high and low growth volatility, such as low volatility of output from the mid-1980s up to 2008 (called the Great Moderation), and increased growth volatility characterizing the late 1960s and 1970s (called the Great Inflation) and from 1929 to the start of World War II (Great Depression). In addition, movements in inequality conform to certain periods of time, including 1945 to 1979 (called the Great Compression) and 1980 to the present (called the Great Divergence). Our analysis provides clarification on the causality between income and wealth inequality and growth volatility, at different frequencies and at a different moments in time. We use data with an annual frequency covering 1917 to 2015 for volatility and income inequality and 1962 to 2014 for volatility and wealth inequality. Data for the quarterly real GNP over 1917Q1 to 2015Q2 come from Omay et al. (2017)[44] and from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis from 2015Q3 to 2015Q4. Using quarterly GNP data, we calculate the annual realized volatility by taking the sum of quarterly squared growth rates. In

[44] The authors explain how they compute the unique dataset, which is the longest possible data on U.S. output available at a quarterly frequency (i.e., the most relevant frequency at which to measure output globally). First, the observations covering the period 1875:Q1-1946:Q4 used by Omay et al. (2017) (and in our case 1917:Q1-1946:Q4) come from National Bureau of Economic Research (NBER), available for download at: http://www.nber.org/data/abc/, with the actual sources being the tables of quarterly data corresponding to Appendix B of Gordon (1986). As Omay et al. (2017) point out, this is the only existing source for the pre-1947 quarterly data on U.S. GNP and the GNP deflator with National Income and Product Account (NIPA) quarterly data series non-existent before 1947. Second, Omay et al. (2017) use data from 1947:1-2015:2 from the FRED database. Note that the dataset compiled by Gordon (1986) runs through 1983:4 with 1972 as the base year of the GNP deflator. Given that nominal GNP and the GNP deflator data based on the NIPA are available from 1947:1, Omay et al. (2017) decided to use, for those variables, the FRED database, rather than the Gordon (1986) one, which, in any case, only runs through 1983:4. Omay et al. (2017) updatethe base year of the GNP deflator for the period 1875:1-1946:4 from 1972 to 2009 to correspond to the base year of the GNP deflator based on the NIPA. Thus, the real GNP is ultimately in constant 2009 prices.

our analysis, we not only use output volatility but we also categorize it into positive/good and negative/bad volatilities. We first create dummy variable, 1 for positive quarterly growth rate of output and 0 otherwise, and multiply the growth rate with the dummy variable. We do the same as above for the cases of negative quarterly growth rates. Then we take sum of the squared positive or negative quarterly growth rates of output over a specific year to obtain a measure of good or bad realized volatility respectively. Income inequality measures - Atkinson Index, Gini Coefficient, the Relative Mean Deviation, Theil's entropy Index, Top 10%, Top 5%, Top 1%, Top 0.5%, Top 0.1%, and Top 0.01%[45] - come from the online data segment of Professor Mark W. Frank's website.[46] Wealth inequality measures – Top 10% net personal wealth (p90p100), Middle 40% (p50p90), Bottom 50% (p0p50), and Top 1% (p99p100) - come from World wealth and income database (WID) with data range from 1962 to 2014.[47] We employ the frequency cycles in the analysis. The first cycle (1-2-years cycle) associates with the short-run, or with high-frequency bands. The second cycle (2-4-years cycle) associates with the long, or with low frequency bands.[48]

6.4 Empirical analysis

We simultaneously look at the correlation and the causal relationship between (i) income and wealth inequality, and growth volatility (ii) income and wealth inequality, and positive volatility, and (iii) income and wealth inequality, and negative volatility.

The results of wavelet coherency indicate correlation between two variables. The wavelet coherency between volatility and the various income inequality measures show statistically significant high coherency across high- and low-frequencies in Fig. 6.1. Across the high- and

[45] Top income shares serve as useful proxies for inequality across the income distribution (Leigh 2007).
[46] See http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed the dataset based on the Internal Revenue Service (IRS) information, which has a limitation of omission of some individual earning less than a threshold level of gross income. For this reason, we focus more on top income shares as primary indicators of inequality measures.
[47] The data is available for download from: http://wid.world/.
[48] We focus on three frequency bands: 1-2 and 2-4 years, as volatility and inequality the most coherent regions are between the 1-4 years band.

low-frequency bands, at least two significant islands exist of high coherency between output volatility and the income inequality measures. With the wealth inequality measures in Fig 6.4, we observe the consistent strong positive correlation between growth volatility and inequality measures at the 2-4 years frequency. Only weak correlation appears with wealth inequality measures across the 1-2 year frequency.

The coherency results of positive volatility and income inequality measures also show statistically significant high coherency islands over the short- and long-term in Fig. 6.2. Especially from 1917 to the 1960s, all income inequality measure indicate strong co-movement across low-frequency. Only weak correlation appears with top income shares across high-frequency band from 1935 to 1997 and with wealth inequality measures across low frequencies in Fig. 6.5. Compared to the aggregate output volatility, positive volatility shows less strong co-movement with top income shares across high-frequency.

The results of negative volatility show statistically significant high coherency across 1-2 year frequency band for all inequality measures in Fig. 6.3. Across the 2-4 years frequency band, we observe a significant island from 1935-1961 and 1942-1963, which relates to World War II. Sign of strong correlation appears with the Top 1%, Top 0.5%, Top 0.1% and Top 0.01% of income inequality and with wealth inequality measures across high-frequency bands in Fig 6.6. Fig. 6.3 also shows stronger correlations between the negative volatility and inequality over the short-term than positive volatility. That is, negative volatility exerts a bigger effect on inequality than positive volatility over the short-term.

Our empirical evidence shows that volatility and inequality relate positively, which a number of studies show. This positive relationship appears in Hausmann and Gavin (1996), Breen and García-Peñalosa (2005), Laursen and Mahajan (2005), and Calderón and Yeyati (2009).

The phase differences of Figs. 6.1 to 6.6 indicate the causality between two series (see Fig. 6.7 for compiled results). Across the 2-4 year frequency band in Fig. 6.7, for all three volatility measures, volatility leads the income inequality measures. The change of direction of causality from volatility leads to inequality leads in the early 2000s probably indicates a structural break.

At low frequency, volatility leads the wealth inequality measures Top 10% (p90p100) and Middle 40% (p50p90) in 1962-2014, whereas Bottom 50% (p0p50) and Top 1% (p99p100) lead volatility. Negative volatility leads Top 10% and Top 1%, whereas Middle 40% and Bottom 50% lead negative volatility in 1962-2014. Positive volatility leads Top 10% and Top 1% through the early 2000s and the direction of causality changes after that. Positive volatility also leads Bottom 50% through the late 1980s and the direction of causality changes after that. Middle 40% leads positive volatility from 1962 through the late 1990s and causality changes after that. For Top 10% at low frequency, aggregate and negative volatility lead wealth inequality. Bottom 50% leads aggregate and negative volatility from 1962 to 2014.

Compared to long-term causality, more movement occurs in changes of direction of causality in the short-term. Volatility leads the Atkinson Index and the Relative Mean Deviation from 1917 to the late 1950s, while the Atkinson Index and the Relative Mean Deviation lead volatility after that. Volatility also leads the Gini coefficient and the Theil index from 1917 to the late 1950s and from the late 1980s to 2014, while the Gini coefficient and the Theil index lead volatility from 1961 to the late 1980s. The Top income shares, however, lead volatility, except in 1917-1921, when volatility leads Top 5%, in 1917-1938, when volatility leads Top 0.1%, and in 1917-1943, when volatility leads Top 0.01%. For high frequencies, the Top 0.1% leads positive volatility and Top 10% leads negative volatility from 1917 to 2015. The direction of causality of the wealth inequality measures Top 10%

(p90p100) and Middle 40% (p50p90) change in the mid and late 1970s. For Bottom 50% (p0p50) and Top 1% (p99p100), the direction of causality changes in the mid-2000s. The 1970s saw two oil price spikes, as OPEC began affecting prices. Also, the Vietnam War covered the 1967-1972 period, where, in turn, productivity growth slowed.

Similar to the causality with aggregate growth volatility, the direction of causality of the wealth inequality measures Top 10% and Middle 40% change in the mid and late 1970s for positive volatility. The Top 10% leads positive volatility from 1917 to 1976, while positive volatility leads Top 10% from 1977 to 2014. In contrast, Middle 40% leads positive volatility from 1979 to 2014, while positive volatility leads Middle 40% from 1962 to 1978. Top 1% leads positive volatility from 1917 to 1988 and positive volatility takes lead from 1989, whereas Bottom 50% leads negative volatility in 1962-2014.

Top 1%, Top 0.5%, Top 0.1%, and Top 0.01% income shares mostly lead positive volatility in our data range. Top 10% and Top 5% show similar patterns and directions of causality. Positive volatility leads the Relative Mean Deviation, and the Theil index in 1917 through the 1960s and in the late 1980s through 2015, while the two measures of inequality lead positive volatility in the rest of period. Positive volatility leads the Gini coefficient from 1917 to 2015 except from 1979 to 1987. Also, positive volatility leads the Atkinson index from 1917 to 1964 and from 2004 to 2015.

With negative volatility at high frequencies, the results show that all the inequality measures lead negative volatility from 1994 to 2015, whereas negative volatility leads all the inequality measures except Top 10% and Top 5% from 1917 to 1940. In the 1940s, the direction of causality changes from negative volatility leads to inequality leads, which relates to wage compression during the 1940s. Negative volatility leads Top 0.01% in 1917-1974 and Top 0.01% leads negative volatility from 1975. For wealth inequality, Top 1% (p99p100) leads negative volatility from 1962 through 2014. The direction of causality of Top 10% and Bottom 50% change mid and late 1980s.

We observe that the directions of causality vary and the changes of direction mostly coincide with the business cycle (NBER). This probably relates to business cycle movements that associate with large permanent effects on the long-run level of output (Nelson and Plosser 1982; Campbell and Mankiw 1987).

We also decompose the time-series into high-, medium- and low-frequency using a Maximal Overlap Discrete Wavelet Transform (MODWT) and employ Granger causality to see in which frequencies the underlying driver lies in.[49] Table 6.15 reports the results of Granger causality tests in the different frequency domain. Top 10% income share and Top 10% net personal wealth (p90p100) are observed to Granger cause volatility in medium- and long term. Gini coefficient does not Granger cause volatilities in medium term. Negative volatility does not cause inequality in short term and over all volatility and positive volatility does not cause income inequality in long term. We find one stable causality holding for the whole sample period which Top 10% income share cause positive negative and overall volatility, however, in general, the causality findings exhibit substantial time- and frequency-dependence.

The phase difference results show that volatility, including positive and negative volatilities, mostly leads income inequality until the 2000s across low frequencies and changes direction from volatility leads to income inequality leads from the 2000s onward. In contrast to the short term, long-term causality patterns and directions are robust to different measures of income inequality. Across high frequencies, the income share inequality measures lead volatilities, but directions of causality vary across frequencies and evolve with

[49] Testing causality in frequency domain collapses the time dimension into a single point in time and information is lost on the time variation in causality.

time. If we restrict our analysis to classical time series, we cannot find any information about differences across frequencies.

6.5 Conclusion

Policy makers attempt to reduce inequality through economic growth, fiscal policy, monetary policy, aid programs, and so on. The relationship between inequality and the various policy instruments receives much discussion and analysis in the existing literature. As numerous variables affect each other simultaneously or at different points of time, rendering net causality and correlation results difficult to document. This paper investigates the causal relationships between U.S. income and wealth inequality measures, and output volatility. We use wavelet analysis, which allows the causal relationship between the two series to vary over time and frequency. Wavelet analysis is robust to lag length (Fan and Gençay 2010), stationarity (Roueff and Sachs 2011), model specification (Percival and Walden 2006) and cointegration as wavelet analysis allows time- and frequency-varying approach. Furthermore, it permits to measure local co-movement between two time series in the time-frequency domain and discover the lead-lag relationship between two time series. We use annual time-series data from 1917 to 2015 for volatility and income inequality and 1962 to 2014 for volatility and wealth inequality, which cover numerous economic expansions and contraction.

Our results show that the periods and directions of short-term causality vary over time. Volatility mainly leads income inequality measures over the long-run through the early-2000s. At high frequencies, causality changes direction – from volatility leading to inequality leading. Our results also show that higher positive and negative volatility leads to increases in inequality. This implies that economic growth does not trickle down to the bottom income group as they experience more fluctuations in output growth. In addition, we find that volatility not only matters for inequality but also inequality matters for volatility, especially in more recent years.

As our long-term results show, changes in the direction of causality from volatility leads to income inequality leads coincides with the end of the Great moderation era. Policy makers can use direct policy, such as enlarging the tax bracket for low-income households, raising taxes on high-income households, or increasing state aid programs, to reduce inequality, which can also moderate volatility. Our findings also imply that stabilization policies can affect income inequality. Thus, stabilization policy can provide an important instrument to reduce income inequality. This finding corresponds with studies[50] that find a significant effect from aid programs and/or remittances on inequality via stabilizing effects on volatility.

To fully understand the effects of volatility on inequality, we need a detailed examination of all possible channels, as different mechanisms may require different policy implications. We leave this issue for future study.

[50] See Chauvet and Guillaumont 2001, 2009; Guillaumont and Wagner, 2014 for the related study

Table 6.1. Wavelet phase difference (Volatility, logarithm of Atkinson index)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1958	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
	1959-2015	$(0, \frac{\pi}{2})$, In-phase	+	Atkin05 → Volatility
Low frequency	1917-1997	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
	1998-2015	$(0, \frac{\pi}{2})$, In-phase	+	Atkin05 → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1964	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
	1965-2003	$(0, \frac{\pi}{2})$, In-phase	+	Atkin05 → Volatility
	2004-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
Low frequency	1917-1998	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
	1999-2015	$(0, \frac{\pi}{2})$, In-phase	+	Atkin05 → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1951	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05
	1952-2015	$(0, \frac{\pi}{2})$, In-phase	+	Atkin05 → Volatility
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Atkin05

Table 6.2. Wavelet phase difference (Volatility, logarithm of Gini coefficient)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1960	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini coefficient
	1961-1983	$(0, \frac{\pi}{2})$, In-phase	+	Gini → Volatility
	1984-1985	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
	1986-1987	$(0, \frac{\pi}{2})$, In-phase	+	Gini → Volatility
	1988-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1978	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
	1979-1987	$(0, \frac{\pi}{2})$, In-phase	+	Gini → Volatility
	1988-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1946	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
	1947-1976	$(0, \frac{\pi}{2})$, In-phase	+	Gini → Volatility
	1977-1993	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini
	1994-2015	$(0, \frac{\pi}{2})$, In-phase	+	Gini → Volatility
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Gini

Table 6.3. Wavelet phase difference (Volatility, logarithm of the Relative Mean Deviation)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1960	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	1961-2015	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
Low frequency	1917-2012	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	2013-2015	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1968	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	1969-1989	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
	1990-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
Low frequency	1917-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	2015	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1945	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	1946-1979	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
	1980-1990	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev
	1991-2015	$(0, \frac{\pi}{2})$, In-phase	+	Rmeandev → Volatility
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Rmeandev

Table 6.4. Wavelet phase difference (Volatility, logarithm of Theil index)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1954	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	1955-1988	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
	1989-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
Low frequency	1917-2012	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	2013-2015	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1961	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	1962-1986	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
	1987-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
Low frequency	1917-2007	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	2008-2015	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1951	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	1952-1978	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
	1979-1992	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil
	1993-2015	$(0, \frac{\pi}{2})$, In-phase	+	Theil → Volatility
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Theil

Table 6.5. Wavelet phase difference (Volatility, logarithm of Top 10%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
Low frequency	1917-2008	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 10%
	2009-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1931	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
	1932-1963	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 10%
	1964-2006	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
	2007-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 10%
Low frequency	1917-2007	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 10%
	2008-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility
Low frequency	1917-2005	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 10%
	2006-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 10% → Volatility

Table 6.6. Wavelet phase difference (Volatility, logarithm of Top 5%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1918	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	1919	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
	1920-1921	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	1922-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
Low frequency	1917-2003	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	2004-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1926	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
	1927-1959	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	1960-2009	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
	2010-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1927	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	1928-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility
Low frequency	1917-2000	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 5%
	2001-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 5% → Volatility

Table 6.7. Wavelet phase difference (Volatility, logarithm of Top 1%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
Low frequency	1917-2001	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	2002-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2012	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
	2013-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
Low frequency	1917-2001	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	2002-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1940	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	1941-1960	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
	1961-1970	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	1971-1972	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
	1973	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	1974-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility
Low frequency	1917-2002	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 1%
	2003-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 1% → Volatility

Table 6.8. Wavelet phase difference (Volatility, logarithm of Top 0.5%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2014	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
	2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1943	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
	1944-1957	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
	1958-1964	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
	1965-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.5%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.5% → Volatility

Table 6.9. Wavelet phase difference (Volatility, logarithm of Top 0.1%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1938	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	1939-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
Low frequency	1917-2004	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	2005-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1946	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	1947-1952	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
	1953-1954	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	1955	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
	1956-1957	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	1958	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
	1959-1972	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	1973-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility
Low frequency	1917-2007	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.1%
	2008-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.1% → Volatility

Table 6.10. Wavelet phase difference (Volatility, logarithm of Top 0.01%)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1943	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%
	1944-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.01% → Volatility
Low frequency	1917-2008	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%
	2009-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.01% → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1929	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%
	1930-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.01% → Volatility
Low frequency	1917-2005	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%
	2006-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.01% → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1917-1974	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%
	1975-2015	$(0, \frac{\pi}{2})$, In-phase	+	Top 0.01% → Volatility
Low frequency	1917-2015	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → Top 0.01%

Table 6.11. Wavelet phase difference (Volatility, Net personal wealth held by p90p100)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1975	$(0, \frac{\pi}{2})$, In-phase	+	p90p100 → Volatility
	1976-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100
Low frequency	1962-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1976	$(0, \frac{\pi}{2})$, In-phase	+	p90p100 → Volatility
	1977-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100
Low frequency	1962-2001	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100
	2002-2014	$(0, \frac{\pi}{2})$, In-phase	+	p90p100 → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1985	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100
	1986-2014	$(0, \frac{\pi}{2})$, In-phase	+	p90p100 → Volatility
Low frequency	1962-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p90p100

Table 6.12. **Wavelet phase difference (Volatility, Net personal wealth held by p50p90)**

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1978	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
	1979-2014	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
Low frequency	1962-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1692-1978	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
	1979-2014	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
Low frequency	1962-1998	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
	1999-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1964	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
	1965-1967	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
	1968-1972	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
	1973-1979	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
	1980-1981	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
	1982-1983	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility
	1984-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p50p90
Low frequency	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p50p90 → Volatility

Table 6.13. Wavelet phase difference (Volatility, Net personal wealth held by p0p50)

Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-2006	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility
	2007-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p0p50
Low frequency	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility
Low frequency	1962-1989	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p0p50
	1990-2014	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1988	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility
	1989-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p0p50
Low frequency	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p0p50 → Volatility

Table 6.14. Wavelet phase difference (Volatility, Net personal wealth held by p99p100)

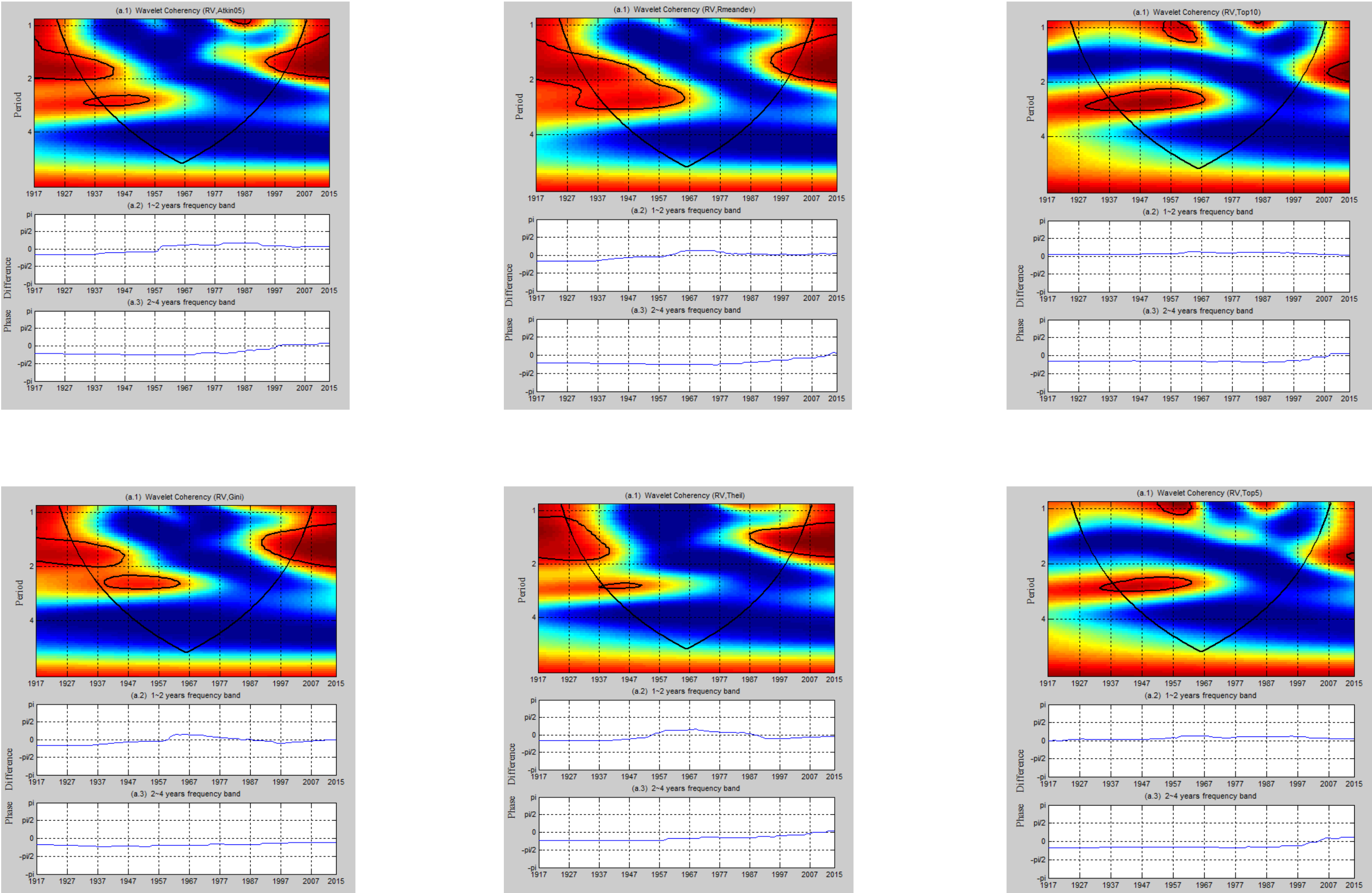
Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-2005	$(0, \frac{\pi}{2})$, In-phase	+	p99p100 → Volatility
	2006-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p99p100
Low frequency	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p99p100 → Volatility
Good / (+) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-1988	$(0, \frac{\pi}{2})$, In-phase	+	p99p100 → Volatility
	1989-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p99p100
Low frequency	1962-2000	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p99p100
	2001-2014	$(0, \frac{\pi}{2})$, In-phase	+	p99p100 → Volatility
Bad / (-) Volatility				
High frequency	Period	Phase	Sign of co-movement	Causality
	1962-2014	$(0, \frac{\pi}{2})$, In-phase	+	p99p100 → Volatility
Low frequency	1962-2014	$(\frac{-\pi}{2}, 0)$, In-phase	+	Volatility → p99p100

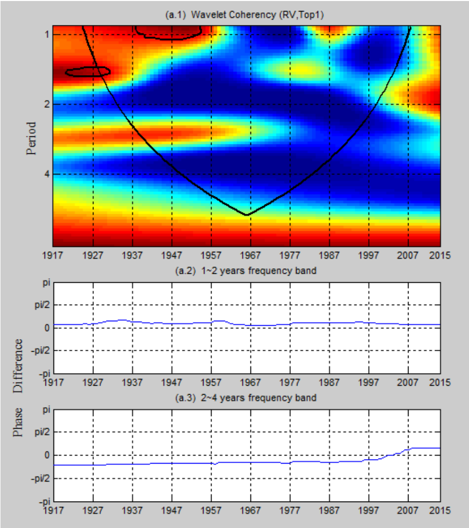
Table 6.15 Results of Granger causality in different frequencies

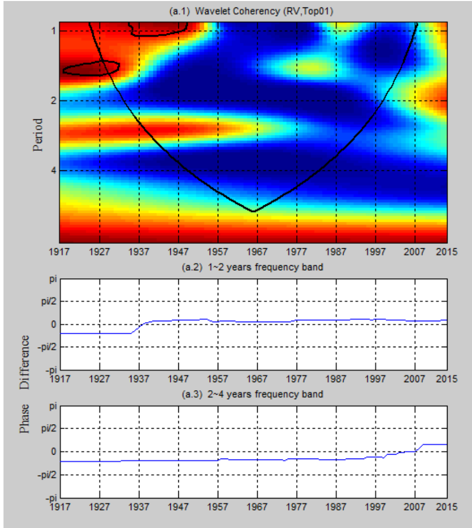
	Frequencies decomposed by the MODWT						Granger causality	
Frequency	Short term		Medium term		Long term		Whole sample period	
Null Hypothesis	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.	F-Stat.	Prob.
BadRV does not Granger Cause Gini	1.493		9.242	***	8.258	***	2.258	
BadRV does not Granger Cause Top10	0.737		2.630	*	2.210		2.581	*
BadRV does not Granger Cause p90p100	1.369		2.964	*	21.689	***	0.238	
GoodRV does not Granger Cause Gini	0.890		3.039	*	1.064		1.620	
GoodRV does not Granger Cause Top10	2.730	*	1.040		2.330		5.097	***
GoodRV does not Granger Cause p90p100	0.074		13.758	***	26.868	***	1.960	
RV does not Granger Cause Gini	4.130	**	9.626	***	0.539		3.296	**
RV does not Granger Cause Top10	0.846		0.170		0.416		2.308	
RV does not Granger Cause p90p100	0.296		8.695	***	45.455	***	2.463	*
Gini does not Granger Cause GoodRV	9.670	***	0.311		12.314	***	3.808	**
Gini does not Granger Cause BadRV	0.521		1.369		20.946	***	0.307	
Gini does not Granger Cause RV	9.725	***	1.219		15.749	***	0.885	
Top10 does not Granger Cause GoodRV	0.384		2.976	*	11.050	***	1.327	
Top10 does not Granger Cause BadRV	11.650	***	6.532	***	23.970	***	0.529	
Top10 does not Granger Cause RV	8.215	***	3.329	**	16.996	***	0.473	
p90p100 does not Granger Cause GoodRV	1.846		3.808	**	4.212	**	0.010	
p90p100 does not Granger Cause BadRV	0.528		2.841	*	1.488		0.093	
p90p100 does not Granger Cause RV	3.135	*	6.765	***	5.508	***	0.040	

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. We use the MODWT based on the Daubechies and decompose our data up to level 8.

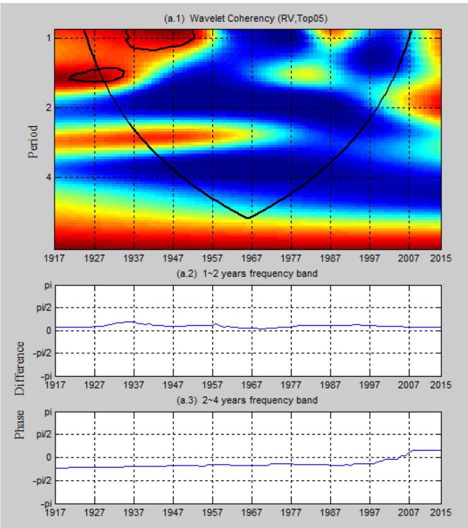
Figure 6.1. Causal relationship between aggregate output volatility and income inequality measures







Note: Wavelet Coherency between the aggregate output volatility and income inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2015.



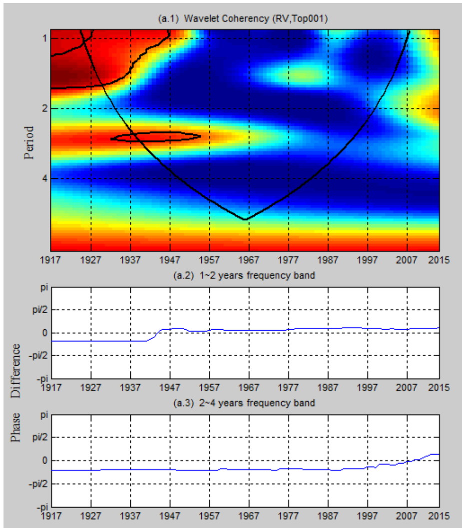
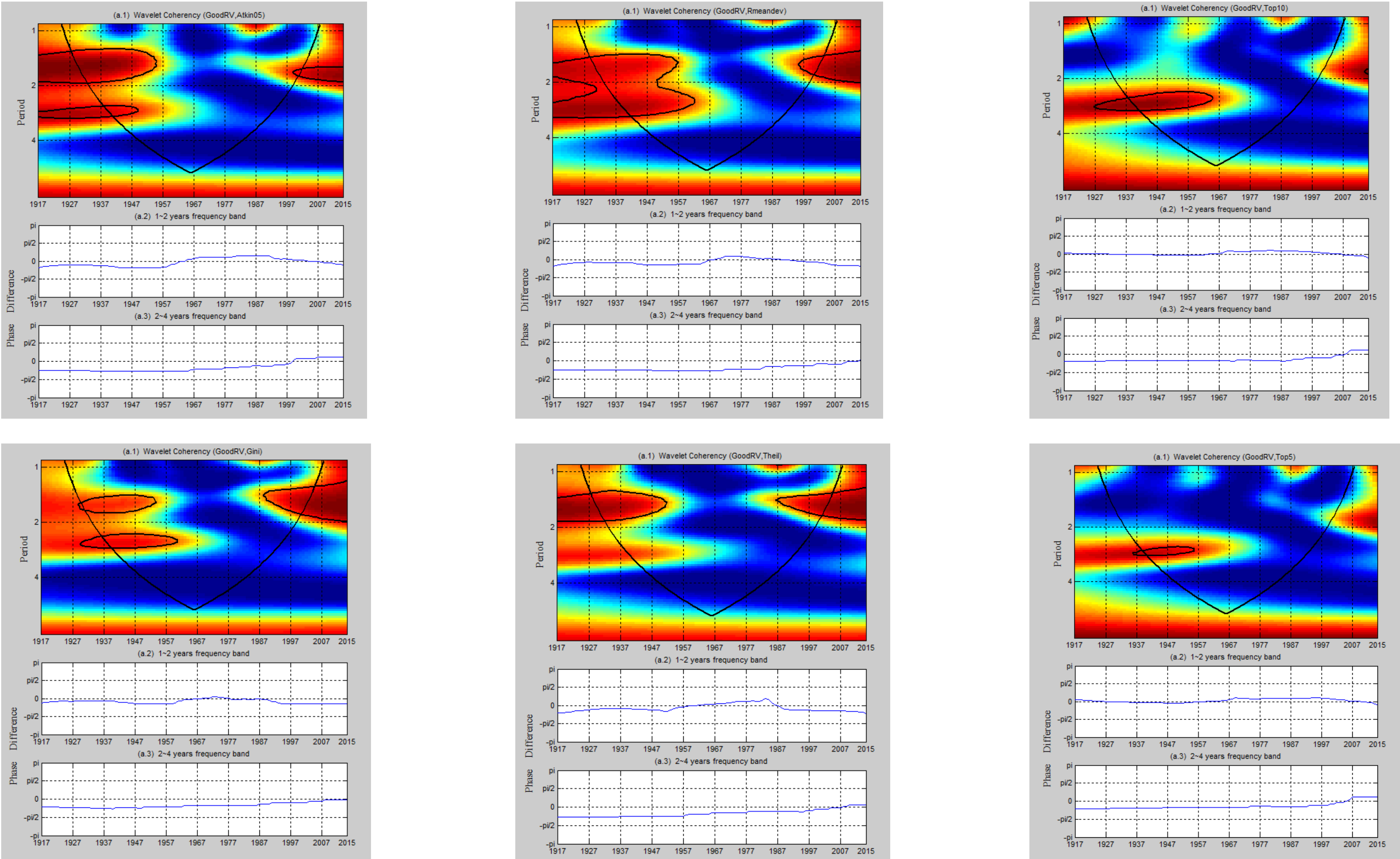
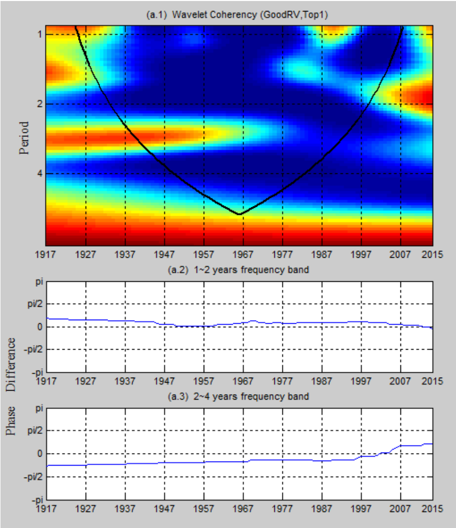
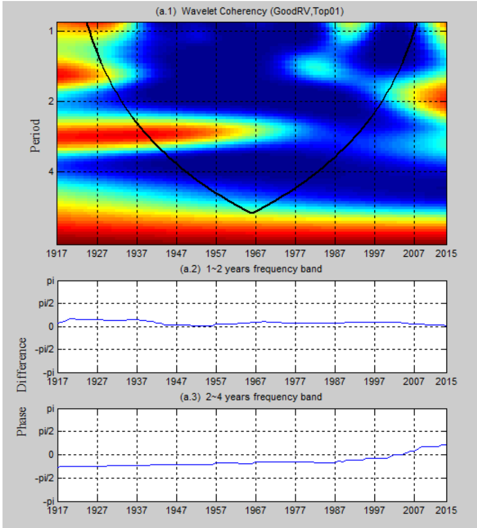


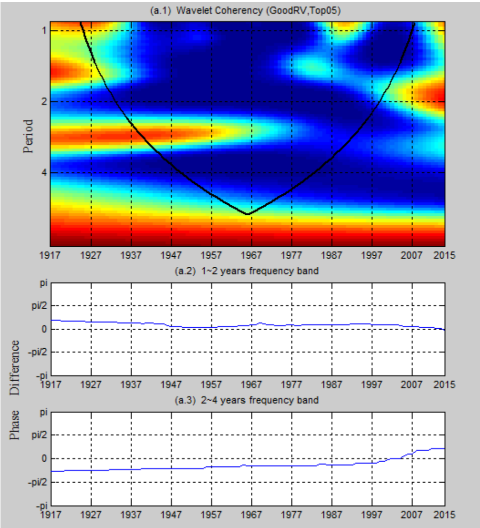
Figure 6.2. Causal relationship between positive output volatility and income inequality measures







Note: Wavelet Coherency between the positive output volatility and income inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2015.



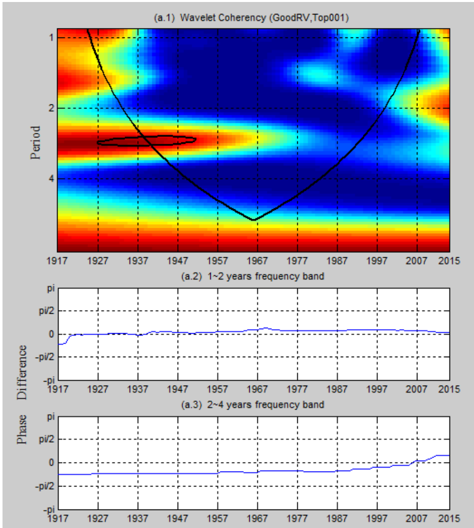
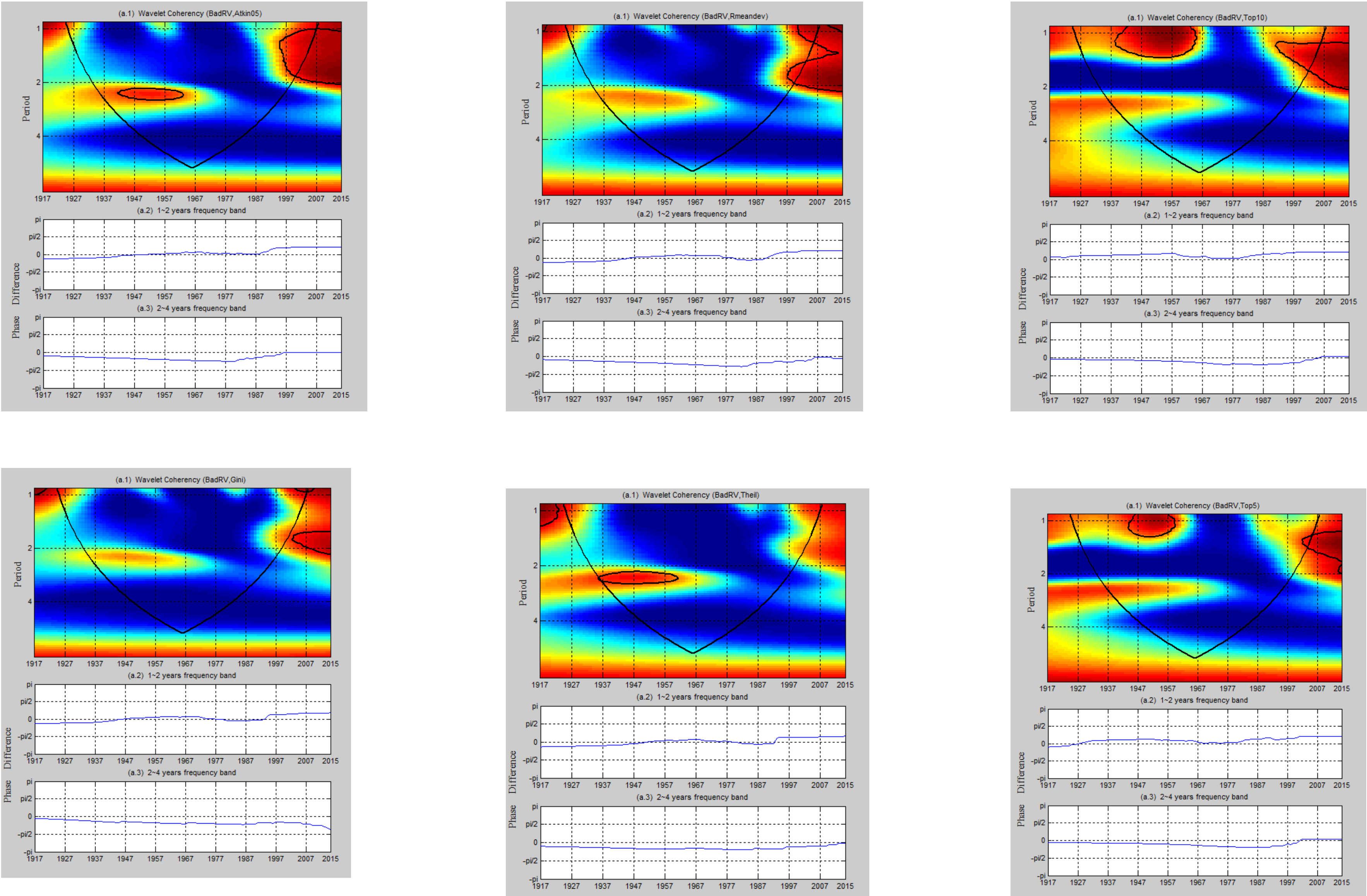
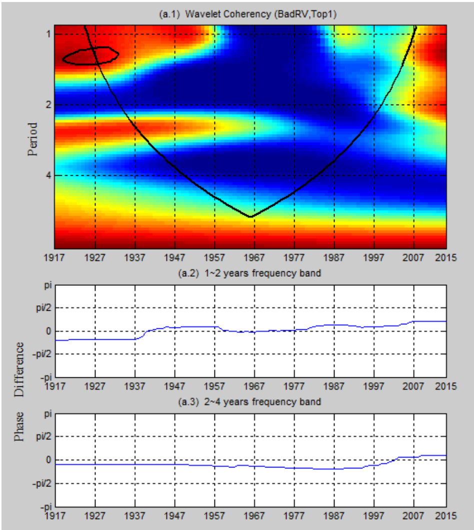
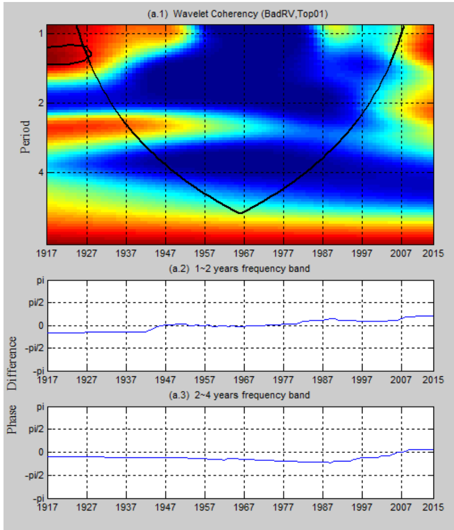
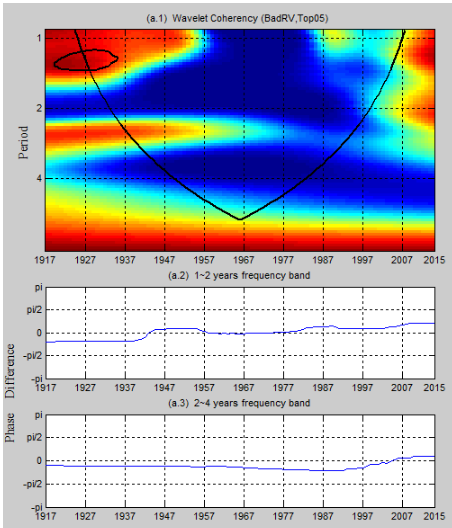


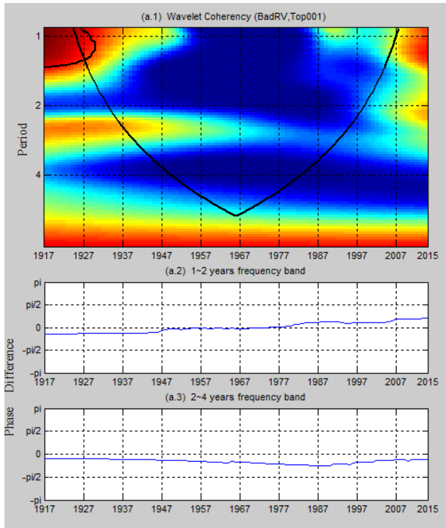
Figure 6.3. Causal relationship between negative output volatility and income inequality measures





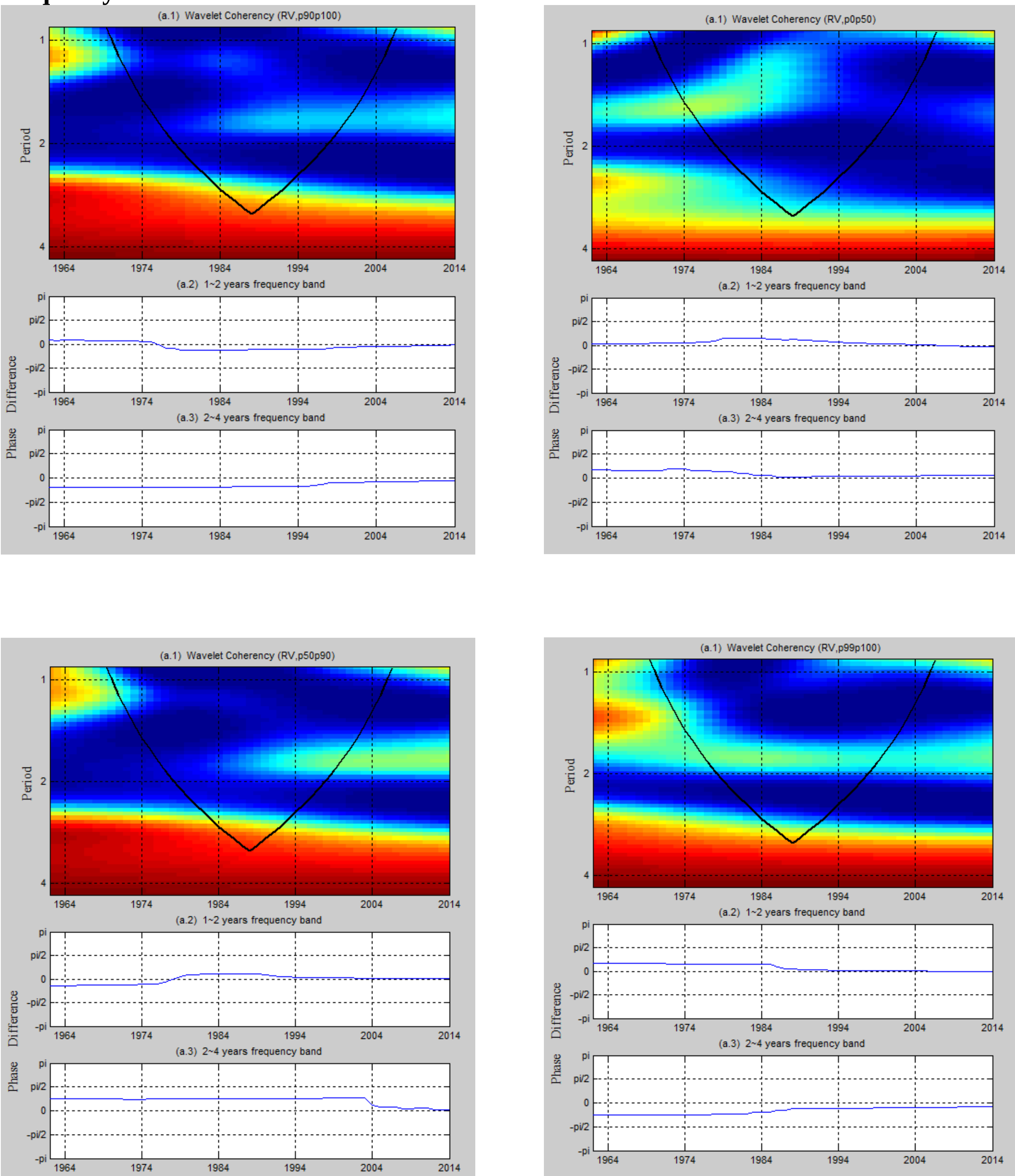






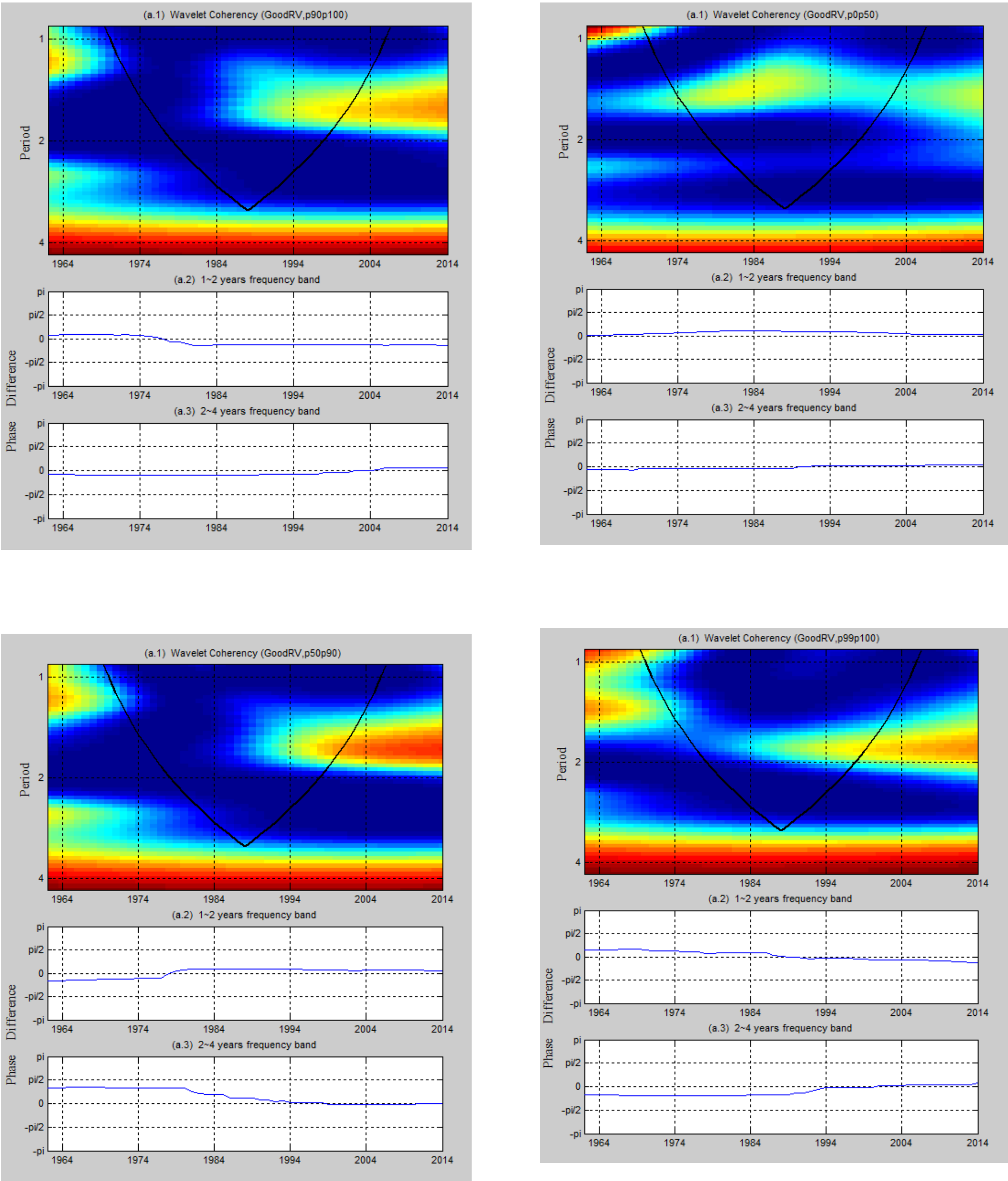
Note: Wavelet Coherency between the negative output volatility and income inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1917-2015.

Figure 6.4. Causal relationship between aggregate output volatility and wealth inequality measures



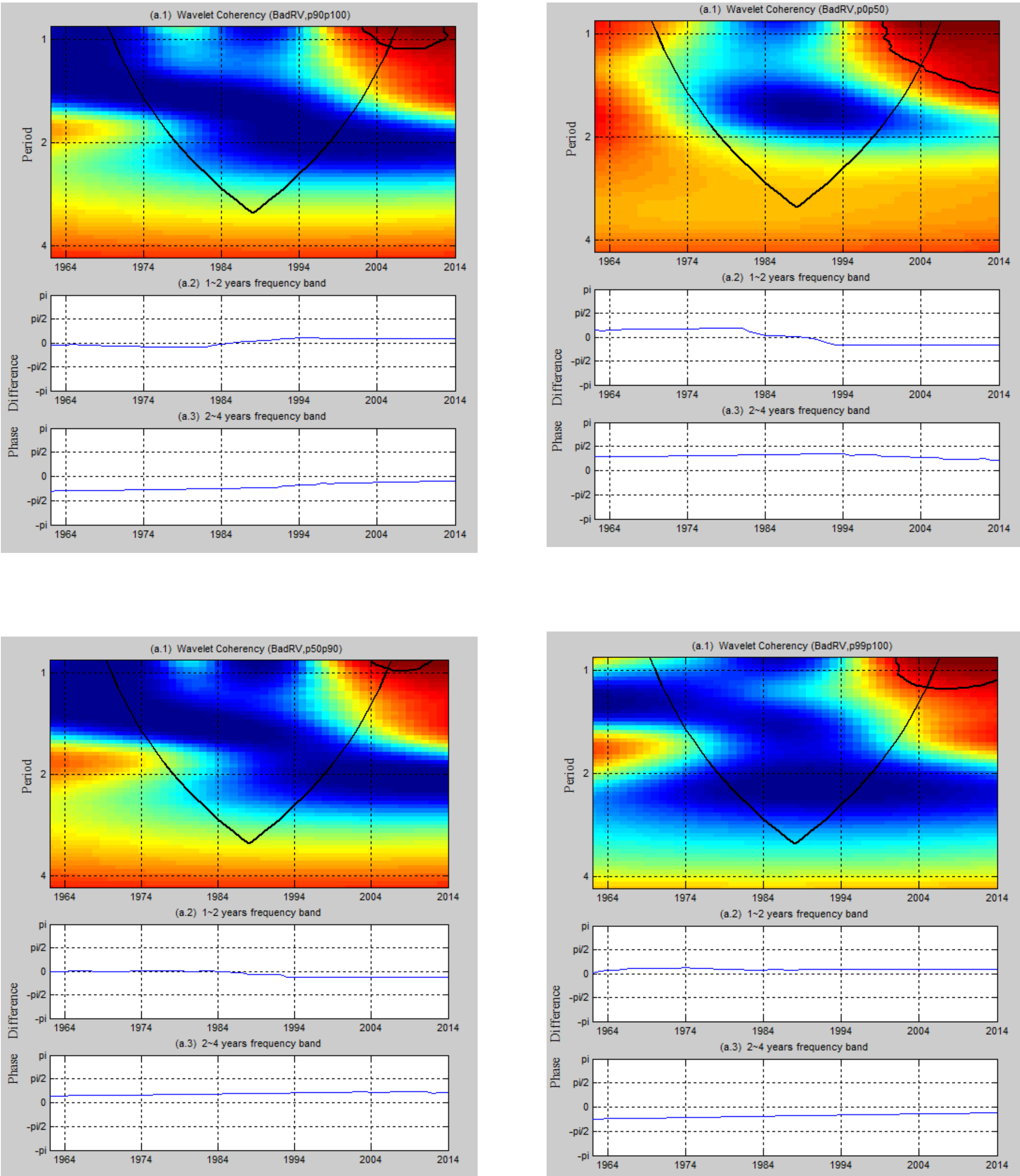
Note: Wavelet Coherency between the aggregate output volatility and wealth inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1962-2014.

Figure 6.5. Causal relationship between positive output volatility and wealth inequality measures



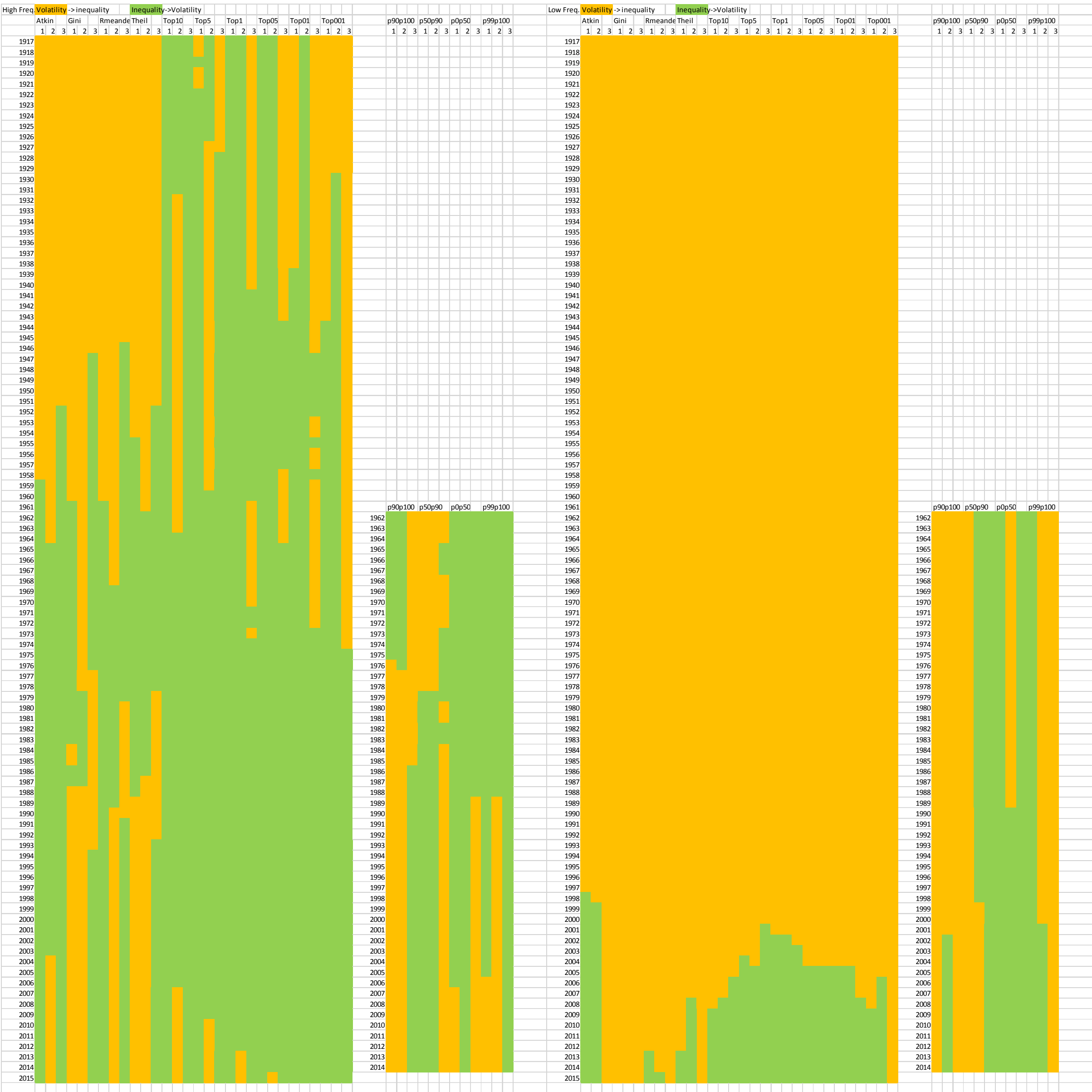
Note: Wavelet Coherency between the positive output volatility and wealth inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase.The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1962-2014.

Figure 6.6. Causal relationship between negative output volatility and wealth inequality measures



Note: Wavelet Coherency between the negative output volatility and wealth inequality measures. The black contour indicates a 5 % significance level. The significance levels are based on 10,000 draws from Monte Carlo simulations estimated on an ARMA(1,1) null of no statistical significance. The line around figure is the cone-of-influence (COI) earmarking the areas affected by the edge effects or phase. The colour code for power ranges from blue (low power) to red (high power). The y-axis refers to the frequencies (measured in years); the x-axis refers to the time period over the period 1962-2014.

Figure 6.7. Short and long run causality



Note: First two figures from the left indicate the short run causality relationship between volatility and inequality. 1, 2 and 3 indicate aggregate volatility, positive volatility and negative volatility. Orange colour indicates that the volatility leads and Green colour indicates that inequality leads. Third and fourth figures from the left show the long run causality. Y-axis indicates the year.

Chapter 7

Conclusion

This thesis has examined the dynamic interaction between income and wealth inequality and macroeconomic variables in the United States. Using a variety of econometric tools that account for underlying issues in inequality analysis, our main empirical investigation supports a bidirectional relationship between U.S. inequality and the macroeconomy. Specifically, the following results are reported.

The second chapter examines the relationship between the U.S. per capita real GDP and income inequality. Wavelet analysis uncovers correlation and causality between the two series in both the time and frequency domains. We find robust evidence of a positive correlation between the growth rate and inequality across frequencies. Yet, directions of causality vary across frequencies and evolve with time. In the time-domain, the time-varying nature of long-run causalities implies structural changes in the two series. These findings provide a more thorough picture of the relationship between the U.S. per capita real GDP and inequality measures over time and frequency, suggesting important implications for policy makers. For example, policies that help to reduce inequality may undermine growth such that a trade-off between inequality and growth seems embedded in policy makers' choice.

The third chapter employs a semiparametric instrument variable (IV) to establish the effects of the inflation rate on income inequality. This allows us to see whether monetary policy and the resulting inflation rate can affect income inequality and improve the well-being of individuals. Our analysis relies on a cross-state panel for the United States, which minimizes the problems associated with data comparability often encountered in cross-country studies related to income inequality. We find the non-linear U-shaped relationship that depends on the level of the inflation rate. Each household owns different combinations of assets/debts, which makes it almost impossible to avoid the redistributive effects of monetary policy. Thus, policy makers should explicitly consider the possible redistributive effects of monetary policy.

The fourth chapter investigates the causal relationship between personal income and income inequality in a panel data and makes use of a causality methodology proposed by Emirmahmutoglu and Kose (2011). Results indicate that when we control for heterogeneity and spatial dependence, a 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 a causal relationship exists for the Top 1 % measure. We focus on inequality across states because inequality-related policy can occur at the state and local levels, which can produce different inequality profiles across states.

The fifth chapter identifies the role of financial development on U.S. state-level income inequality, which, to our knowledge, is the first to examine the role of financial development on U.S. state-level inequality. We find robust results whereby financial development linearly increases income inequality for the 50 states. When we divide the 50 states into two separate groups of higher and lower inequality states than the cross-state average inequality, the effect of financial development on income inequality appears non-linear. Based on our results as well as the existing cross-country studies, whether financial development effect depends on the initial level of income inequality proves an interesting topic for future research.

In an attempt to understand the various components around inequality, the sixth chapter explores the relationship between the U.S. economic growth volatility, and income and wealth inequality using wavelet analysis. This chapter also considers the relationship between output volatility during positive and negative growth scenarios. Our findings provide evidence of positive correlation between the volatility and inequality across high (short-run) and low frequencies (long-run). The direction of causality varies across frequencies and time.

Strong evidence exists that volatilities lead inequality at low-frequencies across income inequality measures from 1917 to 1997. After 1997, however, the direction of causality changes. These findings provide a more thorough picture of the relationship between the U.S. growth volatility and inequality measures over time and frequency domains. Also, the causalities can be linked to the U.S. business cycles for further investigation.

What type of policy intervention can stabilize economic inequality at a low level? This is a difficult question as we need to find a policy that achieves the goal without causing problems in other parts of the complex economic system. As most of the components of the economy interact simultaneously, unless exogenous changes occur, we may face increasing inequality for a while. No one policy can resolve this inequality. Policy makers believe that economic growth can solve the U.S. inequality problem. The benefits of growth do not trickle down to all income groups over the past three decades, however. The United States requires effective policies to restrain negative externalities. Our study finds that the relationship between inequality and its various predictors are nonlinear, and much heterogeneity exists across states and measures of inequality. Therefore, policy makers need to carefully implement policies. Extensions of this research can analyze the effect of fiscal policy. Also, more research can determine the optimal average level of inflation as well as the redistribution effects of unconventional monetary policy, such as forward guidance and quantitative easing. Another extension relates to state-specific causal relationships between personal income and inequality. State-specific causal relationships between technological progresses on inequality can be analyzed.

It is worth noting that this analysis also suffers from several limitations. One of the limitations of this study is data availability as the study had to rely on data, for example quarterly GNP data, from different period and different sources. With wavelet analysis, Dhamala et al. (2008) try to undertake causality in non-parametrical wavelet and mention that the trouble lies in computing the spectral matrix factors in order to derive the minimum phase. This process involves inverse Fourier to communicate between the time and frequency domain.

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