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

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Abstract: This study applies wavelet coherency analysis to examine the relationship between the U.S. per capita real GDP and six income inequality measures over the period 1917 to 2012. Wavelet analysis allows the simultaneous examination of correlation and causality between the two series in both the time and frequency domains. Our findings provide 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.

JEL classification code: C49, D31

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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; Person 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 el 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-Pal 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, 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 el al., 2009; Forbes, 2000; Banerjee and Duflo, 2003; and Halter el 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 allows the extraction of time- and frequency-localized information, which permits deeper investigation of the causality between variables (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). Moreover, we can apply wavelet analysis to non-stationary and locally stationary as well as series with structural breaks (Roueff and Sachs, 2011). 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. Methodology: Wavelet coherency and 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 Sach, 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 S is a smoothing operator.[1] . 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 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. Bloomfield et al. (2004) characterizes the phase difference relationship between $x(t)$ and $y(t)$ such that:

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

where $\mathcal{J}$ 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 $x(t)$ preceding $y(t)$. If $\phi_{xy} \in \ (\pi/2, \pi)$, then the series move out of phase (negatively co-move) with $y(t)$ preceding $x(t)$. If $\phi_{xy} \ \in (-\pi, -\pi/2)$, then the series move out of phase with $x(t)$ preceding $y(t)$. Finally, if $\phi_{xy} \in \ (-\pi/2{,}0)$, then the series move in phase with $y(t)$ preceding $x(t)$. 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

[1] 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.

whole sample period as well as at each frequency (Grinsted et al., 2004; Tiwariet 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).

3. Data

Our analysis relies on the natural logarithm of U.S. per capita real GDP and the four income inequality measures - 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.[2] Real GDP (at constant 2009 prices) comes from the Global Financial Database, whichwe divide by population from the data segment of Shiller website[3], to derive the real per capita GDP..

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. 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. The test results further indicate that the first differences of the series do reject the null of a unit root. Therefore, the unit-root tests indicate that the data conform to I(1) processes.

[See Tables 1 and 2]

The presence of unit roots makes the traditional asymptotic inference invalid by violating asymptotic normality. Toda and Yamamoto (1995) propose an interesting, yet simple,

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[2] http://www.shsu.edu/eco_mwf/inequality.html. Professor Frank constructed 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.

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

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[4] 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. Toda-Yamamoto causality tests show 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 cointegartion 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 Nybolm (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 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.

[4] 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.

[See Table 3]

Table 3 and 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. Tables 3A, 3B, 3D, and 3F 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 Aktin 05, Gini, and Theil index equations. Table 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 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.

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.

[See Table 4]

Table 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.[5]

5. Main analysis

[See Figure 1]

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 Figure 1. Figure 1 also shows positive correlations between the U.S. per capita real GDP and Atkin05 over the short and long term.

[See Table 5]

Across the 2-4 year frequency band, the Atkin05 inequality measure leads U.S. per capita real GDP in 1917-1948 and 1977-2012, while U.S. per capita real GDP leads the Atkin05 inequality measure in 1949-1976. Across the 1-2 year frequency band, we see the causal link running from the Atkin05 inequality measure to per capita real GDP for several periods – 1965-1973, 1978-1987, and 2011-2012.

[See Figure 2]

The Gini coefficient exhibits a strong and statistically significant correlation with U.S. per capita real GDP from 1917 to 1930 and from 1970 to 2012 in Figure 2. Figure 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.

[See Table 6]

[5] The results of cointegration test motivate us to take time-varying approach. One way to implement time-varying cointegration is to use a rolling causality analysis, but we do not do so for the following reasons. First, the results may depend on the optimal window length. Second, rolling causality analysis only works in the time domain.

The Gini coefficient leads per capita real GDP from 1967-1972 at high frequency in Table 6, while per capita real GDP leads the Gini coefficient from 1917-1970 at low frequency. We can see the temporary causality does not determine long-run causality.

[See Figure 3]

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 Figure 3) with an in-phase relation (see Table 7).

[See Table 7]

We observe across the 1-2 year frequency band in Table 7 an in-phase relationship in 1966-1975 with Rmeandev leading. At low frequencies, we see the causal link running from Rmeandev to per capita real GDP from 1917-1948.

[See Figure 4]

Theil index exhibits a strong correlation with U.S. per capita real GDP from 1980 to 2012 across the 1-2 year frequency band in Figure 4.

[See Table 8]

The phase difference shows causality between the U.S. per capita real GDP and the Theil index in Table 8. Throughout the period from 1917 to 2012, Theil index leads U.S. per capita real GDP at low frequency. This indicates that income inequality (Theil) positively affects per capita real GDP. At high frequencies, Theil index leads per capita real GDP repeatedly from 1963-1972.

[See Figure 5]

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 Figure 5. Across the 2-3 years frequency band, we observe a significant island from 1945 to 1957, 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 correlation between U.S per capita real GDP and inequality measures at the 1-2 years frequency at the recent sample years. This can be explained with a Tax Reform Act of 1986. Tax Reform Act lowered the top tax rate and raised the bottom tax rate, which contributes that U.S per capita real GDP leads income inequality in the recent sample years.

[See Table 9]

Table 9 shows causality between the U.S. per capita real GDP and the Top 10%. At high frequency, the Top 10% leads per capita real GDP from 1917-1988. At low frequency, the Top 10% leads per capita real GDP from 1917-1973 and 1979-1984.

[See Figure 6]

In Figure 6, we observe a statistically strong 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.

[See Table 10]

At high frequency, the Top 1% leads per capita real GDP from 1917-1993 and 2003-2012 in Table 10. At low frequency, the Top 1% leads per capita real GDP from 1917-1983 and 1986-2012. These results fall in line with the literature, which focused on whether a higher level of income associates with higher or lower inequality, finding no overall effect (Dollar and Kraay, 2002; Dollar el al., 2013). Overall, we observe the directions of short- and long-term causality vary. If we restricted our analysis to classical time series, we would 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.

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, stationarity, cointegration, and model specification. Furthermore, it permits examining for cointegration and causality. We use annual time-series data from 1917 to 2012 from the US, 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. Therefore, the Granger causality test will not provide reliable results. 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.

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, even though series frequently change their relationships between the short and long term.

To reduce income inequality, 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.

Table 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 percent level of significance.

Table 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	Aktin05 -> 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 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

Table 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

Table 5. Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Atkinson Index)

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

Table 6. Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Gini coefficient)

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

Table 7. Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Rmeandev)

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

Table 8. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Theil Index)**

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

Table 9. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Top 10%)**

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

Table 10. **Wavelet phase difference (logarithm of U.S. per capita real GDP, logarithm of Top 1%)**

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

Figure 1. **Causal relationship between Per Capita Real GDP and Atkison Index**

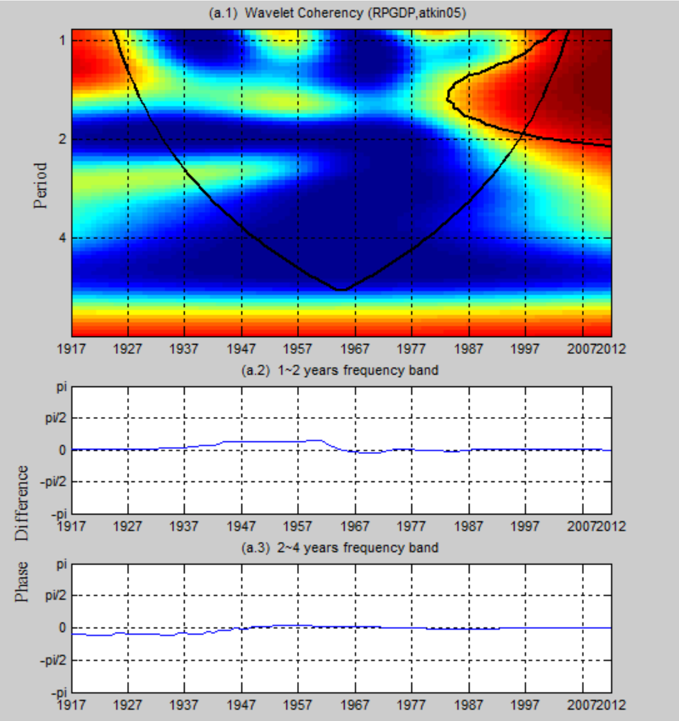


Figure 2. **Causal relationship between Per Capita Real GDP and Gini coefficient**

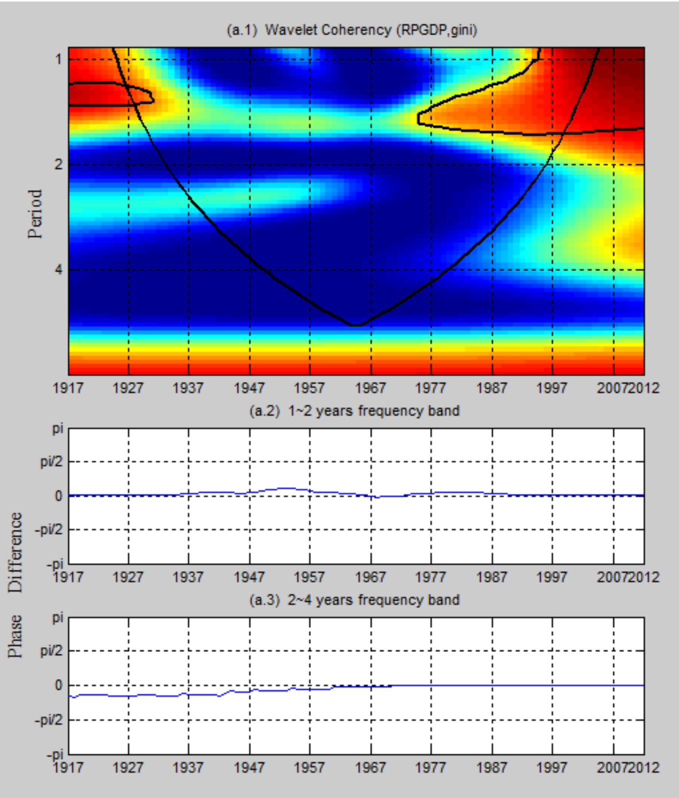


Figure 3. **Causal relationship between Per Capita Real GDP and the Relative Mean Deviation**

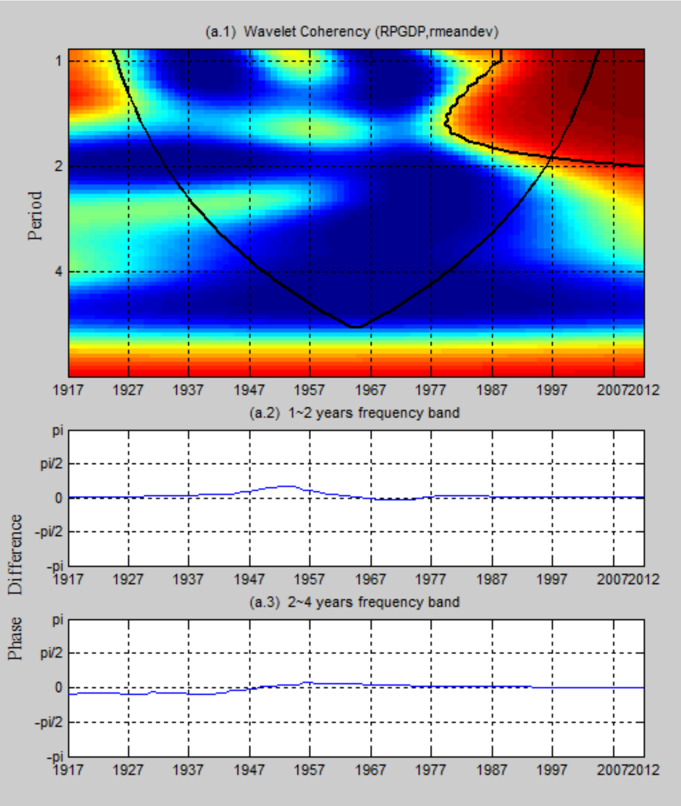


Figure 4. **Causal relationship between Per Capita Real GDP and Theil's entropy Index**

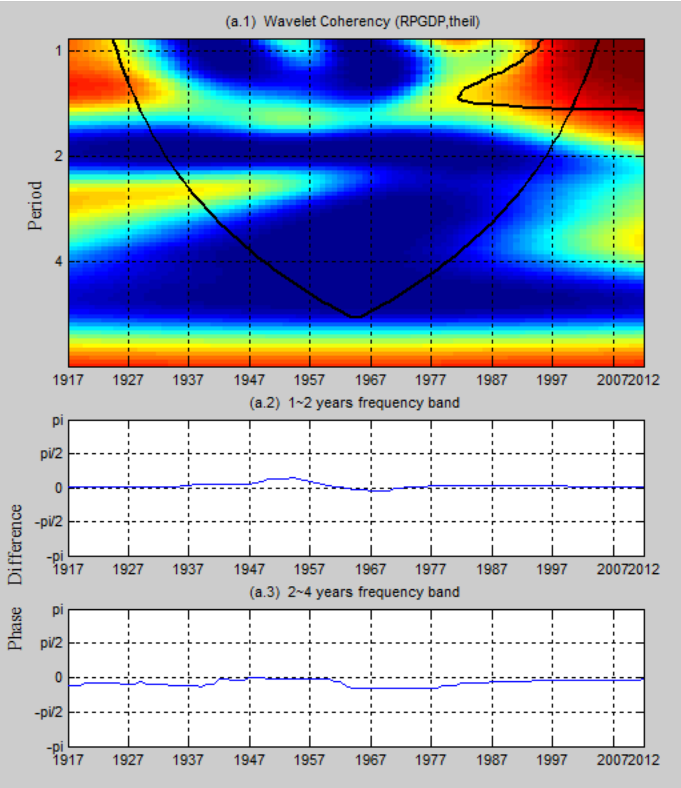


Figure 5. **Causal relationship between Per Capita Real GDP and Top 10% income share**

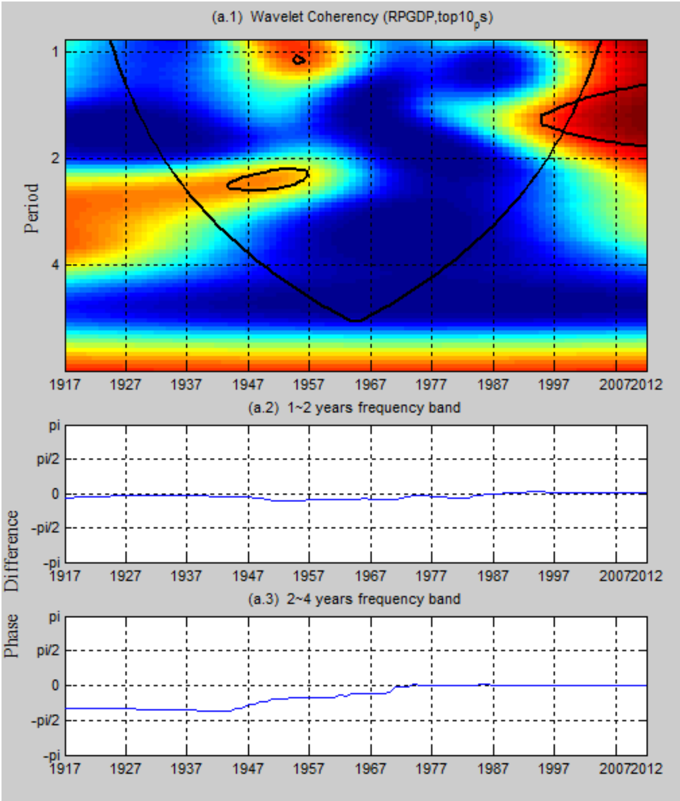
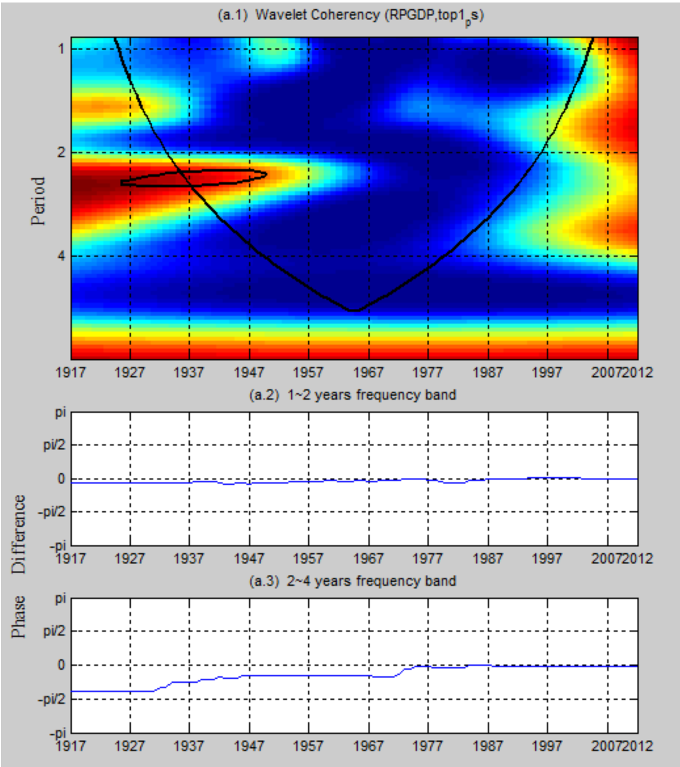


Figure 6. **Causal relationship between Per Capita Real GDP and Top 1% income share**



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