Partisan Conflict, Real Per Capita GDP and Inequality in the United States

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ABSTRACT

The first part of this thesis examines the predictive power of a partisan conflict on income inequality. Our study contribute to the existing literature by using the newly introduced nonparametric causality-in-quantile testing approach to examine how political polarization in the Unites States affects several measures of income inequality and distribution overtime. The study uses annual time-series data between the periods 1917-2013. We find evidence in support of a dynamic causal relationship between partisan conflict and income inequality, except at the upper end of the quantiles. Our empirical findings suggest that a reduction in partisan conflict will lead to a more equal income distribution, but this requires that inequality is not exceptionally high.

Then, we examine the relationship between income inequality and long-run economic growth has gained a growing attention in economic research for over decades. This study employed advanced time series techniques to examine the existence of an inverted U-shaped long-run relationship between income inequality and economic growth, using long-span time series data for the United States between the periods 1917 to 2012. The concepts of summability, balancedness and co-summability was advanced to analyze nonlinear long-run relations among stochastic processes. The empirical results find no evidence in support of nonlinear long-run (inverted U-shaped) relationship for the US, but findings from a vocal set of economists lends strong support and is the basis for the conclusions drawn by this study.

Lastly, the third study examine the existing literature on the short-run and long-run impact of economic growth on income inequality has found that positive and negative output shocks have worsened income distribution in the United States. In this paper, we attempt to empirically examine the opposite, that is, the impact of positive and negative income inequality shocks on the real output level. Using the same time-series data, over the period 1917-2012, in a more comprehensive manner by employing six measures of income distribution, we examine the impact of an increase or decrease in income inequality on economic growth, using the nonlinear Autoregressive Distributed Lag (NARDL) approach. Our empirical result provide an evidence in support of a long-run asymmetric impact between income inequality and real output level, since the long-run coefficients on positive changes have positive signs, while the signs of those on negative changes are negative, indicating that a decrease or an increase in income inequality improves real output level in the US.

Keywords: Partisan Conflict, Income Inequality, GDP per capita, Quantile Causality, Summability, Balancedness, Cosummability, Asymmetry, non-linear ARDL model, United States.

ÖZ

Bu tezin ilk kısmında, partizan çatışmasının gelir eşitsizliği üzerindeki yordayıcı gücü incelenmektedir. Çalışmamızda, Amerika Birleşik Devletleri'ndeki politik kutuplaşmanın gelir eşitsizliği ve zaman boyu gelir dağılımının çeşitli ölçeklerini nasıl etkilediğini incelemek için yeni ortaya konan parametrik olmayan nedensellik-kantil test yaklaşımı kullanılarak mevcut literatüre katkıda bulunulmuştur. Çalışmada 1917-2013 yıllık zaman serisi verileri kullanılmıştır. Kantilin üst ucu hariç, partizan çatışması ve gelir eşitsizliği arasında dinamik nedenselliği destekleyen kanıtlar bulunmuştur. Ampirik bulgularımız, gelir dağılımı eşitsizliğinin çok yüksek olmadığı durumda, partizan çatışmasındaki azalışın daha eşit bir gelir dağılımına yol açacağını destekliyor.

Tezin bir sonraki aşamasında, yıllardır ekonomik araştırmanın dikkat merkezinde olan gelir eşitsizliği ve uzun dönem ekonomik büyüme arasındaki ilişki incelenmiştir. Bu çalışma, gelir eşitsizliği ve ekonomik büyüme arasında var olan ters U şeklindeki uzun dönemli ilişkiyi, ileri zaman serisi teknikleri ile 1917 ve 2012 yılları için uzun dönem zaman serileri verisi kullanarak Amerika Birleşik Devletleri için incelemektedir. Stokastik süreçler arasındaki doğrusal olmayan uzun dönemli ilişkileri analiz etmek için toplanabilirlik, dengelilik ve birlikte toplanabilirlik kavramları geliştirilmiştir. Ampirik sonuçlara göre, Amerika Birleşik Devletler için doğrusal olmayan uzun dönem (ters U şekli) ilişkiyi destekleyecek kanıt bulunamamıştır, fakat bir grup ekonomistten edinilen bulgular bu ilişkiyi destekler nitelikte olup bu çalışmadan çıkarılacak sonuçlar için temel oluşturmaktadır.

Son olarak, üçüncü çalışma ekonomik büyümenin kısa ve uzun vadede gelir eşitsizliği üzerindeki etkisine ilişkin mevcut literatürü incelemektedir, sonuçlar pozitif ve negatif çıktı şoklarının Amerika Birleşik Devletleri'nde gelir dağılımını kötüleştirdiğini ortaya koymuştur. Bu çalışmada, pozitif ve negatif gelir eşitsizliği şoklarının reel çıktı seviyesine etkisi ampirik olarak incelenmiştir. Aynı zaman serisi verisi, 1917-2012 dönemi, ile altı gelir dağılımı ölçüsü kullanarak daha kapsamlı bir şekilde gelir eşitsizliğindeki artış ve azalışın ekonomik büyüme üzerine etkisi doğrusal olmayan otoregresif dağıtılmış gecikme modeli kullanarak incelenmiştir. Ampirik sonuçlarımız, pozitif ve negatif gelir eşitsizliği şoklarının uzun vadede asimetrik etkilere sahip olduğunu göstermektedir. Gelir eşitsizliği şoku olan modellerimizin uzun süreli asimetrik davranışları, ister pozitif ister negatif olsun, Amerika Birleşik Devletleri'nde reel çıktı seviyesi üzerinde uzun dönemli pozitif bir etkiye sahip olduğunu bulduk.

Anahtar Kelimeler: Partizan Çatışması, Gelir Eşitsizliği, Kişi Başına GSYİH, Kantil Nedensellik, Toplanabilirlik, Dengelilik, Birlikte Toplanabilirlik, Asimetri, Doğrusal olmayan ARDL model, Amerika Birleşik Devletleri.

DEDICATION

To My Grandma,

MRS. OLUFUNKE OGEDEBE

She taught me there is dignity in learning.

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I give all the glory to Almighty God for being faithful to His words in my life.

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AD	Average Derivatives.
AIC	Akaike Information Criteria.
BIC	Bayesian Information Criteria.
GDP	Gross Domestic Product.
HDI	Human Development Index.
LSCV	Least Square Cross-Validation.
LM	Lagrange Multipplier.
NARDL	Nonlinear Autoregressive Distributed Lag.
OLS	Ordinary Least Square
PCI	Partisan Conflict Index.
SIC	Schwarz Information Criteria.
US	United States
VAR	Vector Autoregressive.
WWID	World Wealth Income Database.

Chapter 1

INTRODUCTION

The income inequality in the United States has followed a roller coaster pattern over the twentieth century into the early twenty-first century. Goldin and Margo (1992) coined the phrase "Great Compression" to describe the movement in income inequality following the Great Depression. The Great Compression saw a large reduction in income inequality. Krugman (2007) coined the phrase Great Divergence after the Great Compression. This period that continues through the present saw a large increase in income inequality. Piketty and Saez (2003) conclude that the Great Compression ended in the 1970s and then entered the Great Divergence phase. Of course, the Great Depression preceded the Great Compression and the Great Moderation and the Great Recession occurred during the Great Divergence. [1]

Significant efforts attempt to explain the roller coaster movements in income inequality, especially the transition from the Great Compression to the Great Divergence. A number of hypotheses exist in the literature, including diverging returns to different levels of education and training, the decline in unionization rates, trade liberalization, higher rates of immigration, increased presence of single parent families, and the decline in the real minimum wage (see Kuznets 1955; Jenkins 1995; Gottschalk and Smeeding, 1997; Atkinson, 1997, 2000; Li and Zou, 1998)

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[1] Gogas, Gupta, Miller, Papadimitriou, and Sarantitis (2017) described this series of "Great" episodes.

Chapter two of this thesis suggests a significant role for partisan conflict in explaining movements in U.S. income inequality. We investigated the predictive power of a partisan conflict on income inequality. We contribute to the existing literature by using the newly introduced nonparametric causality-in-quantile testing approach to examine how political polarization in the Unites States affects several measures of income inequality and distribution overtime.

In line with the above, chapter three examine the relationship between income inequality and long-run economic growth. We employed advanced time series techniques to examine the existence of an inverted U-shaped long-run relationship between income inequality and economic growth. Using long-span and very recent data for the United States, for the concept of summability, balancedness and co-summability, advanced to analyze nonlinear long-run relations among stochastic processes. The objective of this study is to examine whether there is linear or nonlinear long-run (inverted U-shaped) relationship between real per capita GDP and income distribution for the US.

Furthermore, chapter four examine the existing literature on the short-run and long-run impact of economic growth on income inequality. We attempt to empirically examine the impact of positive and negative income inequality shocks on the real output level, in a more comprehensive manner by employing six measures of income distribution. The objective of this study is to examine asymmetry impact of an increase or decrease in income inequality on economic growth, using the nonlinear Autoregressive Distributed Lag (NARDL) approach.

Finally, chapter five summarizes conclusion from the individual chapters, in such a manner that it convey general idea of the thesis.

Chapter 2

PARTISAN CONFLICT AND INCOME DISTRIBUTION IN THE UNITED STATES: A NONPARAMETRIC CAUSALITY-IN-QUANTILES APPROACH

2.1 Introduction

The income inequality in the United States has followed a roller coaster pattern over the twentieth century into the early twenty-first century. Goldin and Margo (1992) coined the phrase "Great Compression" to describe the movement in income inequality following the Great Depression. The Great Compression saw a large reduction in income inequality. Krugman (2007) coined the phrase Great Divergence after the Great Compression. This period that continues through the present saw a large increase in income inequality. Piketty and Saez (2003) conclude that the Great Compression ended in the 1970s and then entered the Great Divergence phase. Of course, the Great Depression preceded the Great Compression and the Great Moderation and the Great Recession occurred during the Great Divergence. [2]

Significant efforts attempt to explain the roller coaster movements in income inequality, especially the transition from the Great Compression to the Great Divergence. A number of hypotheses exist in the literature, including diverging returns to different levels of education and training, the decline in unionization rates,

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trade liberalization, higher rates of immigration, increased presence of single parent families, and the decline in the real minimum wage (see Kuznets 1955; Jenkins 1995; Gottschalk and Smeeding, 1997; Atkinson, 1997, 2000; Li and Zou, 1998).

Our paper suggests a significant role for partisan conflict in explaining movements in U.S. income inequality. Government can affect income inequality through its efforts at income redistribution (Kelly 2004) as well as setting the rules of the game that conditions markets (Kelly 2009). The degree of partisan conflict affects the efficacy of these methods in affecting income inequality. In the twentieth century, the entry of the United States into World War II marked a significant change in the role of the U.S. federal government in the economy. Moreover, the ability of the federal government to intervene effectively in the economy generally requires the willingness of the two major parties to compromise on legislation. Partisan conflict may have contributed to the movement in unionization rates, immigration flows, trade liberalization, and the decline in the real minimum wage cited above.

Polarization between the two major political parties should drive the partisan conflict to higher levels. The political atmosphere in the United States during the post-WWII period exhibited significant transformation (see McCarty, *et al.*, 2003), where polarization and partisan transformation in the Southern states experienced increase in policy strategy of the Republicans and Democrats. The existing literature documents that the bipartisan agreement among the Congress regarding economic issues (see Poole and Rosenthal, 1984; McCarty *et al.*, 1997) that spread over the 1960s period, stirred up the deep dogmatic divisions experienced in the 1990s. In addition, the literature argues that the formerly orthogonal disputes have been integrated into the conflicts over economic conservatism and liberalism. More especially, issues of economic and social class have become an integral part of the main ideological conflicts over redistribution (see Stone, 1973; Abramowitz, 1994; Hutchings and Valentino, 2004; Valentino and Sears, 2005; Shafer and Johnson, 2009; Tesler and Sears, 2010; Tesler, 2012).

Azzimonti (2015) considers the effect of partisan conflict on private investment, and found an inverse relationship between partisan conflict and investment. The combination of divided government and increasing polarization triggered a higher level of fiscal uncertainty in the United States. Partisan conflict can affect investment in two major ways. On the one hand, the expected return on investment is unpredictable, when size, timing, and basic components of fiscal policy are highly uncertain. As such, the option value of investment, which is largely irreversible, rises, causing delays in pulling the trigger on investment decisions. On the other hand, a higher level of partisan conflict can lead to the inability of the government to respond to negative shocks and to implement policy reforms to offset or reverse those negative shocks (see Alesina and Drazen, 1991). This reduces the expected rate of return on investment, discourages investment, and leads to higher inequality. Thus, we hypothesize that a higher partisan conflict indirectly causes higher inequality.

The partisan-conflict and inequality trends interestingly move together over the years. According to McCarty *et al.* (2003), partisan conflict measures the disparity between the Democratic and Republican parties on a liberal-conservative scale. The proximity of the swings in these two variables, however, is striking. In fact, we can observe a direct relationship between partisan conflict and income inequality, depending on the level of political polarization between the two parties. For instance, the positive effect of partisan conflict on inequality can occur as follows. High political polarization between the two parties stimulates economic instability, which produces lower investment and employment. Finally, the resulting declines in output and growth, hence, widen the inequality gap. Banerjee (2004) also argues that there exists a link between investment and inequality, especially in the absence of perfect markets. Partisan conflict inversely affects investment (i.e., the higher the partisan conflict, the lower the level of investment), which, in turn, lowers real income and economic growth, especially when expected return on investment is unpredictable. In a nutshell, a higher partisan conflict lowers investment that, in turn, reduces growth and widens the inequality gap.

A few existing studies on the relationship between partisan conflict and income inequality/distribution exist. McCarty *et al.* (2003), using party polarization and the Gini coefficient to proxy for partisanship and income inequality, find that partisanship is highly stratified by income in the United States. Anderson and Barimundi (2008), in a comparative analysis that uses democracy, inequality, and representation measures, argue that a nation's political system and institutions play a vital role in determining levels of income inequality in society. Similarly, Pontusson and Rueda (2008), using income inequality and political polarization measures for twelve OECD countries, examine how income inequality influences politics, especially government policy. On the other hand, Finseraas (2010) investigates how political polarization in a non-economic dimension influences redistribution. This study argues that high party polarization in a non-economic policy dimension alters the political response, thus, widening income inequality. None of these studies, however, investigates the causal relationships between income inequality and partisan conflict, using either the newly developed partisan conflict index (PCI) to proxy for partisanship or non-parametric causality-in-quantile econometric techniques in their various analyses.

The current study investigates this causality relationship from partisan conflict to income inequality and vice-versa in the United States, using the PCI data and non-parametric causality-in-quantile test recently introduced by Balcilar, *et al*. (2016). We employ annual data from 1917 to 2013, or 97 observations. The sample period ends at 2013 based on unavailability of updated PCI data.

The causality-in-quantile test technique as introduced by Balcilar *et al.* (2016) is robust based on the following factors. First, this technique discovers the dependence framework of the time series under observation by using non-parametric estimation, thus reducing or eliminating the possibility of model misspecification errors. Second, this approach permits the evaluation of both causality-in-mean and causality-in-variance. Thus, this test can examine higher-order dependency, which is regarded as a crucial factor, since a possibility exists of no causal relationship in the conditional mean for certain periods. Higher-order dependency, however, may exist in the same period even though causality in the mean does not exist. Third, this paper is the first to investigate the predictability of the PCI on income inequality with the non-parametric, causality-in-quantile approach. Empirical results from this current study show that the PCI does Granger cause income inequality. More specifically, a reduction in the PCI leads to a reduction in our measures of income inequality. This causality effect, however, does not exist at the upper end of the quantile distribution. The effect grows as the level of the PCI falls (weakens). This study applies this new, sound, robust, and reliable econometric technique.

The contribution of this study is of twofold. First, unlike other studies that make use of party-income stratification models, we employ a non-parametric causality-in-quantile testing techniques, which allows robust examination of causality relationships between macroeconomic variables. Thus, we can evaluate the useful predictive relationship of the PCI under different income inequality measures. That is, we will determine whether the PCI does predict income inequality, or does not. Second, we employ a novel non-parametric causality-in-quantile test for the causal nexus, if it exists, as proposed by Balcilar *et al.* (2016) to examine whether the PCI causes income inequality. Balcilar *et al.* (2016) causality tests combines nonlinear causality of order k-th proposed by Nishiyama, *et al.* (2011) and the quantile test developed by Jeong, *et al.* (2012). Thus, Balcilar *et al.* (2016) provides an advanced version of the other quantile tests previously developed.

The outline of this paper is as follows: Section 2 discusses the paper's methodology in detail. Section 3 presents the data and brief describes the variables. Section 4 analyzes the results. Section 5 concludes.

2.2 Methodology

We adopt the novel techniques proposed by Balcilar *et al.* (2016), a method built on the model structure of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). This method effectively identifies nonlinear causality via a hybrid approach. Designate the level of income inequality by y_t, and the PCI by x_t. Define the quantile-type causality based on Jeong *et al.* (2012) as follows.[3] In the θ-quantile with regards to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$, x_t does not cause y_t, if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}). \tag{1}$$

In the θ-quantile with regards to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$, x_t causes y_t, if

$$Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t | y_{t-1}, \dots, y_{t-p}) \tag{2}$$

We depict $Q_\theta(y_t | \cdot)$ as the θ-th quantile of y_t, while the conditional quantiles of y_t, $Q_\theta(y_t | \cdot)$, rely on t and the quantiles are confined between zero and one (i.e., $0 < \theta < 1$).

To develop a brief and concise presentation of the causality-in-quantiles tests, we specify the following vectors: $Y_{t-1} = (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} = (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. We also specify the conditional distribution functions as $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$, which represent the distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. We propose that the conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ proves continuous in y_t for all Z_{t-1}. Thus, specifying $Q_\theta(Z_{t-1}) = Q_\theta(y_t|Z_{t-1})$and $Q_\theta(Y_{t-1}) = Q_\theta(y_t|Y_{t-1})$, we observe that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with probability one. Consequently, we test the hypotheses for the causality-in-quantiles that depend on equations (1) and (2) as follows:

$$H_0\text{:}\ \ P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \text{ and} \tag{3}$$

[3] The explanation in this section nearly follows Nishiyama *et al.* (2011) and Jeong *et al.* (2012).

H_1: $P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1$ (4)

Jeong *et al.* (2012), trying to specify a measurable metric for the practical application of the causality-in-quantiles tests, use the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_Z(Z_{t-1})\}$, where ε_t depicts the regression error and $f_Z(Z_{t-1})$ depicts the marginal density function of Z_{t-1}. Hence, the causality-in-quantiles test builds on the regression error ε_t. We generate this regression error ε_t due to the null hypothesis stated in equation (3). This hypothesis is true, only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$. That is, we can rescript the regression error as $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is a signal function. Moreover, following Jeong *et al.* (2012), we can specify the distance metric, based on the regression error, as follows:

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} - \theta\right\}^2 f_Z(Z_{t-1})\right]. \tag{5}$$

In accordance with equation (3) and (4), note that $J \geq 0$. This assertion will persist with an equality (i.e., $J = 0$) only if the null hypothesis [i.e., H_0 specified in equation (3)] is true. But, $J > 0$ holds under the alternative hypothesis H_1 defined in equation (4). The realistic match of the distance measure J defined in equation (5) hands us a kernel-based causality-in-quantiles test statistic for the fixed quantile θ is specified as follows:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \ , \tag{6}$$

where T denotes the sample size, $K(\cdot)$ represent a known kernel function, h represents the bandwidth for the kernel estimation, and p denotes the lag-order applied in specifying the vector Z_t. Jeong *et al.* (2012) in their analysis, however, confirm that the re-scaled statistic $Th^p \ddot{J}_T/\hat{\sigma}_0$ is asymptotically distributed as standard normal, where $\hat{\sigma}_0 = \sqrt{2}\theta(1-\theta)\sqrt{1/(T(T-1)h^{2p})}\sqrt{\sum_{t\neq s} K^2((Z_{t-1}-Z_{s-1})/h)}$. The regression error $\hat{\varepsilon}_t$ becomes the most important element of the test statistic $\hat{J}_T$. In our study, the estimator of the unknown regression error is specified as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \ddot{Q}_\theta(Y_{t-1})\} - \theta. \tag{7}$$

In equation (7), the quantile estimator $\ddot{Q}_\theta(Y_{t-1})$ produce an estimate of the θ-th conditional quantile of y_t considering Y_{t-1}. By employing the nonparametric kernel approach, we evaluate $\ddot{Q}_\theta(Y_{t-1})$ as follows:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{8}$$

Here, $\ddot{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ signifies the *Nadarya-Watson* kernel estimator specified as follows:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)}, \tag{9}$$

where h is the bandwidth and $L(\cdot)$ represents a known kernel function.

In addition, the empirical implementation of causality testing via quantiles necessitates distinguishing three critical options: the bandwidth h, the kernel type for $K(\cdot)$ and $L(\cdot)$ in equations (6) and (9), and the lag order p. For this paper, we use a lag order of 1 based on the Schwarz Information Criterion (SIC) through the vector autoregressive (VAR) model involving the PCI and income inequality. The SIC lag-length selection criteria helps to overcome the issue of over-parameterization commonly encountered when applying the nonparametric frameworks, since the SIC produces a parsimonious number of lags when compared to alternative lag-length selection criteria.[4] Meanwhile, we determine the bandwidth by using the Least Squares Cross-Validation (LSCV) technique.[5] Finally, we employ $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels for our estimation.

Although robust inference on the quantile based causality from the PCI to measures of inequality can reflect the causality-in-quantiles tests given in equation (5), it is also interesting to estimate the magnitude and direction of the effects of the PCI on inequality at various quantiles. Variations in the sign and magnitude of the effect across quantiles will reveal significant evidence on the effect of the PCI on income inequality. We employ a commonly used measure for this purpose -- the first-order partial derivative. Estimation of the partial derivatives for nonparametric models can experience complications because nonparametric methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. Our interest, as in many applications, does not involve the entire derivative curve but rather a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude).

A natural measure of the global curvature is the average derivative (AD). We use the conditional pivotal quantile, based on approximation or the coupling approach of

[4] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterized model, while the SIC is asymptotically consistent.

[5] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

Belloni *et al.* (2011), to estimate the partial ADs. The pivotal coupling approach additionally can approximate the distribution of AD using Monte Carlo simulation. To show the details of the AD estimation, define x_t as the key variable for which we want to evaluate the derivative of y_t and define $R_t = (x_t, v_t)$, where v_t is a vector of other covariates, which includes lagged values in our case. Following Belloni *et al.* (2011), we can model the θ-th quantile of y_t conditional on R_t using the partially linear quantile model:

$$Q_{\theta|R_t}(y_t|R_t) = f(x_t,\theta) + v_t'\gamma(\theta). \quad (10)$$

Belloni *et al.* (2011) develop a series approximation to $Q_{\theta|R_t}(y_t|R_t)$ in equation (8), which we can represent as follows:

$$Q_{\theta|R_t}(y_t|R_t) \approx W(R_t)'\beta(\theta), \quad \beta(\theta) = \left(\alpha(\theta)',\gamma(\theta)\right)', \; W(R_t) = (W(x_t), v_t')'. \quad (11)$$

In equation (11), we approximate the unknown function $f(x_t,\theta)$ by linear combinations of the series terms $W(x_t)\alpha(\theta)'$. Ideally, $W(x_t)$ should include transformations of x_t that possess good approximation properties. The transformations $W(x_t)$ may include polynomials, B-splines, and trigonometric terms. Once we define the transformations $W(x_t)$, we can generate the first order derivative with respect to x_t as follows:

$$h(x_t,\theta) = \partial Q_{\theta|R_t}(y_t|R_t)/\partial x_t = \partial f(x_t,\theta)/\partial x_t = W(x_t)\alpha(\theta)'/\partial x_t. \quad (12)$$

Based on the first-order derivative estimates in equation (12), we can derive the first-order AD with respect to x_t as follows:

$$\bar{h}(\theta) = \int \frac{\partial f(x_t, \theta)}{\partial x_t} d\mu(x_t), \tag{13}$$

where $\mu(x_t)$ is the distribution function of x_t. We approximate the distribution of $\bar{h}(\theta)$ using 50,000 Monte Carlo simulations and construct 95% confidence intervals based on the empirical distribution. The pivotal coupling approximation with Monte Carlo simulation also allows us to test the hypothesis for the AD estimate in equation (13).[6] In particular, we test the null hypotheses that the effect of the PCI on the inequality measure is negative for all θ, $H_0: \bar{h}(\theta) \leq 0$ for all θ, positive for all θ, $H_0: \bar{h}(\theta) \geq 0$ for all θ, and zero for all θ, $H_0: \bar{h}(\theta) = 0$ for all θ. The point wise inference uses the *t*-statistic at each quantile index and covariate value, while the confidence intervals use the maximal *t*-statistic across all values of the covariates and quantile indices in the region of interest. We use a 10th-order polynomial of x_t to construct $W(x_t)$.

2.3 Data and Description of Variables

For our empirical analysis, we employ aggregate annual frequency data for the United States between the periods 1917 to 2013, based on data availability. The PCI data comes from Azzimonti (2014). Recent studies of Azzimonti (2016), Cheng, *et al.* (2016), Hankins, *et al.* (2016), and Gupta, *et al.* (forthcoming) also uses the PCI data in their various empirical analyses. Azzimonti (2016) employs the PCI data to examine the relationship between news, investor's expectation, and partisan conflict in the United States. Cheng *et al.* (2016) use the PCI data to investigate whether U.S.

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[6] In general, the process $\sqrt{T}(\hat{\alpha}(\theta) - \alpha(\theta))$ does not heave a limit distribution; therefore standard asymptotic theory does allow one to test these hypotheses (van der Vaart and Wellner, 1996). In the coupling approach, a process with a known distribution is constructed that lies in the same probability space with $\sqrt{T}(\hat{\alpha}(\theta) - \alpha(\theta))$ and two processes are uniformly close to each other with high probability. We can, then, perform tests based on the constructed coupling process that has a known distribution.

partisan conflict matters in European countries, while Gupta *et al.* (forthcoming) use the PCI data to examine the role of partisan conflict in affecting asset prices and fiscal policy in the United States. Meanwhile, our current study adds to the existing literature that uses the PCI data by examining the causal relationship between partisan conflict and income inequality in the United States. Our study provides a basis for action by policymakers who design, formulate, and execute macroeconomic policies. While partisan conflict is inevitable and necessary for sound functioning of a democracy, policymakers should avoid heightened conflict as it will increase income inequality, given that higher partisan conflict will negatively affect investment and prevent the development of policies in a timely-manner to respond to adverse macro shocks.

This index tracks the magnitude of political differences among U.S. politicians, mainly at the federal level, by gauging or evaluating the frequency and persistence of newspaper articles (dailies) divulging disagreement, especially within a month. High index values imply conflict between the political parties, Congress, and the President of the United States. The Federal Reserve Bank of Philadelphia Research (FRBPR) developed the PCI data, where the index usually rises close to elections and particularly during debates over divisive issues such as foreign policy, budget deficits, and so on. The basic trends in the PCI, based on an HP filter, are as follows: the PCI trends downward from the beginning of the sample in 1891 through the early 1920s, it stabilized and did not trend up or down from the early 1920s through the mid-1960s, and it rose from the mid-1960s through the end of the sample in 2013 (see Azzimonti, 2014, p. 7-8).

Empirical findings suggest that an increase in the PCI widens and promoting uncertainty, which halts or retards economic activities and performance by slowing consumer spending and adversely influencing businesses, and affecting domestic or foreign investment (see Azzimonti, 2014). These effects produce a widening of the income inequality gap. In addition, income inequality data come from Frank (2015)[7]. More specifically, the income inequality measures (e.g., gini, Artkin05, RMeanDev, and Theil) and the Top 10%, Top 5%, Top 1%, Top 0.5%, Top 0.1% and Top 0.01% income inequality measures appear in the World Top Income Database (WTID).

[7] For an exposition on the estimation of this series and file including percentile threshold, see the PDF by Frank, Sommeiller, Price, and Saez posted at the following site: http://www.shsu.edu/eco_mwf/inequality.html. Further explanation on estimation of other measures of income share or distribution should see Frank (2015).

Table 1: Descriptive Statistics

	PCI	Gini	Atkin05	RMeanDev	Theil	Top10	Top5	Top1	Top05	Top01
Mean	65.33	0.22	0.70	0.59	39.79	28.53	14.53	11.03	5.83	2.32
S.D.	24.43	0.05	0.10	0.22	5.66	5.23	4.14	3.65	2.56	1.32
Min	34.01	0.14	0.53	0.36	32.31	21.66	8.86	6.07	2.56	0.85
Max	131.59	0.33	0.92	1.08	50.60	38.82	23.94	19.40	12.28	6.04
Skewness	0.69	0.72	0.45	0.72	0.21	0.29	0.42	0.49	0.72	1.06
Kurtosis	-0.65	-0.84	-1.13	-0.94	-1.49	-1.31	-0.93	-0.81	-0.46	0.14
JB	9.4***	11.2***	8.2**	12.0***	9.4***	7.9**	6.2**	6.4**	9.3***	18.8***
Q(1)	68.6***	86.3***	86.2***	85.9***	90.27***	88.8***	85.6***	84.3***	82.2***	80.0***
Q(4)	246.6***	271.1***	274.2***	271.9***	309.7***	302.4***	278.0***	269.8***	255.2***	240.9***
ARCH(1)	26.6***	69.8***	73.77***	54.5***	58.1***	55.0***	49.3***	47.8***	46.5***	46.1***
ARCH(4)	40.0***	70.1***	75.2***	55.8***	57.0***	53.9***	49.7***	48.3***	46.9***	46.5***

Table reports the descriptive statistics for the PCI and inequality series Gini Coefficient (Gini), Atkinson Index (Atkin05), the Relative Mean Deviation (RMeanDev), Theil's entropy Index (Theil) as well as Top 10 percent (Top10), Top 5 percent (Top5), Top 1 percent (Top1), Top 0.5 percent (Top05), Top 0.1 percent (Top01), and Top 0.01 percent (Top001) income shares. Data is at annual frequency and covers the period from 1917 to 2013 with 97 observations. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fourth [$Q(4)$] autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). The *** and ** represent significance at the 1- and 5-percent levels.

We present the crucial points of the time series data under observation in Table 1. We report the mean, standard deviation, minimum and maximum values, Skewness, Kurtosis, the Ljung-Box first {Q(1)} and the fourth {Q(4)} autocorrelation tests, the Jarque-Bera (JB) normality test, the first {ARCH(1)} and the fourth {ARCH(4)} order of Lagrange Multiplier (LM) tests basically for the autoregressive conditional heteroskedasticity (ARCH) for the PCI, and the observed income inequality and distribution measures. The positive skewness may reflect the increases in the PCI and income inequalities disparities. On the other hand, the Kurtosis indicates a flat tailed distribution for the time series. That is, the crucial findings are that the variables exhibit positive skewness and negative kurtosis, resulting in a non-normal distribution (i.e., the variables show a highly nonlinear relationship). The data confirm this by the rejection of the null hypothesis of normal distribution, using the Jarque and Bera (1980) normality test at the 1- or 5-percent significance level. This justifies the causality-in-quantile test by the flat tailed distribution of the time-series variables. Note that we observe serial correlation between the PCI and all the income inequality measures using the Ljung-Box (1978) statistic that are statistically significant at the 1-percent level. Finally, we confirm ARCH effects in the variables, as reported in the ARCH-LM test, rejecting the null hypothesis at the 1-percent level.

2.4 Results and Empirical Findings

This section reports the empirical results. We investigate the causality-in-quantiles predictive relationship from the PCI to income inequality. We estimate the linear Granger causality test built on a Linear Vector Autoregressive (VAR) model. Table 2 reports the results of the linear Granger causality tests under the null hypothesis that the PCI does not Granger cause inequality. We choose the order (p) of the VAR by the Bayesian Information Criteria (BIC). Out of 10 indicators of income inequality, three measures exhibit weak significance at the 10% level. Thus, we reject the null hypothesis of no Granger causality at the 10% level for three measures of income inequality. That is, we find limited evidence of significant predictability running from the PCI to income inequality in a linear vector autoregressive (VAR) model.

Table 2: Linear Granger Causality Tests

Inequality Series	*F*-statistic	Order of the VAR (*p*)
Gini	2.88^{*}	1
Atkin05	2.634	1
RmeanDev	3.76^{*}	1
Theil	2.91^{*}	1
Top10	0.00	1
Top5	0.15	1
Top1	0.85	1
Top05	0.95	1
Top01	1.42	1
Top001	1.97	1

The table reports the *F*-statistic for the no Granger causality restrictions imposed on a linear vector autoregressive (VAR) model under the null hypotheses H_0. The order (p) of the VAR is selected by the Bayesian Information Criterion (BIC). ***, **, and * indicates rejection of the null of no Granger causality at 1-, 5-, and 10-percent level of significance, respectively.

Table 3: BDS Test

Equation for:	m=2	m=3	m=4	m=5	m=6
Gini	7.47***	9.73***	12.23***	16.46***	21.26***
Atkin05	6.18***	7.25***	9.19***	12.50***	17.39***
RMeanDev	6.97***	8.62***	9.97***	12.25***	14.47***
Theil	2.43**	3.52***	5.98***	8.31***	11.77***
Top10	3.08***	2.97***	5.19***	10.19***	16.12***
Top5	4.47***	2.81***	3.62***	5.09***	4.94***
Top1	0.70	-2.14**	-1.25	-1.54	-2.49**
Top05	0.23	-2.24**	-1.21	-1.25	-1.01
Top01	0.29	-0.25	0.36	-0.04	-2.56**
Top001	1.19	0.93	2.16**	3.75***	3.22***

The entries indicate the BDS test [Brock *et al.* (1996)] based on the residuals from the equation for inequality series in a VAR for various inequality series. *m* denotes the embedding dimension of the BDS test. ***, ** and * indicate rejection of the null of residuals being *iid* at 1-, 5-, and 10-percent levels of significance, respectively.

Table 4: Nonlinear Granger Causality Test

	m=2		*m*=3		*m*=4	
Eq for:	Test statistic	*p*-value	Test statistic	*p*-value	Test statistic	*p*-value
Gini	-0.963	0.832	-1.286	0.901	-0.307	0.620
Atkin05	-0.861	0.805	0.483	0.314	0.078	0.469
RMean	-0.653	0.743	-1.374	0.915	-0.317	0.624
Theil	-0.784	0.784	0.170	0.433	-0.146	0.558
Top10	-0.426	0.665	-0.882	0.811	-0.167	0.566
Top5	-0.620	0.732	-0.674	0.750	-0.054	0.521
Top1	-0.504	0.693	-0.608	0.728	0.778	0.218
Top05	-0.544	0.707	-0.701	0.758	0.754	0.226
Top01	-0.606	0.728	-1.105	0.865	0.140	0.444
Top001	0.196	0.422	0.627	0.265	-0.374	0.646

The *m* denotes the embedding dimension. For test, see Diks and Panchenko (2006).

Using the non-parametric causality-in-quantile techniques, we now evaluate whether a nonlinear dependence exists between the PCI and income inequality. For this purpose, we employ a test for independence proposed by Broock, *et al.* (1996), known as the BDS test on the residuals of first-order vector autoregressive [VAR (1)] model for both series. We conduct the BDS test on the residuals of the PCI and income inequality indicators equation in the first-order vector autoregressive model. In Table 3, we cannot reject the null hypothesis of identically independently distributed *(i.i.d)* for all residuals at different embedding dimensions *(m)*, especially for the income inequality indicators, even when we found statistical significant evidence against linearity. Thus, we posit that strong higher-level evidence of

Table 5: Sign Tests for the Effect of PCI on Inequality Measures

	$H_0: \bar{h}(\theta) \leq 0$ for all θ		$H_0: \bar{h}(\theta) \geq 0$ for all θ		$H_0: \bar{h}(\theta) = 0$ for all θ	
Eq. for:	Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
Gini	2.637**	0.040	2.637	0.940	2.637*	0.081
Atkin05	2.911**	0.045	2.911	0.955	2.911*	0.068
RMean	2.828**	0.043	2.828	0.947	2.828*	0.073
Theil	1.818**	0.010	1.818	0.899	1.818*	0.063
Top10	1.482**	0.025	1.482	0.975	1.482*	0.082
Top5	2.550***	0.005	2.550	0.995	2.550**	0.039
Top1	1.633***	0.004	1.633	0.986	1.633*	0.053
Top05	1.396***	0.006	1.396	0.987	1.396*	0.083
Top01	1.488***	0.003	1.488	0.997	1.488*	0.069
Top001	2.214***	0.006	2.214	0.261	2.214*	0.081

The table reports the p-values of the t-statistic obtained from the 50,000 Monte Carlo simulations of the coupling process. ***, ** and * indicate rejection of the null at 1-, 5-, and 10-percnet levels of significance, respectively.

nonlinearity in income inequality and the PCI exists. By implication, evaluating linear Granger causality test framework when the data conform to a highly nonlinear model can lead to spurious, unreliable, and inconsistent outcomes. Thus, we apply the causality-in-quantile test, which can account for outliers, jumps, nonlinear dependence, and structural breaks, since we confirm the absence of linearity among the series.

Furthermore, the evidence of nonlinearity, leads to an examination of the possible existence of nonlinear Granger causality running from the PCI to income inequality.

We employ the nonlinear Granger causality test of Diks and Panchenko (2006)[8]. Table 4 reports the Diks and Panchenko nonlinear Granger causality test results, where we use the embedding dimension *(m)* in their robust order against the lag length used in the estimation. Table 4 shows that no evidence supports the null hypothesis of no full sample nonlinear Granger causality relationship running from the PCI to income inequality. This outcome holds for all embedding dimensions used. In Table 5, we present one- and two-sided tests for the sign of the effect. For the sign tests, we strongly reject the null hypothesis of a negative sign; we cannot reject the null of a positive sign; and we weakly reject the null hypothesis of a zero effect (rejection of the last hypothesis only occurs mostly at the 10% significance level).

Finding evidence against a full sample nonlinear Granger causality relationship, we proceed to nonparametric causality-in-quantiles test. This test accounts not only for the center of the distribution but all quantiles of the distribution. Figure 1 shows time-series plots of the PCI and income inequality. We observe some extreme jump (high value of income inequality) between the years 1925-1928 in the level of income inequality. Figure 2 reports the results of the quantile causality from the PCI to income inequality series. Also, Figure 3 plots the average derivative estimates for the effect of the PCI. The quantiles appear on the horizontal axis, while the nonparametric causality test statistics appear on the vertical axis, proportional to the quantiles in the horizontal axis.

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[8] See Diks and Panchenko (2006) for more details. The test adjust for the over-rejection problem noticed in Hiemstra and Jones (1994).

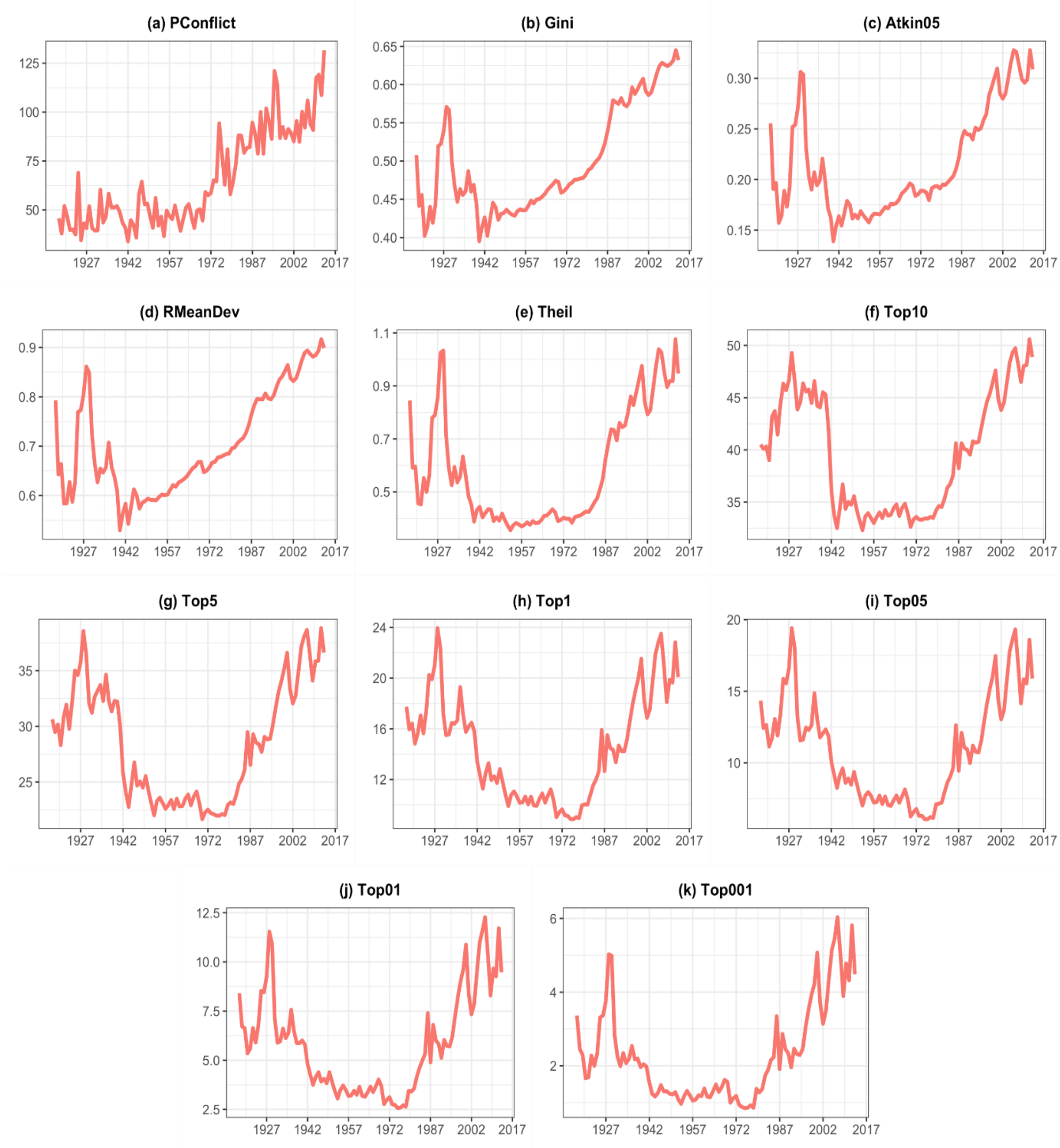


Figure 1: Time series plots of the PCI and inequality series
Figure plots the level of the series for the PCI and inequality series Gini Coefficient (Gini), Atkinson Index (Atkin05), the Relative Mean Deviation (RMeanDev), Theil's entropy Index (Theil) as well as Top 10 percent (Top10), Top 5 percent (Top5), Top 1 percent (Top1), Top 0.5 percent (Top05), Top 0.1 percent (Top01), and Top 0.01 percent (Top001) income shares. Data is at annual frequency and covers the period from 1917 to 2013 with 97 observations.

In Figure 2, the horizontal thin lines identify the 5-percent significance level. According to Figure 2, we find evidence of strong causality across a wide range of quantiles from the PCI to income inequality. We reject the null hypothesis of no causality for quantiles generally below 0.65 or up to 0.80. Given that we transform the data into natural logarithm first differences,[9] the PCI only fails to Granger cause at extreme quantiles. The upper quantiles correspond to those high jump values of income inequality (i.e., between 1925 and 1928) discussed earlier and we do not find Granger causality at those extremes.[10]

The plots of the data and the relationship among the variables of interest provide an explanation as to why no evidence of useful predictability from the PCI to income inequality measures exists at the upper quantiles of the variables. As we noted earlier, the no rejection ranges of the quantiles for the causality relationship correspond to quantiles above either 0.65 or 0.80 for income inequalities. Higher levels of inequality fall in the quantiles above these ranges. During the periods where income inequalities experience big jumps and we see a high level of the PCI, then the PCI does not significantly affect average income inequality. This result supports the findings of McCarty *et al.* (2003).

We observe robust causal relationships running from the PCI to income inequality measures, barring the upper end of the conditional distribution of inequality growth,

[9] All the data are non-stationary at level.

[10] Based on the suggestion of an anonymous referee to accommodate for the possibility of an important omitted variable such as real GDP per capita growth (Chang et al., 2016), we undertook an indirect approach of testing the robustness of our causality-in-quantiles test. Unlike linear tests of causality, which can be multivariate, all known nonlinear tests of causality are, in fact, bivariate (see, for example, Heimstra and Jones (1994), Diks and Panchenko (2005, 2006), Nishiyama et al., (2011), Jeong et al., (2012)). Our indirect approach involves two steps: First, we estimate a linear causality model with economic growth only in the regression involving inequality growth. Second, we recover the residuals from these models and apply our nonparametric causality-in-quantiles test on these residuals, with PCI growth as the predictor. So, we create a filtered series for the inequality growth, whose movements are now no longer due to the GDP growth. In general, our results are qualitatively similar to those reported in Figure 2. Complete details of these results are available upon request from the authors.

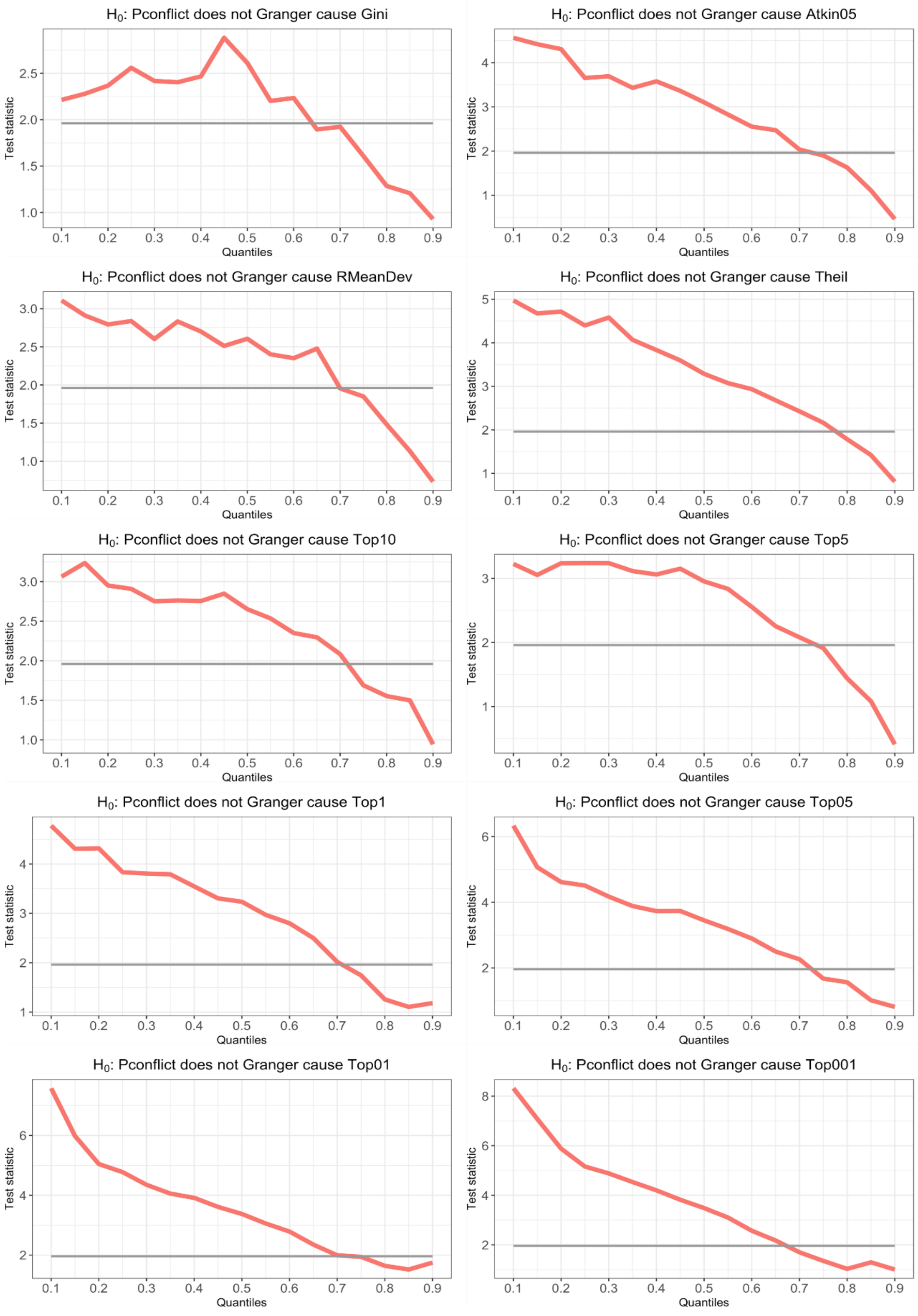


Figure 2: Tests of Granger causality from PCI to inequality series.
The estimates of the nonparametric causality-in-quantiles tests at various quantiles. Horizontal thin lines represent the 5-percent value

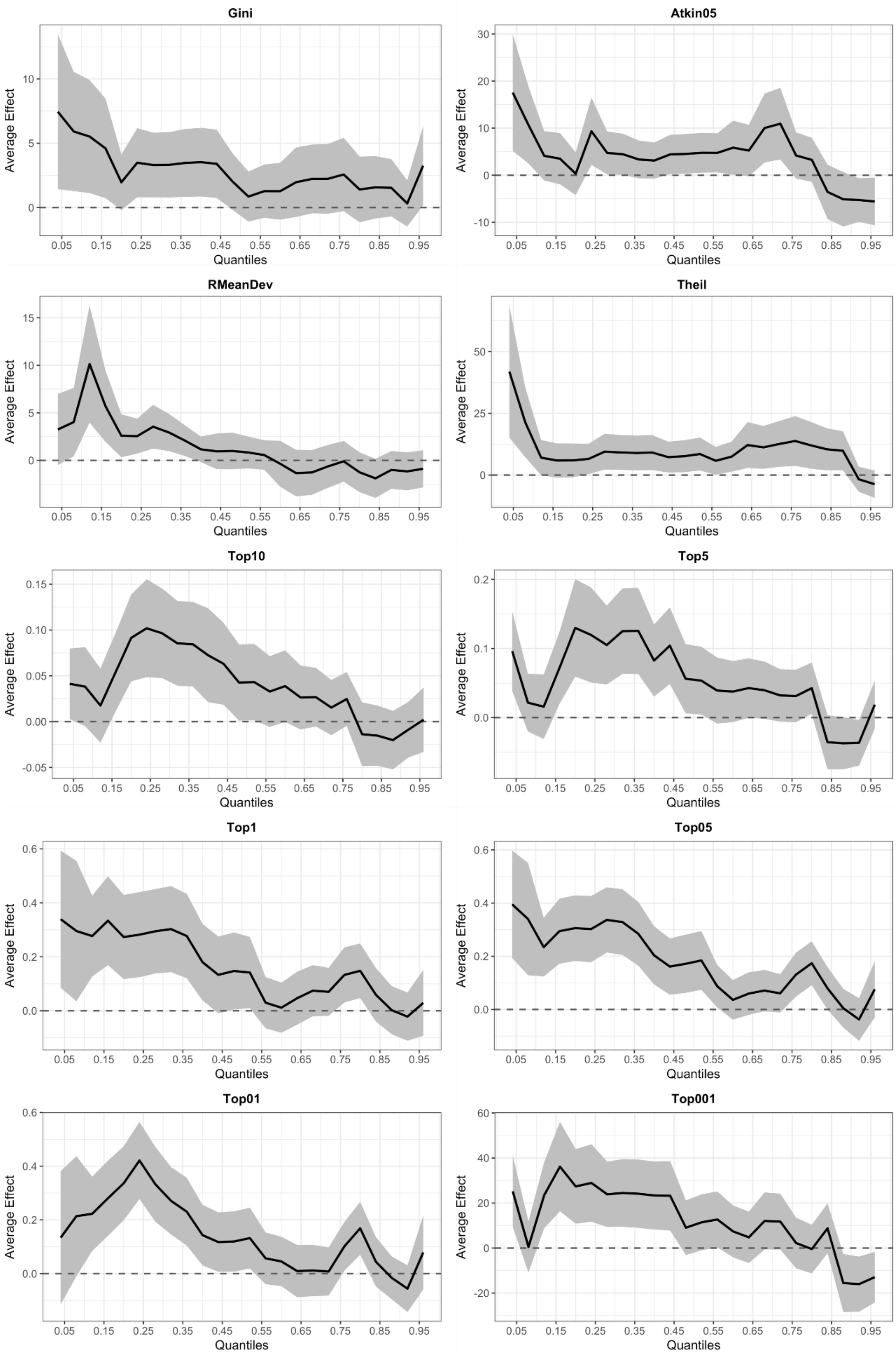


Figure 3: Average derivative estimates for the effect of PCI.
The estimates of the average derivative estimates. Gray region represents the 95-percent confidence interval. A dashed horizontal line is drawn at zero.

across the various measures of the same. A researcher who examines only the mean of the conditional distribution of income inequality would conclude that the PCI does not cause income inequality, even if nonlinearity is modeled. Using the causality-in-quantiles test, however, we show that in fact the PCI does predict inequality, barring the upper end of the conditional distribution of inequality. Our results, thus, not only highlight the importance of modeling nonlinearity through the nonparametric approach, but also going beyond the conditional mean based approach to study the entire conditional distribution of the dependent variable under consideration.

Finally, this result also confirms the results in Chang, *et al.* (2015) on the causality nexus between real GDP and income inequality in the United States, where the direction of causality evolves over time and differs across frequencies. The results shown in Figure 2 reveal that the evidence of causality from the PCI to income inequality measures exhibits concave-shaped distribution patterns across quantiles. The concave-shaped pattern of causality results from using a nonparametric causality-in-quantiles test. The effect of the PCI on income inequalities measure is generally positive; where reductions in the PCI lead to a reduction in our measures of income inequality, and vice versa.

2.5 Conclusion

The existing literature examines the relationship between partisan conflict and various macroeconomics variables. This study adds to the existing literature by investigating the causality relationship, if any, between the PCI and income inequality. We use annual time-series data to evaluate the standard linear Granger causality test, and found no significant causality evidence. Nonlinearity tests show that the relationship between the PCI and income inequality follows a highly nonlinear relationship. The linear causality test is prone to model misspecification and may result in spurious and unreliable inferences. We employ nonparametric causality-in-quantile test approach to avoid these problems, integrating the test for nonlinear causality of k-th order proposed by Nishiyama *et al.* (2011) with the Jeong *et al.* (2012) causality-in-quantiles test.

The nonparametric causality tests indicate that the PCI exerts a strong causal link to the income inequality. The null hypothesis that the PCI does not Granger cause income inequality is strongly rejected. The outcomes of the relationship between the PCI and the income inequality generally indicate the importance of detecting and modelling nonlinearity when investigating causal relationships.

In addition, the concave-shaped form in the causality-in-quantiles tests, which we observe from the PCI to income inequality test, demonstrate that strong causal effects occur, in general, for moderate income inequality rather than high income inequality. The findings of this study, however, do not rule out the possibility that other factors such as wage/income differences, trade, technology, institutions, and growth volatility (see Piketty and Saez, 2003; Frank, 2009; Fang, *et al.* 2015; Rubin and Segal, 2015) contribute to the level income inequality. Rather, our findings emphasize that policymakers who design, formulate, and execute macroeconomic policies should examine the entire conditional distribution of income inequality, when considering the causal effects of the PCI on income inequality.

We can infer several crucial facts from this analysis, which policymakers who design and structure growth and developmental programs may find useful. Our study links the PCI to income inequality. Thus, when considering income inequality, specific measure of political polarization should receive consideration. The effect of the PCI on income inequality, however, evolves over time. Moreover, we also failed to reject the null hypothesis of no causal relationship at the upper quantiles of the income inequality. Thus, our findings suggest that causal relationship from the PCI to income inequality does not exist in periods with high income inequality. Finally, PCI can be included in the decision-making support systems, such as, for example, in Duclos and Araar (2006).

Chapter 3

KUZNETS CURVE FOR THE US: A RECONSIDERATION USING COSUMMABILITY

3.1 Introduction

A study conducted by Kuznets in 1955 is continuously referenced by most of the research evaluating the possible relationship between economic growth and income inequality and/or vice versa. Simon Kuznets carried out the study on three great industrialized economies of United States, Germany and United Kingdom. The empirical findings were based on the hypothesis that income inequality rose at the wake of industrialization process and later declined as development processes increased (inverted U-curve). Interestingly, Kuznets neither gave sufficient empirical evidence for testing this assumption for a long temporal change in income inequality, nor could the stages be explicitly dated. Anand and Kanbur (1993)[11] in their analysis, provided a valid explanation for this swing in income inequality for developing countries. Hence, it becomes expedient to consistently take a closer look at Kuznets' study while taking caution when analyzing the relationship between income inequality and economic growth.

[11] For interested reader see the work of Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, 45(1), 1-28; and Anand, S., & Kanbur, S. R. (1993). The Kuznets process and the inequality—development relationship. *Journal of Development Economics*, *40*(1), 25-52.

The relation between income inequality and economic growth has long been a subject of discussion among economists. Tracing this back to the 1960s, President John F. Kennedy once qualified the relationship between inequality and growth as a rising tide that lifts all boats to illustrate the idea that economic growth is beneficial to both the poor and rich in the society. In spite of this, whether the poor can access the gains of growth equally as the rich poses debatable questions. The conflicting experience in the aftermath of the Second World War between the East Asia and Latin America cannot be over-emphasized. During this period, Latin America experienced high level of income inequality and moderate growth, while the reverse was the case with East Asia where there was a moderate level of income inequality and glowing economic growth[12].

The positive relationship between income inequality and economic growth is illustrated as follows. It is expected that in developed economies, the saving habit of the few rich (privileged) should be higher than that of the poor masses (less privileged). Thus, income re-distribution from the few rich to poor masses would automatically lower the aggregate saving rate or habit of the entire economy and by implication cause a decrease in economic growth. On the other hand, income redistribution could possibly decrease incentive for the few rich to work hard, which could also cause a decrease in the level of economic growth. On this premise, it is hypothesized that income inequality at a particular time can negatively influence economic growth and other times positively influence economic growth.

[12] In this study we use income per capita and economic growth synonymously.

In addition, the inverse relationship that has been widely assumed to exist between economic growth and income inequality can be likened to the following illustration. In most developing countries, the less privileged are not considered credit worthy, and so they do not have access to capital. Thus, this scenario incapacitates investment opportunities for the poor, while those who are extremely poor can hardly actively participate in production, thereby resulting to what is obviously an inequality gap. Hence, a decline in the level of economic growth is occasioned by income inequality which leads to social-economic and political instability. To augment this claim, Tuominen (2016a) while reassessing the relationship between economic growth and top-end inequality for 25 countries (developing and developed countries) between the periods 1920 to 2000, exploits the top 1% income distribution and addresses issues regarding nonlinearity, found that, there exists a significant negative relationship between the top 1% income distribution and economic growth, especially in developed economies, with this relationship becoming weaker as the quest for economic development rises; though, there is a tendency for a positive relationship between the observed variables at the subsequent phases of development (Tuominen, 2015). Thus, it is hypothesized that income inequality at a particular time can negatively influence economic growth and at other times positively influence economic growth[13].

In examining the existence of the Kuznets' inverted-U shape relationship, most of the previous studies follow the parametric quadratic specification by regressing only Gini coefficients as a measure of income inequality on real GDP per capita and its

[13] There are many reasons why income inequality would negatively or positively influence economic growth. For more details see Weil (2005) and Tachibanaki (2005).

squared term (see Ahluwalia, 1976; Hsing and Smyth, 1994; Jacobsen and Giles 1998). Empirical findings of a positive and significant estimated coefficient on the real GDP per capita and a negative coefficient on its squared term are perceived as an evidence for the Kuznets' inverted-U shape proposition. However, this econometric method may be subject to model misspecification, so that their empirical results and conclusions may be misleading. A more suitable and simple approach is to allow the data to speak for themselves by using a more flexible and reliable time series methodology such as cosummability, instead of imposing a particular statistical functional form.

Our current study revisits the Kuznets' inverted U-shaped hypothesis for United States. Primarily, the focus of this study is to investigate whether there exists nonlinearity (inverted U-shaped hypothesis) long-run relationship between economic growth and income inequality in the case of United States or not. This study intends to contribute to the growth-inequality literature in three ways. First, this study unlike the others, employed a long and relatively more recent dataset on income inequality and economic growth for the period from 1917 to 2012 using 96 observations. For a study like this, long-span data is required and sufficient for evaluating the inverted U-shaped relationship as it incorporates the transition processes in the economy of United States from certain stages of economic growth to its recent economic status. Second, unlike previous studies that use Gini coefficient only to proxy for income inequality, in our current study we employ six (6) measures of income distribution such as Gini coefficient, Theil, Atkinson, Rmeandev, Top 10% and Top 1% to proxy and as measure of income inequality. This is considered more suitable to capture the inherent existing relationships between economic growth and income inequality, at different levels of income distribution/inequality. Third, to examine the quadratic (nonlinear) econometric techniques of Hsing and Smyth (1994), Jacobsen and Giles (1998), and other existing findings, this study evaluate Kuznets inverted U-shaped relationship using the idea of co-summability. The econometric framework behind cosummability is explained below. To examine linear relationships among continuous economic non-stationary time series data, the cointegration techniques is no doubt a perfect framework. However, the intrinsic linearity in the framework of integration and co-integration makes it inappropriate to evaluate nonlinear long-run relations among non-stationary processes, which is the case when evaluating Kuznets inverted U-curve.

In order to achieve our study objective, we employ the concept of cosummability proposed by Berenguer-Rico and Gonzalo (2013) and the order of summability introduced by Berenguer-Rico and Gonzalo (2014) to deal with nonlinear transformations of time series data. It is assumed that, a cosummable relationship is balanced, when the variables under observation exhibit same order of summability and portray a long-run equilibrium relationship that are nonlinear, provided that the errors have least order of summability. Based on our knowledge, this study appears to the first to use the idea of cosummability proposed by Berenguer-Rico and Gonzalo (2013) to investigate inverted U-shaped relationship between economic growth and income inequality for the United States, using a long-span time series data. The novelty of this study lies in the application of sound, reliable and new time series econometric methods.

The empirical analysis of this study focuses on whether there exists nonlinearity long-run relationship between economic growth and income inequality in the case of United States or not. This study does not consider issues related to direction of causality, which we assume not to have any statistical contribution and validity to our research outcomes. The empirical results of this study provide evidence in support of a long-run linear relationship between income inequality and economic growth for the United States. Our empirical findings provide no evidence in support of the Kuznets' (inverted U-shaped) nonlinear long-run relationship between economic growth and income inequality for the sampled country.

This paper is organized in five other sections. The second section discuss the literature in brief, while third section considers a detail discussion on the concept of summability, balancedness and cosummability. This is followed by the data and the empirical model used in section four. In section five, the results and empirical findings are discussed, while conclusion is drawn in the last section.

3.2 Literature Review in Brief

Based on existing literature, there are studies conducted primarily on income inequality-economic growth relationship, which have reported extensive conflicting outcomes. These several empirical cross-country surveys chiefly include but is not limited to Alesina and Rodrik (1994), Persson and Tabellini (1994) and other studies (see Wan, Lu, and Chen, 2006; Sukiassyan, 2007; Majumdar and Partridge, 2009; Ogus Binatli, 2012; Wahiba and El Weriemmi, 2014; Hender, Qian and Wang, 2015; Tuominen 2015; 2016a, b; Babu, Bhaskaran and Venkatesh, 2016) all of which have confirmed the negative relationship. Lately, many research endeavors have found direct (positive) relationship between growth and income inequality (see Li and Zou, 1998; Forbes, 2000; Partridge, 2007; Frank, 2009; Muinelo and Roca, 2013; Chan, Zhou and Pan, 2014; Cingano, 2014; Fang, Miller and Yeh, 2015; Nahum, 2015; Rubin and Segal, 2015; Saari and Dietzenbacher, 2015; Ward and Charles, 2015). While Barro (2000) posits that the relationship between the variables is inconclusive, others found mixed relationship between income inequality and economic growth (see Chen, 2003; Voitchovsky, 2005; Shin, 2012). Notably, the empirical difference in existing datasets, estimation techniques and/or model specifications have been proposed as possible reasons for the differing results from previous studies.

To the best of authors knowledge, there exist only few studies (see Robinson, 1976; Braulke, 1983; Ram, 1991; Fosu, 1993; Hsing and Smyth, 1994; Nielsen and Alderson, 1997; Jacobsen and Giles, 1998; Banerjee and Duflo, 2000; Chen, 2003; Huang, 2004; Lin and Weng, 2006; Lin, 2007; Lin, Suen and Yeh, 2007; Kim, Huang and Lin, 2011; Huang, Lin and Yeh, 2012; Lessmann, 2014; Theyson & Heller, 2015), which have specifically investigated the inverted U-shaped relationship between economic growth and income inequality. Using non-parametric estimation techniques in the US for the period from 1947 to 1991, Jacobsen and Giles (1998) could not find evidence in support of Kuznets inverted U-shaped relationship between economic growth and income inequality.

On the other hand, Banerjee and Duflo (2000) revealed through their cross-country analysis that economic growth is an inverted U-shaped function of income inequality. Chen (2003) documented an inverted U-shaped relationship, using Gini coefficient to proxy for income inequality and real gross domestic product (GDP) to proxy for economic growth for a panel countries 54 countries, by employing the

Barro-type model over a 22 year period from 1970 to 1992. Huang (2004) employs flexible nonlinear inference method as advanced by Hamilton (2001, 2003) to examine the validity of the Kuznets hypothesis in a cross-country analysis, found an evidence in support of nonlinearity and inverted U-shaped relation between GDP per capita and inequality, thus, confirming the Kuznets hypothesis.

In contrast to the conventional parametric quadratic methods for examining Kuznets hypothesis, Lin, Huang and Weng (2006) employ semi-parametric to examine existence of an inverted U-shaped relationship between inequality and GDP per capita in a cross-country analysis and document evidence in support of Kuznets hypothesis, similarly Huang (2007) in a cross-country analysis, found that, Kuznets hypothesis only exist in countries with moderate income inequality, however, and not in countries with extremely low or extremely high income inequality. Furthermore, Huang and Lin (2007) in their empirical investigation to validate Kuznets hypothesis for 75 countries, using the data obtained from Iradian (2005) unlike the previous studies, found asymmetric relationship between GDP per capita and income inequality. Lessmann (2014) found a strong evidence in support of an inverted U-shaped relationship between spatial inequality and economic development using the same econometric approach for 56 countries for the period from 1980 to 2009, through parametric and semi-parametric regression. Meanwhile, Theyson and Heller (2015) examine the relationship between economic growth/development and income inequality, where Human Development Index (HDI) was used as a proxy for economic development in the context of Kuznets hypothesis for 147 countries between the periods 1997 – 2007, using time series and panel data analysis. They concluded that using various economic indicators to proxy for development remarkably influence the shape of the Kuznets curve, while increase in the level of income inequality may not be essential part of a nation's developmental process.

Kim, Huang and Lin (2011) using the pooled mean group (PMG) estimator as advanced by Pesaran, Shin and Smith (1999) observed a long-run equilibrium relationship between real GDP per capita and inequality for the United States. According to their findings, the relationship between inequality and per capita GDP is U-shaped rather than the conventional inverted U-shaped proposed by Kuznets hypothesis. This resonate with the findings of Huang, Lin and Yeh (2012) on the Kuznets hypothesis for the United States. Patriarca and Vona (2013) examined an inverted U-shaped relationship between structural change and income distribution, and found that in an economy where technology and preference adjust over time, several long-term growth are mostly occur due to various distributive rules controlling the task of innovative rents between entrepreneurs and workers.

3.3 Methodology

In this section, the concepts of summability, balancedness and co-summability as well as the estimation method employed in our empirical analysis are explained as follows.

3.3.1 Summability

The idea of summability was conceived in Gonzalo and Pitarakis (2006), and recently expounded upon by Berenguer-Rico and Gonzalo (2013, 2014). According to scholars, a random process $\left(y_t\right)$ will be summable of order β, represented as $S\left(\beta\right)$, if and only if, non-random sequence $\left(m_t\right)$ exist in such a way that,

$$S_T = \frac{1}{T^{1/2+\beta}} L(T) \sum_{t=1}^{T} \left(y_t - m_t \right) = O_P(1) \text{ as T} \to \infty, \tag{1}$$

where, β denotes the least real number such that S_T is stochastically bounded, and $L(T)$ represents a slowly ranging function.

This concept generalizes the idea of integration in linear form and gives room for establishing order of summability for several nonlinear models. As expected, if a linear $\left(y_t \right)$ time series is *I*(*d*), thus, it will be summable of order *d*, that is, $S\left(d \right)$. In a situation, where time series $\left(y_t \right)$ is a nonlinear transformation, this demands the use of the concept of summability. In this empirical application, the focus is to evaluate the order of summability of the variables of interest to be incorporated in the polynomial specifications or framework.

3.3.2 Balancedness

Once the assumption regarding the concept of summability is established, then the balance specification or requirement of the empirical relationship that exist between the variables is then evaluated. That is, evaluating whether both parts of the empirical equation of the model maintain a matching order of summability. The empirical equation specified for the model is given as: $y_t = f\left(x_t, \theta \right)$ where y_t is assumed to be balanced, if $y_t \sim S\left(\beta_y \right)$; $f\left(x_t, \theta \right) \sim S\left(\beta_f \right)$ and $\left(\beta_y = \beta_f \right)$ Therefore, we specified the null and alternative hypotheses of balancedness as:

$$H_0 : \beta_y - \beta_f = 0$$
$$H_1 : \beta_y - \beta_f \neq 0$$

It is pertinent to observe that, under the null hypothesis of balancedness, the related confidence interval includes zero. Therefore, evaluating the variables for balancedness is crucial for the soundness and credibility of the empirical specification in this study.

3.3.3 Cosummability

Cosummability is a crucial pre-estimation test that should be conducted, to evaluate the validity of an empirical model specified for use along with the balancedness test. Besides, two summable random processes $x_t \sim S\left(\beta_x\right)$ and $y_t \sim S(\beta_y)$ are assumed to be co-summable, if and only if there exists $f\left(x_t, \theta_f\right) \sim S\left(\beta_y\right)$ in such a way that $u_t = y_t - f\left(x_t, \theta_f\right)$ is $S(\beta_u)$, where $\beta_u = \beta_y - \beta$, β is greater than zero. Then we say that $\left(y_t, x_t\right) \sim CS\left(\beta_y, \beta\right)$.

However, the parametric function of $f\left(\cdot, \theta_f\right)$ can be substituted with a conventional nonlinear function. While β, β_y and β_x are unknown in application, Berenguer-Rico and Gonzalo (2014) introduced a consistent and more reliable estimator with slow convergence rate of $\frac{1}{\ln\left(T\right)}$. Considering that, the strong cosummability will indicate that, the order of summability β_u of u_t is statistically not different from zero. It is worth noticing that under the null hypothesis, we specified that, the confidence interval contains zero.

3.3.4 Estimation and Inference

The estimation method that we use to estimate the order of summability goes back to McElroy and Politis (2007) and was also detailed by Berenguer-Rico and Gonzalo (2014). For simplicity, let's assume that L(T) in equation (1) is equal to 1. Then, y_t is summable of order β if

$$S_T = \frac{1}{T^{\frac{1}{2}+\beta}} \sum_{t=1}^{T} (y_t - m_t) = O_p\,(1)$$

In addition, to properly use this estimation method, we assume that $P(S_T = 0) = 0$ for all $T = 1,2,3 \ldots$ and subsequently we obtain (see McElroy and Politis (2007))

$$U_T = \ln S_T^2 = \ln\left(T^{-(1+2\beta)}\left(\sum_{t=1}^{T}(y_t - m_t)\right)^2\right) = O_p\,(1)$$

which can be re-written as

$$Y_k = \alpha \ln k + U_k, \quad k = 1,2,\ldots,T. \qquad (2)$$

where $\alpha = 1 + 2\beta$, $Y_k = \ln\left(\sum_{t=1}^{k}(y_t - m_t)\right)^2$ and $U_k = O_p\,(1)$.

In our paper, the deterministic component m_t is assumed to be a constant plus trend $m_t = m_0 + m_1 t$. Berenguer-Rico and Gonzalo (2014) show that, for this parametric form, the appropriate $\widehat{m}_t$ that satisfies $(y_t - \widehat{m}_t) \sim S(\beta)$ is a double partial demeaning

$$\widehat{m}_t = \frac{1}{t}\sum_{j=1}^{t} y_j + \frac{2}{t}\sum_{j=1}^{t}\left(y_j - \frac{1}{j}\sum_{j=1}^{j} y_j\right)$$

By estimating the regression (2) using the least squares we obtain

$$\hat{\alpha} = \frac{\sum_{k=1}^{T} Y_k \ln k}{\sum_{k=1}^{T} (\ln k)^2}$$

and therefore, the ordinary least squares (OLS) estimator of the order of summability β is given by $\hat{\beta} = \frac{\hat{\alpha}-1}{2}$.

With regard to the asymptotic properties of this estimator, the authors have shown that

$$\hat{\alpha} - \alpha = \frac{\sum_{k=1}^{T} U_k \ln k}{\sum_{k=1}^{T} (\ln k)^2} = o_p(1)$$

Berenguer-Rico and Gonzalo (2014) show that the OLS estimator of $\hat{\alpha}$ is log T-consistent. They have shown in their proposition 4 that under the assumption of the stochastic boundedness of U_T, if $\frac{1}{T}\sum_{k=1}^{T} U_k \Rightarrow D_U$ and $\frac{1}{T}\sum_{k=1}^{T} |U_k|^p = O_p(1)$, for some $1 < p < \infty$ and D_U a random variable, then $\ln T\,(\hat{\alpha} - \alpha) \Rightarrow D_U$.

As far as we know, there are no results on the asymptotic distribution of $\hat{\alpha}$ and so critical values cannot be tabulated. In order to overcome this problem, we follow Berenguer-Rico and Gonzalo (2014) by using the subsampling methodology of Politis *et al.* (1999) to obtain inferences on the order of summability. Note that L(T) in equation (1) is not necessarily equal to 1. In our case, we assume, as in Berenguer-Rico and Gonzalo (2014), that L(T) is a constant c different from zero. As a result, equation 2 becomes

$$Y_k = \gamma + \alpha \ln k + U_k, \quad k = 1,2,\dots,T. \qquad (3)$$

With $\gamma = -2\ln c$. To overcome the identification problem of the parameter γ, we subtract the first observation from Y_k, which gives the following the regression

$$Y_k^* = \alpha \ln k + U_k^*, \quad k = 1,2,\dots,T. \qquad (4)$$

Where $Y_k^* = Y_k - Y_1$ and $U_k^* = O_p(1)$

We then obtain the least squares estimator

$$\hat{\alpha}^* = \frac{\sum_{k=1}^{T} Y_k^* \ln k}{\sum_{k=1}^{T} (\ln k)^2}$$

Which possesses the same asymptotic properties as $\hat{\alpha}$ and gives the OLS estimator$\hat{\beta}^* = \frac{\hat{\alpha}^* - 1}{2}$

The subsampling inference method of Politis et al. (1999) is employed here for constructing confidence intervals for the summability order $\hat{\beta}^{*}$. In doing so, the above procedure is applied to $T - b + 1$ subsamples of size $b = \lfloor\sqrt{T}\rfloor + 1$, where $\lfloor\cdot\rfloor$ is the integer part function.

3.4 Data and Empirical Model

In this section, the data, sources of data and empirical model considered in this study are discussed. Using the assertion by Berenguer-Rico and Gonzalo (2013), the relationship between economic growth and income inequality in a polynomial form is given as:

$$y_t = \beta_0 + \beta_1 z_t + \beta_2 z_t^2 + \cdots + \beta_k z_t^k \qquad (5)$$

where, z_t is a measure of economic growth and y_t measures different levels of income distribution. It is crucial to emphasize the following points associated with equation (5) above. First, with regards to the measures chosen for z_t, the most commonly used measure of economic growth is the real gross domestic product per capita i.e. real GDP per capita. In this study, the real GDP per capita is employed to measure the level of economic growth based on data availability for the period from 1917 to 2012. Although reliable data of the real GDP is available until 2015, the data for income distribution is available up to 2012, which is probably the latest data on income distribution. Secondly, for analyzing the relationship between GDP per capita and income inequality, the order of polynomial previously used in the existing literature has either been quadratic or cubic. For quadratic (see Robinson, 1976; Banerjee and Duflo, 2000; Chen, 2003; Patriarca and Vona, 2013) and cubic (see Lessmann, 2014). In our analysis, following the methodology of Berenguer-Rico and

Gonzalo (2013), we use polynomials of up to 4th order, i.e. k = 4. Thirdly, y_t and z_t are often used in their level forms (see Banerjee and Duflo, 2000; Chen, 2003; Rubin and Segal, 2015) or at times in natural logarithms forms (see Lessmann, 2014), while in other cases, they are compared both in levels and natural logarithmic transformation forms (see Muinelo-Gallo and Roca-Sagalés, 2013; Babu *et al*. 2016). Note that equation (5) allows for testing the various forms of the relationship between inequality and GDP per capita; (1) $\beta_1 > 0$ and $\beta_i = 0$, for $i > 1$, suggests a monotonically increasing linear relationship, meaning that rising incomes are accompanied by rising levels of inequality; (2) $\beta_1 < 0$ and $\beta_i = 0$, for $i > 1$, presents a monotonically decreasing linear relationship; (3) $\beta_1 > 0, \beta_2 < 0$ and $\beta_i = 0$, for $i > 2$, reveals an inverted-U quadratic relationship between inequality and GDP per capita, indicating that high levels of income are associated with decreasing levels of inequality once a certain level of income is reached. The peak of this quadratic curve is reached at the turning point where $z = -\beta_1 / 2\beta_2$; (4) $\beta_1 < 0, \beta_2 > 0$ and $\beta_i = 0$, for $i > 2$, suggests a quadratic relationship in U pattern; (5) $\beta_1 > 0, \beta_2 < 0, \beta_3 > 0$ and $\beta_i = 0$, for $i > 3$, indicates a cubic polynomial, representing the N-shaped pattern, where the inverted-U hypothesis occurs up to a certain point, from which inequality increases again. (6) $\beta_1 < 0, \beta_2 > 0, \beta_3 < 0$ and $\beta_i = 0$, for $i > 3$, reveals a cubic polynomial, representing the inverted-N shape.

Therefore, evaluating the inverted U-shaped relationship between economic growth and income inequality for the raw data (levels) and natural logarithm forms of real GDP per capita is done at constant 2009 US dollar values, while measuring different levels of income distribution for income inequality. The data was sought for income distribution from the work of Frank (2009)[14], inequality measures for Gini, Artkin05, RMeanDev and Theil, Top 10% and Top 1% as put together for World Wealth and Income Database (WWID), while data on real GDP per capita was obtained from Global Financial Database (GFD).

3.5 Results and Empirical Discussion

This section contains the results and discussion on the empirical findings from several estimations carried out. In order to achieve the research objective of investigating the inverted U-shaped relationship between economic growth and income inequality in United States, the idea of cosummability was adopted to choose the suitable model specification for the study data. The cosummability technique is built on two distinct tests of summability and balancedness as earlier discussed. Based on the idea of summability, an evaluation of balancedness was carried out i.e. the test for the order of summability of our dependent variable (income inequality) in a hypothesized model specification, is not different from that of the exogenous variables. On the other hand, if balancedness of the variables are confirmed, then it is not out of place to evaluate for cosummability i.e. to test whether the random term of the hypothesized model specification is of a lower order of summability. It is crucial to bear in mind that the model specifications confirming the balancedness and co-summability existence are probably most suitable for the data.

[14] For an exposition on the estimation of this series and file including percentile threshold see Frank, Sommeiller-Price and Saez. Interested reader for further explanation on estimation of other measures of income share or distribution should see Frank, Mark. W. 2009 "Inequality and Growth in the United States: Evidence from a New State-Level Panel of Income Inequality Measure" *Economic Inquiry*, Volume 47, Issue 1, Pages 55-68:

Table 6: Estimated Order of Summability

Variables	$\hat{\beta}^*$	I_{low}	I_{up}
Raw data			
Atkin05	0.317	-0.156	0.791
Gini	0.298	-0.118	0.714
Rmeandev	0.327	-0.182	0.837
Theil	0.314	-0.128	0.756
Top10	1.072	0.473	1.671
Top1	0.603	0.156	1.051
GDP	0.824	0.396	1.252
$(GDP)^2$	1.055	0.522	1.587
$(GDP)^3$	1.287	0.641	1.934
$(GDP)^4$	1.520	0.741	2.299
Log-transformed data			
Ln(Atkin05)	0.356	-0.274	0.985
Ln(Gini)	0.291	-0.150	0.731
Ln(Rmeandev)	0.360	-0.184	0.905
Ln(Theil)	0.396	-0.033	0.826
Ln(Top10)	1.069	0.489	1.649
Ln(Top1)	0.634	0.067	1.202
Ln(GDP)	0.526	-0.026	1.079
$Ln(GDP)^2$	0.570	0.024	1.117
$Ln(GDP)^3$	0.608	0.210	1.007
$Ln(GDP)^4$	0.643	0.275	1.010

Note: $\hat{\beta}^*$ represents the estimated order of summability from equation (4) and computed of all variables included in equation (5) . I_{low} and I_{up} denotes lower and upper bounds of the corresponding 95 percent confidence intervals which are constructed using the subsampling inference method of Politis et al. (1999). All the variables have been partially detrended.

In Table 6, we present the estimation results of the order of summability for all the variables included in equation (5), as well as the corresponding 95 percent confidence intervals over the coverage period for specified model in equation (5), up to k = 4. Interestingly, the confidence intervals for the tests on real GDP per capita and on two measures of income distribution (Top 10% and Top 1%) in levels, does not include zero, thus, rejecting the null hypothesis of summability of order zero. However, the estimated orders of summability for Atkin05, Gini, Rmeandev and Theil are in contrast very close to zero. Therefore, the null hypothesis that these income distribution measures are $S(0)$ cannot be rejected. These results are almost identical to when log forms are used, with the exception of the linear term $(\ln GDP)$ which is $S(0)$ in this case. These empirical findings give prominence to the crucial persistence of the data and presents a strong incentive for the analysis over time series properties earlier posited to be of ultimate significance when evaluating the economic growth and income inequality relationships. In relation to the integrated data, there is possibility of having spurious results, if there is failure to confirm that the specified empirical models are balanced and co-summable.

Table 7: Test for Balancedness

Dependent Variables	Exogenous Variables	$\hat{\beta}$	I_{low}	I_{up}
Atkin05	GDP	-3.043	-5.235	-0.852
Atkin05	$(GDP)^2$	-5.770	-9.361	-2.179
Atkin05	$(GDP)^3$	-8.424	-13.489	-3.358
Atkin05	$(GDP)^4$	-11.047	-17.755	-4.339
Gini	GDP	-3.028	-5.004	-1.051
Gini	$(GDP)^2$	-5.755	-9.223	-2.286
Gini	$(GDP)^3$	-8.409	-13.497	-3.320
Gini	$(GDP)^4$	-11.032	-17.777	-4.286
Rmeandev	GDP	-2.802	-4.629	-0.976
Rmeandev	$(GDP)^2$	-5.529	-8.900	-2.158
Rmeandev	$(GDP)^3$	-8.183	-13.231	-3.134
Rmeandev	$(GDP)^4$	-10.806	-17.512	-4.100
Theil	GDP	-2.709	-4.529	-0.889
Theil	$(GDP)^2$	-5.436	-8.705	-2.166
Theil	$(GDP)^3$	-8.090	-12.919	-3.261
Theil	$(GDP)^4$	-10.713	-17.163	-4.263
Top10_p	GDP	-2.941	-5.015	-0.866
Top10_p	$(GDP)^2$	-5.667	-9.371	-1.964
Top10_p	$(GDP)^3$	-8.321	-13.546	-3.097
Top10_p	$(GDP)^4$	-10.944	-17.670	-4.219
Top1_ps	GDP	-3.078	-5.266	-0.890
Top1_ps	$(GDP)^2$	-5.805	-9.589	-2.021
Top1_ps	$(GDP)^3$	-8.459	-13.767	-3.151
Top1_ps	$(GDP)^4$	-11.082	-17.902	-4.262
LAtkin05	L(GDP)	**0.006**	**-0.901**	**0.913**

LAtkin05	$L(GDP)^2$	**-0.803**	**-2.035**	**0.429**
LAtkin05	$L(GDP)^3$	**-1.523**	**-3.130**	**0.083**
LAtkin05	$L(GDP)^4$	-2.207	-4.170	-0.243
LGini	L(GDP)	**-0.224**	**-1.021**	**0.572**
LGini	$L(GDP)^2$	-1.034	-1.998	-0.069
LGini	$L(GDP)^3$	-1.754	-3.093	-0.415
LGini	$L(GDP)^4$	-2.437	-4.133	-0.741
LRmeandev	L(GDP)	**-0.066**	**-0.875**	**0.743**
LRmeandev	$L(GDP)^2$	-0.875	-1.708	-0.042
LRmeandev	$L(GDP)^3$	-1.595	-2.797	-0.393
LRmeandev	$L(GDP)^4$	-2.279	-3.833	-0.724
LTheil	L(GDP)	**0.076**	**-0.872**	**1.024**
LTheil	$L(GDP)^2$	**-0.733**	**-1.650**	**0.184**
LTheil	$L(GDP)^3$	-1.453	-2.643	-0.264
LTheil	$L(GDP)^4$	-2.137	-3.700	-0.574
LTop10_p	L(GDP)	**-0.093**	**-0.836**	**0.650**
LTop10_p	$L(GDP)^2$	-0.902	-1.696	-0.108
LTop10_p	$L(GDP)^3$	-1.623	-2.760	-0.485
LTop10_p	$L(GDP)^4$	-2.306	-3.850	-0.762
LTop1_ps	L(GDP)	**0.034**	**-0.873**	**0.941**
LTop1_ps	$L(GDP)^2$	**-0.775**	**-1.652**	**0.102**
LTop1_ps	$L(GDP)^3$	-1.495	-2.738	-0.253
LTop1_ps	$L(GDP)^4$	-2.179	-3.854	-0.503

Note: $\hat{\beta}_T = \hat{\beta}_y - \hat{\beta}_f$, $\hat{\beta}_y$ and $\hat{\beta}_f$ represent the estimated order of summability of the dependent variable and the sum of the explanatory variables respectively. All the variables have been partially detrended. It tests the null hypothesis $H_0: \beta_y - \beta_f = 0$ against the alternative $H_1: \beta_y - \beta_f \neq 0$ where β_y and β_f are the summability orders of the dependent variable y_t and the sum of the explanatory variables $\sum_{i=1}^{k} z_t^i$, respectively, in the regression given by equation (5). $\hat{\beta}_y$ and $\hat{\beta}_f$ are obtained by OLS of equation (2). I_{low} and I_{up} represents lower and upper bounds of the corresponding 95 percent confidence intervals. which are constructed using the subsampling inference method of Politis et al. (1999).

In Table 7, the results of balancedness tests are contained for both levels and natural logarithms for the coverage periods in this study. It tests the null hypothesis $H_0: \beta_y - \beta_f = 0$ against the alternative $H_1: \beta_y - \beta_f \neq 0$ where β_y and β_f are the summability orders of the dependent variable y_t and the sum of the explanatory variables $\sum_{i=1}^{k} z_t^i$, respectively, in the regression given by equation (5). Note that the summability estimated orders $\hat{\beta}_y$ and $\hat{\beta}_f$ are obtained by OLS of equation (2), while the confidence intervals are constructed using the subsampling inference method of Politis et al. (1999). For the sampled periods, results reveal that balancedness is only confirmed when data are taken in logarithms, but with a maximum polynomial order that differs from one variable to another; until *k* = 3 for Atkin05, that is, under linear, quadratic and cubic polynomial specifications, since zero is included in the corresponding confidence intervals; until *k* = 2 for Theil and Top 1%; k = 1 for Gini, Rmeandev and Top 10%. Consequently, based on these results, it is of no use to further consider the data in levels (raw data). In a nutshell, the null hypothesis of balanced specifications cannot be rejected for the specified models.

In addition, Table 8 reports the results for co-summability tests of the variables taken in natural logarithms form. Note that this table shows only the regressions for which the balancedness is achieved. The testing procedure is a residual based test for the null hypothesis of strong co-summability $H_0: \beta_{\hat{\varepsilon}} = 0$ against the alternative

$H_1: \beta_{\hat{\varepsilon}} \neq 0$ where $\beta_{\hat{\varepsilon}}$ is the summability order of the residuals obtained using the ordinary least squares (OLS) estimation method of equation (5). Note that the summability estimated order $\hat{\beta}_{\hat{\varepsilon}}$ is obtained by OLS of equation (4), while the

Table 8: Test of Cosummability

Dep. Var.	L(Atkin05)	L(Atkin05)	L(Atkin05)	L(Atkin05)	L(Atkin05)	L(Atkin05)	L(Gini)	L(Gini)	L(Rmeandev)	L(Rmeandev)
1	-3.453***	2.541*	38.306***	40.842***	-90.003	-75.259	-2.123***	1.191*	-1.756***	2.199**
T	.	0.016***	.	-0.006*	.	-0.005	.	0.009***	.	0.011***
L(GDP)	0.193***	-0.501***	-8.453***	-9.167***	31.366	26.856	0.145***	-0.239***	0.142***	-0.316***
$L(GDP)^2$	.	.	0.446***	0.495***	-3.663	-3.219	.	.	.	.
$L(GDP)^3$	.	.	.	.	0.141*	0.127	.	.	.	.
$\hat{\beta}^*_{\hat{\varepsilon}}$	0.329	0.414	-0.070	-0.479	-0.087	-0.416	0.307	0.396	0.283	0.378
I_{low}	-0.361	-0.014	-0.933	-1.559	-0.814	-1.269	-0.297	-0.117	-0.430	-0.133
I_{up}	1.020	0.843	0.794	0.601	0.639	0.437	0.912	0.909	0.996	0.888
AIC	-0.359	-0.516	-1.296	-1.307	-1.311	**-1.315**	-1.794	**-2.008**	-1.319	**-1.503**
BIC	-0.305	-0.435	**-1.216**	-1.200	-1.204	-1.182	-1.740	**-1.927**	-1.266	**-1.423**
LRT_1		17.057***	91.984***	94.993***	95.403***	97.819***		22.508***		19.652***
LRT_2				3.009*	3.419*	5.835*				

Dep. Var.	L(Theil)	L(Theil)	L(Theil)	L(Theil)	L(Top10)	L(Top10)	L(Top1)	L(Top1)	L(Top1)	L(Top1)
1	-2.355***	7.509***	72.253***	78.479***	-0.918***	5.465***	-1.826***	6.963***	61.463***	65.898***
T	.	0.027***	.	-0.014***	.	0.017***	.	0.024***	.	-0.010**
L(GDP)	0.179***	-0.963***	-15.268***	-17.020***	-0.002	-0.741***	-0.015	-1.033***	-13.119***	-14.367***
L(GDP)^2			0.796***	0.917***					0.675***	0.761***
L(GDP)^3										
$\hat{\beta}_{\hat{\varepsilon}}^{*}$	0.408	0.536	0.022	-0.075	1.082	0.625	0.656	1.722	0.446	0.645
I_{low}	-0.159	0.108	-0.734	-0.892	0.440	0.244	0.050	0.832	-0.241	-0.122
I_{up}	0.975	0.964	0.777	0.742	1.724	1.006	1.262	2.612	1.133	1.412
AIC	0.661	0.509	-0.555	**-0.627**	-1.053	**-1.494**	0.343	0.174	-0.845	**-0.886**
BIC	0.714	0.589	-0.475	**-0.520**	-1.000	**-1.414**	0.397	0.254	-0.765	**-0.779**
LRT$_1$		16.62***	118.74***	127.65***		44.30***		18.29***	116.10***	122.05***
LRT$_2$				8.910***						5.953**

Note: $\hat{\beta}_{\hat{\varepsilon}}^{*}$ represents the estimated order of summability of the residual, after subtracting the first observation, calculated from the regression (5) as proposed by Berenguer-Rico & Gonzalo (2013), while I_{low} and I_{up} represents lower and upper bounds of the corresponding 95 percent confidence intervals which are constructed using the subsampling inference method of Politis et al. (1999). All residuals series have been partially demeaned. LRT$_1$ and LRT$_2$ are the likelihood ratio tests of the null hypotheses of linear and quadratic forms (without trend), respectively. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

confidence intervals are constructed using the subsampling inference method of Politis et al. (1999). For the log-transformed data, results show that co-summability is not rejected for all considered specifications except the linear form for some variables; the rejection is observed only for Theil in the case of linear form with deterministic trend and for Top 10% and Top 1% in the case of a linear form both with and without deterministic trend.

Based solely on balancedness and cosummability results, there is some ambiguity about the adequate form to use for each variable. Indeed, there exists more than one potential specification for some variables; linear, quadratic or cubic form for Atkin05; linear or quadratic form for Theil. For Top 1%, quadratic form seems to be the most appropriate (see Tuominen, 2016b) while the linear form is adequate for Gini and Rmeandev. For Top 10%, cosummability is however rejected. In order to select, for each inequality measure, the most appropriate specification among those for which both balancedness and cosummability are achieved, we use three fitness tests for model selection; Akaike information criteria (AIC), Schwarz information criteria (BIC) and the Likelihood Ratio Test (LRT). As for the comparison between AIC and BIC, we observe that the selection results of BIC are identical with AIC, with the exception for Atkin05 inequality measure. In the case of Atkin05, despite the fact that cubic form with deterministic trend is selected by the AIC criterion, the likelihood ratio test confirms the result of the BIC criterion by not rejecting the null hypothesis of quadratic form without deterministic trend at conventional 5% level**.** To summarize, our results indicate that the relationship between income and inequality has generally either linear or quadratic form. Indeed, out of six measures of inequality used in this study, three among them give evidence to a quadratic relationship; quadratic form without deterministic trend for Atkin05; and quadratic form with deterministic trend for Theil and Top 1%. The measures of inequality providing evidence in favor of linear relationship with deterministic trend are Gini and Rmeandev. In addition, by analyzing the signs of the coefficient estimates for the selected quadratic regressions we found that $\beta_1 < 0$ and $\beta_2 > 0$, which implies a quadratic relationship in U pattern. Hence, there is no evidence of an inverted U-shaped relationship between income and inequality in United States.

Consequently, based on the empirical results and current findings, the researchers conclude as in Hsing and Smyth (1994) and Jacobsen and Giles (1998) that the Kuznets inverted U-shaped hypothesis is not applicable to United States. This implies that relative to Hsing and Smyth (1994) and Jacobsen and Giles (1998), using long and very recent data with advanced econometric techniques that capture nonlinearity in the long-run relationship between income inequality and economic growth, does not help with evidence in support of the inverted U-shaped curve theory.

3.6 Conclusion

This study employed more sophisticated econometric techniques to investigate the existence of the popular Kuznets inverted U-shaped hypothesis in the long-run equilibrium relationship between economic growth and income inequality at various measures for United States. Motivated by the plethora of controversial arguments and differing conclusions regarding the relationship between growth and inequality levels, this study employed long and very recent data to capture transformation processes of the sampled country, using the idea of cosummability, which is proposed to analyze nonlinear long-run relations among stochastic processes. The empirical results and findings, however, present no evidence in support of the Kuznets inverted U-shape for United States.

The findings challenge some of the prevailing conclusions regarding the existence of an inverted U-shaped relationship between economic growth and income inequality in the United States. However, this is not a claim that high income inequality level should not bother the policymakers or that income inequality in the short-run may not be harmful to growth. Alternatively, emphasis is placed on the absence of evidence for nonlinear methodology for the relationship between economic growth and income inequality. If the long-run relationship between economic growth and income inequality implies causality, then current empirical findings have policy implications, such that a country with negligible income inequality can influence its growth by broadening its income inequality level, while one with a high income inequality can enhance its growth by lowering its income inequality level. With the confirmation of linear form at some point, there seems to be a relationship between changes in income inequality and level of income. Variations in income inequality, whatever the direction may be, are related with lower and/or higher level of income. However, since this model did not capture a relationship of causality, then such policy recommendations should be taken with cautiousness.

Chapter 4

ASYMMETRIC EFFECTS OF INEQUALITY ON REAL OUTPUT LEVEL IN THE UNITED STATES

4.1 Introduction

The relationship between economic growth and income inequality has long been of importance in the field of economics. Substantial number of study have asserted that income inequality has positive impacts on economic growth (see Benabou, 2000; Deininger and Olinto, 2000; Nahum, 2005; Lopez, 2006; Frank, 2009; Chan, Zhou and Pan, 2014; Wahiba and EI Weriemmi, 2014; Henderson, Qian, and Wang, 2015; Saari, Dietzenbacher and Los, 2015; Babu, Bhaskaran and Venkatesh, 2016), while some claimed opposite view (see Alesina and Rodrik, 1994; Perotti 1996; Deininger and Squire, 1998; Knowles, 2005; Ostry, Berg and Tsangarides, 2014; Wan, Lu and Chen, 2006; Sukiassyan, 2007; Nissim, 2007; Majumdar and Partridge, 2009; Ogus Binatli, 2012; Fang, Miller, Yeh, 2015; Muinelo and Roca, 2013; Rubin and Segal, 2015). The theoretical reasoning for a negative and positive relationship between income inequality and economic growth is discussed as follows:

The negative relationship between income inequality and economic growth can be explained via the theory of credit market imperfection. This theory, according to Galor and Zeira (1993), Piketty (1997) and Aghion et al. (1999) highlights that an inverse relationship exists between income inequality and economic growth as a result of inadequate funds of low-income households for investment. It is argued that, low-income household has insufficient and limited access to investment funds, owing to the fact that there are imperfections in the credit market. This, in one way or another, makes it difficult for these households to invest their available resources. Thus, investments are only feasible for the few rich with high incomes and consequently, a decline in the marginal productivity of capital and lagging economic growth.

In addition, Bertola (1993), Perotti (1993), Alesina and Rodrik (1994), Persson and Tabellini (1994), and Benabou (1996) using more extensive political economy ideology argued that economic inequality would probably lead to distorted redistribution policies, a situation that could reduce labor incentives and retard economic growth. Even if veritable redistribution policies are not executed, persuasion to obstruct their establishment and successive political misrepresentation could impede economic growth by squandering economic resources that would otherwise be used to further enhance production activities in the economy. Similarly, Gupta (1990), Alesina and Perotti (1996), Benhabib and Rustichini (1996) in their socio-political instability views are of the opinion that, an increase in income inequality could raise the possibility of poor masses engaging in highly damaging activities such as rioting, revolution and crime etc. While the resulting economic and/or political instability and skepticism in the whole economic system could lead to a decrease in investment stimulus, thereby impeding economic growth in the long-run.

On the positive relationship between income inequality and economic growth, it has been argued that, income inequality could increase in the early stages of economic development. According to Galor and Tsiddon (1997a), this is only feasible when a native environment externality is the dominant factor in the human capital accumulation before the dominance of the general technological externality in the distribution of human capital. In the period featured by the significant technological advancements, reduction in the relative significance of initial conditions enhances inequality. At the same time, an accumulation of sound and highly capable individuals in technologically advanced sectors can enhance economic growth (Galor and Tsiddon, 1997b). Forbes (2000), on the other hand, argued that a positive relationship between income inequality and economic growth could be feasible in the short and/or medium-term. He posits that the relationship between income inequality and economic growth could possibly be negative in the long-run and positively significant in the short-run. This finding is in line with Li and Zou (1998) study, using a fixed effect model in a cross-country panel analysis. Despite the extensive existing literature on income inequality and economic growth, there remains considerable disagreement on the effect of income inequality on economic growth.

Inferring from the above, it will be theoretically correct to assume that an increase[15] in income inequality level will have a different effect on economic growth than a decrease in income inequality. Following the relationship between the variables, an increase in income inequality (negative shock) indicates bad news, while a decrease in income inequality (positive shock) signifies good news on real output level. For an

[15] A negative income inequality in this study refer to as decrease in income inequality level which is expected to have a positive (impact) shock on the real output or income level, and vice versa.

instance, a decrease in income inequality level through tax reduction would have a positive shock on economic growth. It was argued that, progressive taxation with negative net tax rates for the low income earner are meant to provide lowest level of consumption and also to reduce income inequality among various groups. According to Biswas et al. (2017), taxation at various levels of the income distribution has heterogeneous effects on individuals and/or households' motivation to work, invest, and consume. However, reducing income inequality through poverty alleviation programs and schemes, between low and median income individuals and families stimulates small and medium business growth, female labor supply and consumption expenditure and hence economic growth. On the contrary, reducing income inequality between median and high-income families reduces economic growth through reduction in job creation, small business growth and female labor supply. These asymmetric economic growth effects are associated with both the demand- and supply-side factors, that is, changes in labor supply and small-scale business activity (Biswas et al., 2017). For example, total US trends in income inequality have been examined in the study of Piketty and Saez (2003, 2006) where they constructed several time-series measures of US top income shares between the periods 1913 and 1998. They find that income inequality in the US has shown a definite U-shaped (negative and positive) pattern. At the wake of this century, income inequality decreased considerably, most especially during World War II and the Great Depression.

As discussed earlier, the increase in income inequality level is conducive to the adoption of distortionary redistributive and economic growth retarding policies, which slow down the growth process (see Persson and Tabellini, 1994; Alesina and

Rodrik, 1994; Benhabib and Rustichini, 1996). In addition, due to the financial market imperfections, an increase in income inequality level would overemphasize the negative impacts of credit constraints on small business growth and human capital accumulation, thus reducing economic growth (Galor and Zeira, 1993; Galor and Moav, 2004). Moreover, increase in income inequality might increase economic growth. According to Guvenen *et al.* (2014), a rise in inequality creates motivation to work better, invest more, and assume risks in order to enjoy high rates of returns. This can also stimulate gross savings and thus capital accumulation, since the few rich have a lower marginal propensity to consume (Biswas *et al.*, 2017). Our empirical results show that increasing and/or decreasing income inequality do have asymmetric impacts on economic growth. Based on our knowledge, these asymmetric effects of income inequality on economic growth have not been examined empirically in the literature.

Several authors have investigated the impact of income inequality on economic growth, and vice versa, using time-series econometric models. While some have employed panel data-based approaches, others have focused solely on the United States, due to availability of long-span time-series data. At the cross-country level, one could mention Forbes (2000) who investigated the hypothesis for a panel of 45 countries and concluded that, both in the short- and medium-run, a rise in country's level of income inequality has a positive significant relationship with economic growth. This result was in line with the work of Li and Zou (1998) where they concluded that income inequality is not harmful to economic growth. The opposite was the case with Alesina and Rodrik (1994), Persson and Tabellini (1994) and Banerjee and Duflo (2003). Banerjee and Duflo (2003) using non-parametric approaches. These studies revealed that the economic growth rate is an inverted-U shaped function of the net variations in income inequality. According to them, variations in the level of income inequality, no matter the direction, are related to reduce economic growth. The non-linearity approaches employed in their studies, made their empirical findings sufficient enough to highlight why previous studies on the existing relationship reported between income inequality and economic growth are in conflict with each other.

Using time-series models to examine the relationship between the level of income inequality and economic growth for the United States, Ram (1991) concluded that, there is an inverse relationship between income inequality and economic growth. This result was confirmed by Hsing and Smyth (1994) and Jacobsen and Giles (1998). Meanwhile, in a panel framework, the same modelling approach was employed by Frank (2009), where he constructed annual indicators of income inequality over the period 1945-2004 for individual states in the US. Using panel autoregressive distributed lag (ARDL) model, it was concluded that, in the long-run income inequality has contributed positively to economic growth. A recent study by Bahmani-Oskooee and Motavallizadeh-Ardakani (2018) on the impact of growth on inequality, using the nonlinear autoregressive distributed lag (NARDL) model for each state in the US over the period of 1959-2013, shows that economic growth has impacted positively on income inequality, but within 20 states. It was revealed that economic growth has an asymmetric impact on income inequality both in the short- and long-run. They found that, an increase or a decrease in real output level have worsened income inequality.

It is on this premise, our study seeks to examine the presence of short- and long-run asymmetric effects of income inequality on real GDP per capita, i.e., the impact of an increase or decrease of the income inequality on the real output level in the US. This study uses a larger sample size over the period of 1917-2012 (96 years). Our sample size appears to be large enough to cover different economic growth/development stages of the US, hence a reliable and robust time-series empirical outcomes. Second, unlike previous studies that used only Gini coefficient as the measure of income inequality for the US, our study employs six measures of income distribution, namely; Atkinson index, Gini coefficient, relative mean deviation (Rmeandev), Theil's entropy index, Top 10% and Top 1% income share respectively. The choice of these income inequality indicators is supported by the fact that, it is important to examine the reliabilities of the income inequality proposition under different inequality indicators. Using diverse indicators would allow more meaningful empirical analysis about the pathogenic impacts of inequalities in varying parts of the income scale (see Wagstaff, 2002; Weich, Lewis and Jenkins, 2002). Third, unlike Bahmani-Oskooee and Motavallizadeh-Ardakani (2018) that examined the impact of growth on inequality for the US, this study examines the opposite. We investigate the impact of inequality on output growth, the effects of negative inequality and positive inequality shocks (increase and decrease of inequality) on economic growth of the US.

The major objective of this study is to examine the short- and long-run (increase and decrease) asymmetric effects of income inequality on real output level over the long time-span in the United States. In order to achieve the research objective, we employ nonlinear ARDL model approach recently developed by Shin, Yu and Greenwood-

Nimmo (2014) which is an asymmetric extension of the linear ARDL cointegration model proposed by Pesaran, Shin and Smith (2001) to capture short- and long-run asymmetric behavior of the model. We found that, the long-run coefficients on positive changes have positive signs while the signs of those on negative changes are negative indicating that, a decrease or an increase in income inequality improves real output level in the US.

The remaining sections of this study is as follow. Section two discusses in details, data and methodology employed in this study. In section three we report empirical results and discussion of findings with concluding remarks in section four.

4.2 Data and Variables

In this study, the real GDP per capita measure the level of economic growth over the period 1917 to 2012, measured at constant 2009 US dollar values. We proxy income distribution for income inequality. Income distribution dataset was obtained from the work of Frank (2009)[16], income inequality measures for Gini, Artkin05, RMeanDev and Theil, Top 1% and Top 10% as put together for World Wealth and Income Database (WWID), while data on real GDP per capita was sourced from Global Financial Database (GFD).

4.3 Methodology

In this paper, we use the Nonlinear Autoregressive Distributed Lag (NARDL) approach, recently developed by Shin et al. (2014), to examine the presence of short-run and long-run asymmetric effects of inequality on real GDP per capita. To

[16] For an exposition on the estimation of this series and file including percentile threshold see Frank, Sommeiller-Price and Saez. Interested reader for further explanation on estimation of other measures of income share or distribution should see Frank, Mark. W. 2009 "Inequality and Growth in the United States: Evidence from a New State-Level Panel of Income Inequality Measure" *Economic Inquiry*, Volume 47, Issue 1, Pages 55-68:

measure income inequality, six measures of income distribution were used; the Atkinson Index, the Gini coefficient, the Relative Mean Deviation, Theil's entropy Index, Top 10% income shares and Top 1% income shares.

The NARDL model extends the linear autoregressive distributed lag (ARDL) cointegration model developed by Pesaran *et al.* (2001) to allow for short and long run asymmetric behavior in the adjustment process. To capture this asymmetric behavior, both in the short and long run, the authors split the explanatory variables into their positive and negative partial sums as follow: $x_t = x_0 + x_t^+ + x_t^-$. Here, the two components x_t^+ and x_t^- are, respectively, positive and negative partial sum decompositions of x_t, such as

$$x_t^+ = \sum_{i=1}^{t} \Delta x_i^+ = \sum_{i=1}^{t} \max\left(\Delta x_i ,0\right) \text{ and } x_t^- = \sum_{i=1}^{t} \Delta x_i^- = \sum_{i=1}^{t} \min\left(\Delta x_i ,0\right).$$

This approach of partial sum decomposition was initially used by Granger and Yoon (2002) in advancing the concept of hidden cointegration, and Schorderet (2001) in the context of the nonlinear relationship between unemployment and output. The usefulness of this decomposition is that positive and negative partial sums reflect, respectively, the increase and decrease of the explanatory variable.

The NARDL model has the following error correction form

$$\Delta y_t = c + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \sum_{j=0}^{q-1} \left(\varphi_j^+ \Delta x_{t-j}^+ + \varphi_j^- \Delta x_{t-j}^-\right) + \varepsilon_t$$

Where $x_t = x_0 + x_t^+ + x_t^-$ is a $k \times 1$ vector of exogenous regressors entering the model asymmetrically via the partial sums x_t^+ and x_t^- as defined above. ρ is the symmetric long-run parameter while θ_x^+ and θ_x^- are the asymmetric long-run parameters[17]. φ_j^+ and φ_j^- are the asymmetric short-run coefficients. They denote the short-run adjustments to the positive and negative shocks affecting the asymmetric regressors. γ_i are the autoregressive parameter and ε_t is i.i.d. zero mean random variable with finite variance σ_ε^2. p and q represent the respective lag orders for the dependent variable y_t and the exogenous variables x_t in the distributed lag component.

If the coefficients associated with the partial sum variables in the short run, the long run, or both components, differ significantly, then an asymmetric impact on the dependent variable can be established. In addition, we can compute the asymmetric positive and negative long-run coefficients, respectively as follows: $L_{X^+} = \frac{-\theta^+}{\rho}$ and $L_{X^-} = \frac{-\theta^-}{\rho}$.

Statistical significance of these coefficients provides insights about the long-term relationships between the dependent variable and the respective independent variables. Positive sign of these coefficients indicates that positive or negative shocks in the exogenous variables have positive or negative long run effect, respectively, on the dependent variable while negative sign implies opposite effects.

In addition, the short-run symmetry can be tested by using a standard Wald test (WSR) of the null hypothesis $H_0: \sum_{j=0}^{q-1} \varphi_j^+ = \sum_{j=0}^{q-1} \varphi_j^-$. Similarly, the long-run symmetry is also tested through a Wald test (WLR) for the null hypothesis

[17] The parameter ρ is assumed to be negative to have a cointegration relationship among the variables.

$H_0: L_{x^+} = L_{x^-}$. In the case where both null hypotheses are not rejected, the NARDL model is reduced to the traditional linear ARDL, meaning that no asymmetry is present between the two variables.

The NARDL model offers many benefits over traditional methods investigating the cointegration relationship, such as Engle and Granger (1987), Johansen and Juselius (1990), etc. One is that it can test for long and short run asymmetries between the independent and dependent variables. Also, it has the ability to combine $I(0)$ and $I(1)$ regressors and to capture the hidden cointegration which is not possible within the standard methods.[18] In addition, it performs better in testing for cointegration relationships in small samples compared to alternative cointegration procedures (Romilly et al., 2001).

For the purpose of our analysis, we use the NARDL model to investigate the possible existence of both long run and short-run asymmetries in the response of the real GDP per capita to increases/decreases in inequality measures. We consider the following four regressions of the NARDL based error correction model presented above:

SS: $$\Delta GDP_t = c + \rho GDP_{t-1} + \theta Ineq_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta GDP_{t-i} + \sum_{j=0}^{q-1} \varphi_j \Delta Ineq_{t\text{-}j} + \varepsilon_t \qquad (1)$$

AS: $$\Delta GDP_t = c + \rho GDP_{t-1} + \theta Ineq_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta GDP_{t-i} + \sum_{j=0}^{q-1} \left(\varphi_j^+ \Delta Ineq_{t\text{-}j}^+ + \varphi_j^- \Delta Ineq_{t\text{-}j}^- \right) + \varepsilon_t \qquad (2)$$

SA: $$\Delta GDP_t = c + \rho GDP_{t-1} + \theta^+ Ineq_{t\text{-}1}^+ + \theta^- Ineq_{t\text{-}1}^- + \sum_{i=1}^{p-1} \gamma_i \Delta GDP_{t-i} + \sum_{j=0}^{q-1} \varphi_j \Delta Ineq_{t\text{-}j} + \varepsilon_t \qquad (3)$$

[18] According to Granger and Yoon (2002), two times series are hidden cointegrated if their positive and negative components are cointegrated with each other.

AA: $$\Delta GDP_t = c + \rho GDP_{t-1} + \theta^+ Ineq^+_{t-1} + \theta^- Ineq^-_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta GDP_{t-i} + \sum_{j=0}^{q-1} \left(\varphi_j^+ \Delta Ineq^+_{t-j} + \varphi_j^- \Delta Ineq^-_{t-j} \right) + \varepsilon_t \qquad (4)$$

Where *GDP* is the real gross domestic product per capita while *Ineq* is the inequality measure. Note that all variables are taken in natural logarithm. Since the data are on an annual basis, the maximum order of the lags in the NARDL model is chosen to be 3.

4.4 Empirical Results and Discussion

We first subject each time series to the augmented Dickey-Fuller (1981) and Phillips-Perron (1988) unit root tests. The results of these tests are given in Table 1. Clearly, both ADF and PP unit root tests concluded that all variables are stationary at first difference and there is no *I*(2) variable which meets the requirement to proceed to the bounds testing procedure.

The methodology adopted in this paper is as follow: The equations (1)-(4) presented above are estimated by Ordinary Least Squares (OLS) for all considered inequality measures. For each equation, following Shin et al. 2014, we start with a maximum lag order, $p_{max} = q_{max} = 3$, and then drop all insignificant stationary regressors sequentially.

Table 9: Augmented Dickey-Fuller and Phillips-Perron Unit Root Tests Results.

Variables	Exogenous	ADF		PP	
		stat.	pval.	stat.	pval.
Level					
RGDPpc	*c,t*	-3.649	0.031	-2.665	0.253
Atkin05	*c,t*	-2.037	0.574	-2.795	0.203
Gini	*c,t*	-2.578	0.291	-2.787	0.206
Rmeandev	*c,t*	-2.300	0.430	-3.183	0.094
Theil	*c,t*	-1.453	0.839	-2.098	0.540
Top10%	*c,t*	-0.794	0.962	-0.788	0.963
Top1%	*c,t*	-1.162	0.912	-1.022	0.935
First-Difference					
ΔRGDPpc	*C*	-6.655	0.000	-6.773	0.000
ΔAtkin05	*C*	-5.550	0.000	-8.781	0.000
ΔGini	*C*	-5.374	0.000	-9.630	0.000
ΔRmeandev	*C*	-5.949	0.000	-9.165	0.000
ΔTheil	*C*	-8.392	0.000	-8.381	0.000
ΔTop10%	*C*	-8.788	0.000	-8.747	0.000
ΔTop1%	*C*	-9.748	0.000	-9.809	0.000

Estimation results are given in Tables 10-13. Table 10 reports estimation results for the symmetric ARDL regression (SS). In this model, both long run and short run relationships between GDP per capita and inequality measures are assumed to be symmetric. The estimated long-run coefficients (L_X) are not significant for all considered inequality measures. Table 11 indicates that similar results are also obtained when only allowing the short run relationships to be asymmetric (regression AS). However, assuming that there are asymmetric long run relationships, estimation results of equations (3) and (4) in Table 12 and 13, respectively, provide evidence of statistical significant asymmetric long run coefficients for some cases. For both equations, long-run coefficients on positive changes (L_{X^+}) are statistically significant at conventional 5% level for atkin05, theil and top 10%, while those on negative changes (L_{X^-}) are statistically significant for theil, top 10% and top 1% except for theil in equation (4). For Gini and Rmeandev inequality measures, long-run coefficients on both positive and negatives changes are insignificant at conventional 5% level. Note that long run coefficients on positive changes have positive signs, while the signs of those on negative changes are negative. This indicates that an inequality shock, whether positive or negative, have a positive long run effect on GDP. Our finding is consistent with the work of Frank (2009) that income inequality interacts positively with the real output level.

Table 10: NARDL Model Estimation (Short-run and Long-run Symmetry (SS))

Variable	Atkin05		Gini		Rmeandev		Theil		Top10%		Top1%	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
C	0.011	0.108	-0.054	0.125	0.017	0.102	0.058	0.078	0.110	0.085	0.085	0.085
y_{t-1}	-0.002	0.008	0.003	0.010	-0.001	0.009	-0.005	0.008	-0.009	0.008	-0.009	0.008
x_{t-1}	-0.018	0.024	-0.064	0.050	-0.029	0.041	-0.008	0.014	0.015	0.036	-0.007	0.018
Δy_{t-1}	0.463***	0.088	0.394***	0.093	0.416***	0.089	0.479***	0.087	0.396***	0.096	0.394***	0.096
Δy_{t-2}												
Δy_{t-3}	-0.184**	0.082	-0.212**	0.084	-0.182**	0.085	-0.178**	0.081				
Δx_{t}	0.211***	0.066			0.209**	0.101	0.182***	0.050				
Δx_{t-1}			0.381***	0.134								
Δx_{t-2}	-0.223***	0.066	-0.494***	0.130	-0.359***	0.099	-0.159***	0.051				
Δx_{t-3}												
L_X	-7.310	32.417	23.213	73.070	-25.413	234.352	-1.626	4.264	1.709	4.499	-0.806	2.147
Test	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.
R-Bar	0.356		0.340		0.323		0.355		0.142		0.142	
SC(3)	6.725	0.081	1.717	0.633	3.463	0.326	5.603	0.133	0.105	0.991	0.177	0.981
RRT	0.860	0.354	0.065	0.798	0.116	0.733	1.092	0.296	3.010	0.083	3.136	0.077
JB	38.566	0.000	50.297	0.000	40.302	0.000	28.918	0.000	20.453	0.000	18.580	0.000
HT	1.263	0.261	0.284	0.594	0.702	0.402	0.822	0.365	0.358	0.550	0.186	0.666

Notes: y_t and x_t are the GDP and the inequality measure, respectively, taken in natural logarithms at year t. L_X is the symmetric long-run coefficients. R-Bar denotes the adjusted R-square. SC(k) refers to the Godfrey (1978) test for kth order serial correlation. RRT denotes the Ramsey (1969) RESET test of functional form. JB denotes the Jarque-Bera (1980) test statistic for normality. HT is the LM test for heteroscedasticity. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

Table 11: NARDL Model Estimation (Short-run Asymmetry and Long-run Symmetry (AS))

Variable	Atkin05		Gini		Rmeandev		Theil		Top10%		Top1%	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
C	0.326^{**}	0.134	0.413^{**}	0.158	0.033	0.110	0.263^{***}	0.089	0.185^{**}	0.084	0.159^{*}	0.084
y_{t-1}	-0.027^{***}	0.010	-0.036^{***}	0.013	-0.003	0.010	-0.022^{***}	0.008	-0.013^{*}	0.008	-0.009	0.008
x_{t-1}	0.019	0.026	0.045	0.054	-0.045	0.040	0.018	0.016	0.027	0.035	0.018	0.019
Δy_{t-1}	0.448^{***}	0.088	0.413^{***}	0.093	0.372^{***}	0.089	0.455^{***}	0.085	0.404^{***}	0.092	0.426^{***}	0.095
Δy_{t-2}	---	---	---	---	---	---	---	---	---	---	---	---
Δy_{t-3}	---	---	---	---	-0.190^{**}	0.088	-0.195^{**}	0.081	---	---	---	---
Δx_t^+	---	---	---	---	0.353^{**}	0.161	---	---	---	---	---	---
Δx_{t-1}^+	---	---	---	---	---	---	---	---	---	---	---	---
Δx_{t-2}^+	-0.435^{***}	0.119	-0.873^{***}	0.237	-0.549^{***}	0.161	-0.346^{***}	0.094	---	---	-0.312^{**}	0.121
Δx_{t-3}^+	---	---	---	---	---	---	---	---	-0.740^{***}	0.259	---	---
Δx_t^-	0.386^{***}	0.119	0.559^{**}	0.238	---	---	0.301^{***}	0.087	---	---	0.213^{**}	0.095
Δx_{t-1}^-	---	---	0.419^{**}	0.205	---	---	---	---	---	---	---	---
Δx_{t-2}^-	---	---	---	---	---	---	---	---	---	---	0.210^{**}	0.103
Δx_{t-3}^-	---	---	---	---	---	---	---	---	0.555^{**}	0.218	---	---
L_X	0.717	0.821	1.270	1.222	-15.245	62.022	0.827	0.623	2.100	2.953	2.051	2.844
Test	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.
WSR_x	23.805	0.000	23.221	0.000	0.723	0.398	26.155	0.000	10.406	0.002	11.185	0.001
R-Bar	0.336		0.316		0.315		0.360		0.217		0.222	
SC(3)	2.169	0.538	2.268	0.519	1.407	0.704	8.433	0.038	0.628	0.890	1.647	0.649
RRT	2.774	0.096	0.485	0.486	1.550	0.213	1.241	0.265	1.743	0.187	3.026	0.082
JB	18.241	0.000	8.555	0.014	7.613	0.022	10.571	0.005	34.725	0.000	15.087	0.001
HT	0.055	0.814	0.007	0.935	2.081	0.149	0.152	0.696	0.356	0.551	0.102	0.750

Notes: y_t and x_t are the GDP and the inequality measure, respectively, taken in natural logarithms at year t. L_X is the symmetric long-run coefficients. WSR_x denotes the Wald test of the additive short-run symmetry by testing the null hypothesis: $H_0: \sum_{j=0}^{q-1}\varphi_j^+ = \sum_{j=0}^{q-1}\varphi_j^-$. R-Bar denotes the adjusted R-square. SC(k) refers to the Godfrey (1978) test for kth order serial correlation. RRT denotes the Ramsey (1969) RESET test of functional form. JB denotes the Jarque-Bera (1980) test statistic for normality. HT is the LM test for heteroscedasticity. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

Table 12: NARDL Model Estimation (Short-run Symmetry and Long-run Asymmetry (SA))

Variable	Atkin05		Gini		Rmeandev		Theil		Top10%		Top1%	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
C	0.576**	0.245	0.415*	0.235	0.354	0.259	0.623***	0.223	1.000***	0.355	1.221***	0.359
y_{t-1}	-0.069**	0.030	-0.050*	0.029	-0.041	0.031	-0.075***	0.027	-0.116***	0.042	-0.141***	0.042
x_{t-1}^{+}	0.056	0.038	0.055	0.073	0.062	0.073	0.031	0.019	0.124**	0.054	0.008	0.018
x_{t-1}^{-}	-0.018	0.024	-0.060	0.050	0.000	0.043	-0.030*	0.017	-0.070	0.047	-0.088***	0.029
Δy_{t-1}	0.474***	0.088	0.411***	0.091	0.443***	0.092	0.466***	0.086	0.453***	0.095	0.451***	0.094
Δy_{t-2}												
Δy_{t-3}			-0.188**	0.083								
Δx_{t}	0.272***	0.073	0.353**	0.145	0.240**	0.110	0.228***	0.052				
Δx_{t-1}			0.327**	0.133							0.124**	0.056
Δx_{t-2}	-0.191***	0.068	-0.410***	0.131	-0.377***	0.100	-0.108**	0.054				
Δx_{t-3}												
L_{X+}	0.805**	0.312	1.088	0.974	1.504	0.917	0.409**	0.179	1.065***	0.308	0.057	0.124
L_{X-}	-0.264	0.365	-1.203	1.254	-0.005	1.045	-0.400**	0.201	-0.600*	0.306	-0.625***	0.124
Test	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.
WLR_x	64.27	0.000	25.70	0.000	17.26	0.000	90.53	0.000	189.27	0.000	291.33	0.000
R-Bar	0.357		0.376		0.299		0.370		0.195		0.239	
SC(3)	4.161	0.245	1.713	0.634	2.283	0.516	3.106	0.376	8.859	0.031	0.911	0.823
RRT	0.049	0.825	0.139	0.709	0.002	0.964	0.394	0.530	2.093	0.148	0.045	0.831
JB	46.798	0.000	31.861	0.000	60.446	0.000	30.011	0.000	28.375	0.000	25.194	0.000
HT	0.004	0.953	0.231	0.631	0.144	0.704	0.298	0.585	0.629	0.428	0.003	0.955

Notes: y_t and x_t are the GDP and the inequality measure, respectively, taken in natural logarithms at year t. L_{x^+} and L_{x^-} are the asymmetric positive and negative long-run coefficients. WLR_x denotes the Wald test for long-run symmetry by testing the null hypothesis $H_0: L_{x^+} = L_{x^-}$. R-Bar denotes the adjusted R-square. SC(k) refers to the Godfrey (1978) test for kth order serial correlation. RRT denotes the Ramsey (1969) RESET test of functional form. JB denotes the Jarque-Bera (1980) test statistic for normality. HT is the LM test for heteroscedasticity. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

Table 13: NARDL Model Estimation (Short-run and Long-run Asymmetry (AA))

Variable	Atkin05		Gini		Rmeandev		Theil		Top10%		Top1%	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
C	0.613**	0.239	0.406*	0.225	0.230	0.255	0.606***	0.212	1.041***	0.343	1.061***	0.365
y_{t-1}	-0.066**	0.029	-0.053*	0.028	-0.026	0.031	-0.069***	0.026	-0.120***	0.041	-0.120***	0.043
x_{t-1}^{+}	0.059	0.038	0.044	0.071	0.005	0.073	0.034*	0.020	0.115**	0.052	0.024	0.019
x_{t-1}^{-}	0.014	0.027	-0.113*	0.059	-0.036	0.042	-0.016	0.020	-0.080	0.049	-0.059*	0.031
Δy_{t-1}	0.455***	0.087	0.389***	0.091	0.384***	0.090	0.470***	0.083	0.503***	0.094	0.450***	0.095
Δy_{t-2}	---	---	---	---	---	---	---	---	---	---	---	---
Δy_{t-3}	---	---	-0.255***	0.088	-0.185**	0.088	-0.163**	0.081	---	---	---	---
Δx_{t}^{+}	---	---	0.725***	0.246	0.419**	0.181	0.215**	0.097	---	---	---	---
Δx_{t-1}^{+}	---	---	0.614**	0.256	---	---	---	---	0.500**	0.247	---	---
Δx_{t-2}^{+}	-0.392***	0.122	-0.573**	0.248	-0.532***	0.162	-0.269***	0.096	---	---	-0.259**	0.121
Δx_{t-3}^{+}	---	---	---	---	---	---	---	---	-0.539**	0.258	---	---
Δx_{t}^{-}	0.427***	0.122	---	---	---	---	0.230**	0.097	---	---	---	---
Δx_{t-1}^{-}	---	---	---	---	---	---	---	---	---	---	---	---
Δx_{t-2}^{-}	---	---	---	---	---	---	---	---	---	---	0.207**	0.102
Δx_{t-3}^{-}	---	---	---	---	---	---	---	---	0.493**	0.210	---	---
L_{X+}	0.895 .***	0.326	0.822	0.993	0.173	2.621	0.489**	0.208	0.957***	0.297	0.199	0.150
L_{X-}	0.211	0.403	-2.106	1.532	-1.385	2.731	-0.227	0.266	-0.669**	0.301	-0.490***	0.153
Test	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.	stat.	pval.
WLR_x	9.809	0.002	18.428	0.000	5.946	0.017	35.755	0.000	184.37	0.000	220.68	0.000
WSR_x	23.968	0.000	2.517	0.116	0.203	0.654	2.075	0.153	1.133	0.290	6.021	0.016
R-Bar	0.344		0.349		0.312		0.399		0.279		0.240	
SC(3)	1.203	0.752	0.976	0.807	1.168	0.761	4.299	0.231	1.117	0.773	1.395	0.707
RRT	2.168	0.141	0.004	0.950	0.990	0.320	0.107	0.744	1.314	0.252	3.095	0.079
JB	24.699	0.000	8.405	0.015	8.135	0.017	5.705	0.058	17.225	0.000	18.775	0.000
HT	0.002	0.960	1.964	0.161	1.547	0.214	0.264	0.607	1.079	0.299	0.194	0.660

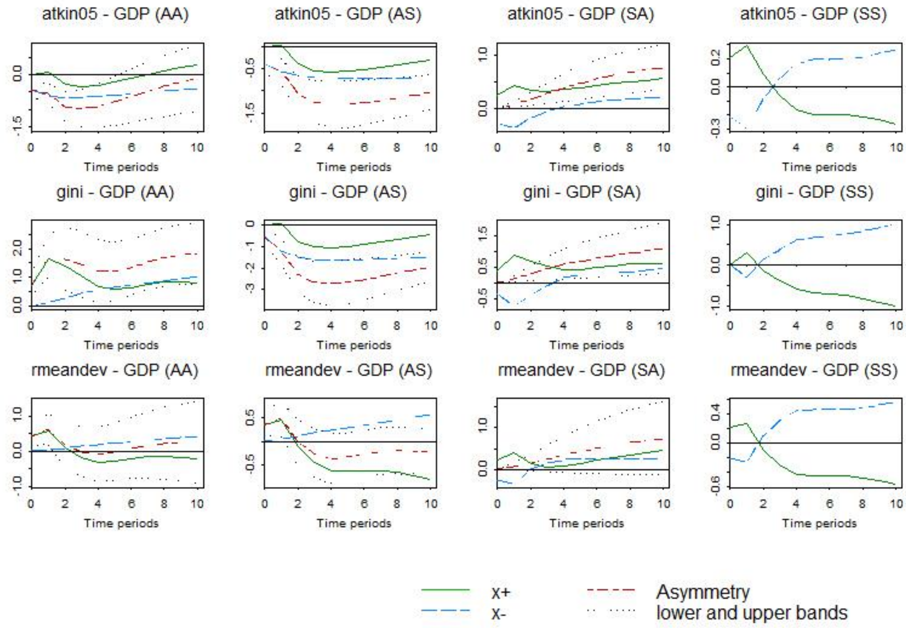
Notes: y_t and x_t are the GDP and the inequality measure, respectively, taken in natural logarithms at year t. L_{x^+} and L_{x^-} are the asymmetric positive and negative long-run coefficients. WLR_x denotes the Wald test for long-run symmetry by testing the null hypothesis $H_0: L_{x^+} = L_{x^-}$. WSR_x denotes the Wald test of the additive short-run symmetry by testing the null hypothesis: $H_0: \sum_{j=0}^{q-1} \varphi_x^+ = \sum_{j=0}^{q-1} \varphi_x^-$. R-Bar denotes the adjusted R-square. SC(k) refers to the Godfrey (1978) test for kth order serial correlation. RRT denotes the Ramsey (1969) RESET test of functional form. JB denotes the Jarque-Bera (1980) test statistic for normality. HT is the LM test for heteroscedasticity. ***, ** and * represent significance at the 1, 5 and 10 percent levels respectively.

Further, we have employed the Wald tests to check the suitability of a nonlinear model and to examine the long-run and the short-run asymmetries. More interestingly, from the results in Tables 12-13, the Wald tests (WLR_x) indicate a clear rejection, at a level of 5%, of the null hypothesis of long-run symmetry in all cases, showing strong nonlinear long-run relationship between income inequality and output. With regard to the analysis of short-run dynamic asymmetry, we find that for equation (2), the Wald test (WSR_x) rejects the null hypothesis of short-run symmetry for all cases except that when Rmeandev is considered as an explanatory variable (see Table 11). However, when we also allow for long-run asymmetry (equation (4)), the Wald test rejects the null hypothesis of short-run symmetry only for the cases of Atkin05 and Top1%.

In addition, we carry out various diagnostic test statistics to confirm the robustness of the model. In Table 10-13, we report the SC(k) which is the Godfrey (1978) test for kth order of serial correlation, the RRT which depict Ramsey's (1969) RESET test statistic to check model specification and functional form, the Jarque-Bera (1980) test statistic for normality and the LMtest statistic for heteroscedasticity. These statistics are chi-square distributed. The insignificant coefficients of these various diagnostic tests, except normality test, provide support that the model is correctly specified nonlinear model, auto-correlation and heteroscedasticity free. Lastly. The size of the coefficient of determination is reported to judge the model goodness of fit.

We move to the dynamic multipliers[19] which indicate the patterns of dynamic asymmetric adjustment of the real output level from its initial long-run equilibrium to new long-run equilibrium in the long-run, after a positive or negative unit shock affecting a particular level of income inequality/distribution. The predicted dynamic multipliers for the nonlinear adjustment of the real output level to the shock in different measures of income inequality are shown in Figure 1. These dynamic multipliers are conducted based on 4 best-fitting nonlinear ARDL discussed earlier. The blue dashed line and the green line curves display the asymmetric adjustment to negative and positive shocks, respectively, at a specific forecast horizon. In addition, the red dashed line (asymmetry) curve depicts the linear combination of the dynamic multipliers related with negative and positive shocks and is plotted simultaneously with its lower and upper bands (dotted black lines) at 95% bootstrap confidence interval level.

[19] The cumulative dynamic multiplier effects of a unit change in x_t^+ and x_t^- on y_{t+j} can be computed, respectively, as follows: $m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^+}$ and $m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^-}, h = 0,1,2 \ldots$. Note that as $h \to \infty, m_h^+ \to L_{X^+}$ and $m_h^- \to L_{X^-}$ where L_{X^+} and L_{X^-} are the long-run coefficients on positive and negative changes, respectively.



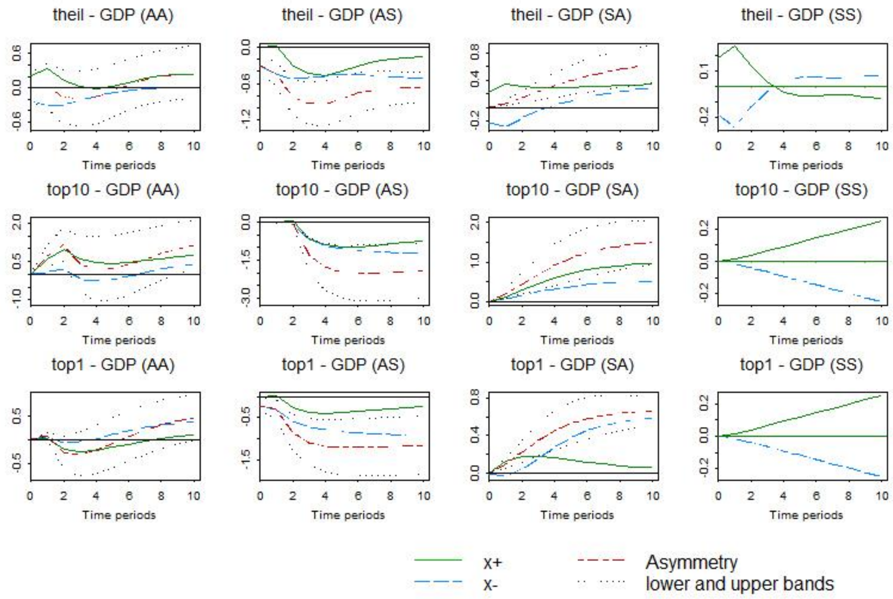


Figure 4. US income inequality-output dynamic multipliers.
(AA) LR and SR asymmetry. (AS) LR symmetry and SR asymmetry. (SA) LR asymmetry and SR symmetry. (SS) LR and SR symmetry

Generally, the pattern of the dynamic multipliers varies when short- or long-run asymmetry or both are incorporated into the model. Considering the best-fitted model for inequality–output case, i.e., model long-run symmetry (AA) and short-run asymmetry (SA), the long-run adjustment path displays a higher reaction of the real output level to a unitary increase or decrease in income distribution. The cumulative income inequality responses are significantly positive or negative. The new long-run equilibrium state between the income inequality and real output level is reached after 2 years. The asymmetric income inequality pass-through is however persistent over time and virtually takes a period of time to converge to the long-run multipliers.

In short-run, the dynamic multipliers patterns when both short-run and long-run asymmetries are considered (AA) show that an income inequality positive shock has a greater positive effect on GDP than a negative shock for Gini, Rmeandev and Top10%. For Theil inequality measure, a positive shock has a smaller positive impact on GDP compared with the negative impact of a negative shock. When considering Top1% indicator as a measure of inequality, it seems that a positive shock has a greater negative effect on GDP than a negative shock, while the opposite is observed for the Atkin05 indicator. Turning now to the long-run patterns of dynamic multipliers for the (AA) regression, a negative shock to inequality has a greater positive impact on GDP than a positive shock for Gini and Top1% indicators, while the opposite occurs for Theil and Top10%. For Atkin05 inequality indicator, a negative shock impacts negatively the long-run GDP while a positive shock has a less important positive effect. Finally, the dynamic multipliers for Rmeandev show, at the long-run, a negative response of the GDP to a positive shock while a negative shock has a larger positive effect.

With regard to the (SA) regression, i.e., when only the long-run asymmetry is incorporated in the model, the dynamic multiplier graphs show that both positive and negative shocks in the inequality have positive effects on the long-run real output in all cases. It is also worth noting that the effects are quantitatively larger for a positive than negative shock for all considered inequality measures except Top1%.

4.5 Concluding Remarks

The examination of nonlinearity properties of time-series variables has recently assumed a significant and notable role in empirical studies. This shows that researchers have come to realize the importance of asymmetry behaviors inherent in time series data, particularly in social science research and also in this present complex modern economies. In this paper we have examined the presence of short- and long-run asymmetric effects of inequality on real GDP per capital, using a time series annual frequency data, between the periods 1917-2012 for the United States. Unlike Frank (2009) panel model, Bahmani-Oskooee and Motavallizadeh-Ardakani (2018) nonlinear autoregressive distributed lag (NARDL), as well as previous studies, that examine if economic growth has linear and/or nonlinear asymmetric impacts on income inequality, our study do the opposite in order to substantiate and confirm the causal effects between income inequality and economic growth. We investigate whether increase or decrease in income inequality has a short-run and/or a long-run asymmetric effects on real output level.

In summary, the strengths of the nonlinear ARDL approach as discussed earlier have been established in the case of the long- and short-run asymmetric effects of the inequality-output relationship. Due to the different measures of income distribution employed in this study (rather than using only Gini coefficient as a measure of income inequality), our empirical findings suggest that imposing long-run linear (symmetry) relationship where the primary relationship is nonlinear (asymmetric) will counter efforts to examine for the presence of a stable long-run relationship and lead to pseudo dynamic analysis. We found that, income inequality shock, whether positive or negative have a positive long-run impact on real output level with effects being quantitatively larger for a positive than negative shock. This is an addition to inequality-output literature. In addition, our empirical results emphasis the significance of accurately capturing short-run and long-run symmetries/asymmetries in the quest to substantiate the potential differences in the response of real output level to negative and positive income inequality shocks using different measures of income distribution. Our empirical result provide an evidence in support of a long-run asymmetric impact between income inequality and real output level, since the long-run coefficients on positive changes have positive signs, while the signs of those on negative changes are negative, indicating that a decrease or an increase in income inequality improves real output level in the United States. Economic growth appears not to be a feasible policy solution to deal with increase or decrease in income inequality, as it has worsen income inequality in the US (Frank, 2009; Bahmani-Oskooee and Motavallizadeh-Ardakani, 2018). Therefore, in order to curb income inequality shocks and inequitable income distribution, alternative economic welfare policies must be put in place.

Chapter 5

CONCLUSION

As stated earlier, this study is a significant efforts attempt to explain the roller coaster movements in income inequality, especially as it relates to partisan conflict and real per capita GDP of the United States.

In chapter two on the causality relationship between partisan conflict index and income inequality, we find evidence in support of a dynamic causal relationship between partisan conflict and income inequality, except at the upper end of the quantiles. Our empirical findings suggest that a reduction in partisan conflict will lead to a more equal income distribution, but this requires that inequality is not exceptionally high.

On the existence of an inverted U-shaped long-run relationship between income inequality and economic growth in chapter three, empirical results find no evidence in support of nonlinear long-run (inverted U-shaped) relationship for the US, but findings from vocal set of economists strongly lends the basis upon which conclusions are drawn in this study.

Conclusively, chapter four on the asymmetry impact of inequality on growth contribute to the income inequality-economic growth literature using the nonlinear Autoregressive Distributed Lag (NARDL) approach. Our empirical result provide an evidence in support of a long-run asymmetric impact between income inequality and real output level, since the long-run coefficients on positive changes have positive signs, while the signs of those on negative changes are negative, indicating that a decrease or an increase in income inequality improves real output level in the United States.

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