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Partisan Conflict and Income Distribution in the United States: A Nonparametric Causality-in-Quantiles Approach

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Abstract

This study examines the predictive power of a partisan conflict index on income inequality. Our study adds 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 from 1917-2013. We find evidence of a causal relationship running from partisan conflict to income inequality, except at the upper end of the quantiles. The study suggests that a reduction in partisan conflict will lead to a more equal income distribution.

Keywords: Partisan Conflict; Income Distribution; Quantile Causality.

JEL Codes: C22, O15

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1. Introduction

The income distribution 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 (Atkinson, 1997).

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

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

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 (PCI) index 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 recently, however, issues of economic and social class have become an integral part of the main ideological conflicts over redistribution.

Azzimonti (2015) considers the effect of partisan conflict on private investment, finding an inverse relationship between PCI 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 PCI 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 PCI indirectly causes higher inequality.

Banerjee (2004) also argues that there exists a direct link between investment and inequality, especially in the absence of perfect markets. PCI inversely affects investment (i.e., the higher the PCI, 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 PCI 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) find that partisanship has been highly stratified by income. Other related studies of this issues include Huber (1989), Rosenthal (2004), Anderson and Barimundi (2008), Pontusson and Rueda (2008), Lupa and Pontusson (2008), Kelly (2009), Finseraas (2010), Garand (2010), Gelman, Kenwothy, and Su (2010), and Burgoon (2013). None of these studies investigates the causality relationships between the variables of interest, using non-parametric causality-in-quantile techniques.

The current study investigates this causality relationship from partisan conflict to income distribution and vice-versa in the United States, using the 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 data for the partisan conflict index.

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 partisan conflict under different income inequality measures. That is, we will determine whether

partisan conflict 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 partisan conflict causes income inequality. Balcilar *et al* (2016) causality tests combines nonlinear causality of order k-th proposed by Nishiyama, Hitomi, Kawasaki and Jeong (2011) and the quantile test developed by Jeong, Hardle, and Song (2012). Thus, Balcilar *et al* (2016) provides an advanced version of the other quantile tests previously developed.

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 partisan conflict on income inequality with the non-parametric, causality-in-quantile approach. Our findings show that a reduction in partisan conflict leads to more equality of income. That is, partisan conflict does Granger cause income distribution. This causality effect, however, does not exist at the upper end of the quantile distribution. The effect grows as the level of partisan conflict falls (weakens). This study applies this new, sound, robust, and reliable econometric technique.

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. 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 distribution by y_t, and the partisan conflict (PCI) by x_t. Define the quantile-type causality based on Jeong *et al* (2012) as follows.[2] 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

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

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

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

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

$F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with probability one. Consequently, we test the hypotheses for the causality-in-quantiles that depend on equations (1) and (2) as follows:

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

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

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 $Th^p\hat{J}_T/\hat{\sigma}_0$ 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:

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

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

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

Here, $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ 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 partisan conflict and income distribution. 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.[3] Meanwhile, we determine the bandwidth by using the Least Squares Cross-Validation (LSCV) technique.[4] Finally, we employ $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels for our estimation.

[3] 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.

[4] 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).

Although robust inference on the quantile based causality from the partisan conflict 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 partisan conflict on inequality at various quantiles. Variations in the sign and magnitude of the effect across quantiles will reveal significant evidence on the effect of partisan conflict 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 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:

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

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:

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

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:

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

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

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

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).[5] In particular, we test the null hypotheses that the effect of the partisan conflict 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 $W(x_t)$.

3. Data and description of variables

For our empirical analysis, we employ aggregate annual frequency data for the United States between the periods of 1917 to 2013, based on data availability. The partisan conflict data

[5] 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.

comes from Azzimonti (2014). 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 partisan conflict index, 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 partisan conflict 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 distribution data come from Frank (2015)[6]. 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 distribution measures appear in the World Top Income Database (WTID).

<Insert Table 1 here>

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)

[6] For an exposition on the estimation of this series and file including percentile threshold see Frank, Sommeiller-Price and Saez. Further explanation on estimation of other measures of income share or distribution should see Frank, M. (2015). Frank-Sommeiller-Price Series for Top Income Shares by U.S. States since 1917. *WTID Methodological Notes*.

normality test, the first {ARCH(1)} and the fourth {ARCH(4)} order of Lagrange Multiplier (LM) tests basically for the autoregressive conditional heteroscedasticity (ARCH) for partisan conflict, and the observed income inequality and distribution measures. The positive skewness may reflect the increases in partisan conflict 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) test at the 1-percent significance level. This justifies the causality-in-quantile test by the flat tailed distribution of the time-series variables. Note that we observe significant serial correlation for partisan conflict index and all the income distribution measures as proposed by Ljung-Box (1978). Finally, we confirm ARCH effects in the variables, as reported in the ARCH-LM test.

4. Results and empirical findings

This section reports the empirical results. We investigate the causality-in-quantiles predictive relationship from partisan conflict to income distribution. 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-percent level. Thus, we reject the null hypothesis of no Granger causality at the 10-percent level for three measures of income inequality. That is, we find limited evidence of significant predictability running from partisan conflict to income inequality in a linear vector autoregressive (VAR) model.

<Insert Table 2 here>

<Insert Table 3 here>

<Insert Table 4 here>

<Insert Table 5 here>

Using the non-parametric causality-in-quantile techniques, we now evaluate whether a nonlinear dependence exists between partisan conflict and income inequality. For this purpose, we employ a test for independence proposed by Broock, Scheinkman, Dechert and LeBaron (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 partisan conflict and income distribution 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 nonlinearity in income inequality and partisan conflict 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 have confirmed 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 partisan conflict to income inequality. We employ the nonlinear Granger causality test of Diks and Panchenko (2006)[7]. 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

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

Granger causality relationship running from partisan conflict 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-percent 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 partisan conflict and inequality series, we observed 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 partisan conflict index to income distribution series. Also, Figure 3 plots the average derivative estimates for the effect of partisan conflict. 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.

<Insert Figure 1 here>

<Insert Figure 2 here>

<Insert Figure 3 here>

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 partisan conflict index to income inequality. We reject the null hypothesis of no causality for quantiles generally below 0.65 or up to 0.80. Given that the data are transformed into natural logarithm first differences,[8] partisan conflict only fails to Granger cause at extreme quantiles. The upper quantiles correspond to those high jump values of income

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

inequality (i.e., between 1925 and 1928) discussed earlier and we do not find Granger causality at those extremes. In general, our findings show that the partisan conflict index and income inequality measures Granger cause each other. That is, they are useful predictors of one another except around the upper quantiles.

The results show that partisan conflict and income inequality predict each other except around high jump values of inequality. This implies that the causal effects only matter when the level of partisan conflict falls to lower levels, since the relationship is highly nonlinear. In case of income inequality measures, the partisan conflict index, in general, influences the variance over the whole conditional distribution, since the findings apply for all of the income inequality measures considered. Exceptions, however, exist when partisan conflict does not predict income inequality for high levels of inequality

The plots of the data and the relationship among the variables of interest provides an explanation as to why no evidence of useful predictability from partisan conflict 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 partisan conflict, then partisan conflict does not significantly affect average income inequality. This result supports the findings of McCarty *et al* (2003).

Finally, this result also confirms the results in Chang, Gupta, and Miller (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 reveals that the evidence of causality from partisan conflict index 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 partisan conflict index on income inequalities measure is generally positive; where reductions in partisan conflict lead to more equal income distribution, and vice versa.

5. Conclusion

The existing literature has examined the relationship between partisan conflict index and various macroeconomics variables. This study adds to the existing literature by investigating the causality relationship, if any, between partisan conflict 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 partisan conflict and income distribution 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 partisan conflict exerts a strong causal link to the income distribution. The null hypothesis that partisan conflict index does not Granger cause income distribution is strongly rejected. The outcomes of the relationship between partisan conflict and the income distribution generally indicate the importance of detecting and modelling nonlinearity when investigating causal relationships.

We can infer several crucial facts from this analysis, which policy makers who design and structure growth and developmental programs may find useful. Our study links partisan conflict to income inequality. Thus, when considering income inequality, specific measure of political polarization should receive consideration. The effect of partisan conflict 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 distribution. Thus, our findings suggest that causal relationship from partisan conflict to income inequality does not exist in periods with high income inequality.

References

Anderson, C., Barimendi, P. 2008. Income inequality and democratic representation. *Democracy, Inequality, and Representation in Comparative Perspective*, 1.

Alesina, A. and Drazen, A. 1991. Why are stabilizations delayed?" *American Economic Review*, 81(5), 1170-1188.

Atkinson, A. B. 1997. Bringing Income Distribution in from the Cold, *Economic Journal*, 107, 297-321.

Azzimonti, M. 2014. Partisan Conflict. FRB of Philadelphia Working Paper No. 14-19. SSRN: https://ssrn.com/abstract=2457406 or http://dx.doi.org/10.2139/ssrn.2457406.

Azzimonti, M. 2015. Partisan conflict and private investment. NBER Working Paper No. w21273. Available at SSRN: https://ssrn.com/abstract=2618661

Balcilar, M., Bekiros, S., Gupta, R., 2016. The role of news-based uncertainty indices in predicting oil markets: a hybrid nonparametric quantile causality method. Empirical Economics, forthcoming. DOI: 10.1007/s00181-016-1150-0.

Banerjee, A. 2004. *Inequality and Investment*. Massachusetts Institute of Technology. Cambridge, Massachusetts.

Belloni, A., Chernozhukov, V., Chetverikov, D., Fernandez-Val, I., 2011. Conditional quantile processes based on series or many regressors. ArXiv e-prints.

Broock, W. A., Scheinkman, J. A., Dechert, W. D., LeBaron, B. 1996. A test for independence based on the correlation dimension. *Econometric reviews*, *15*(3), 197-235.

Burgoon, B. 2013. Inequality and anti-globalization backlash by political parties. *European Union Politics*, *14*(3), 408-435.

Chang, S., Gupta, R., Miller, S. M. 2015. Causality between per capita real gdp and income inequality in the US: Evidence from a wavelet analysis. *Social Indicators Research*, 1-21.

Diks C., Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics & Control 30, 1647–1669.

Finseraas, H. 2010. What if Robin Hood is a social conservative? How the political response to increasing inequality depends on party polarization. *Socio-Economic Review*, *8*(2), 283-306.

Frank, M. 2015. Frank-Sommeiller-Price Series for Top Income Shares by US States since 1917. *WTID Methodological Notes*.

Garand, J. C. 2010. Income inequality, party polarization, and roll-call voting in the US Senate. *The Journal of Politics*, *72*(4), 1109-1128.

Gelman, A., Kenworthy, L., Su, Y. S. 2010. Income inequality and partisan voting in the United States. *Social Science Quarterly*, *91*(5), 1203-1219.

Gogas, P., Gupta, R., Miller, S. M., Papadimitriou, T., and Sarantitis, G. A. 2017. Income inequality: A state-by-state complex network analysis. *Physica A* 483, 423-437.

Goldin, C., and Margo, R., 1992. The Great Compression: The wage structure in the United States at mid-century. *Quarterly Journal of Economics* 107, 1-34.

Huber, J. D. 1989. Values and partisanship in left-right orientations: Measuring ideology. *European Journal of Political Research*, *17*(5), 599-621.

Hiemstra, C., Jones, J., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. J. Finance 49, 1639–1664.

Hurvich, C. M., Tsai, C.-L., 1989. Regression and time series model selection in small samples. Biometrika 76, 297–307.

Jarque, C. M., Bera, A. K. 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters*, *6*(3), 255-259.

Jeong, K., Härdle, W.K., Song, S., 2012. A consistent nonparametric test for causality in quantile. *Economic Theory* 28, 861–887.

Kelly, Nathan J. 2004. Does politics really matter? Policy and government's equalizing influence in the United States." *American Politics Research* 32(3), 264-284.

Kelly, N. J. 2009. *The Politics of Income Inequality in the United States*. New York: Cambridge University Press.

Krugman, P., 2007. *The Conscience of a Liberal*. W.W. Norton & Company, New York, 124-128.

Li, Q., Racine, J. 2004. Cross-validated local linear nonparametric regression. *Statistica Sinica*, 485-512.

Ljung, G. M., Box, G. E. 1978. On a measure of lack of fit in time series models. *Biometrika*, 297-303.

McCarty, N., Poole, K. T., Rosenthal, H. 2003. Political polarization and income inequality. Working Paper, Princeton University.

Nishiyama, Y., Hitomi, K., Kawasaki, Y., and Jeong, K., 2011. A consistent nonparametric test for nonlinear causality - specification in time series regression. *Journal of Econometrics* 165, 112-127.

Piketty, T., and Saez, E., 2003. Income inequality in the United States, 1913-1998. *Quarterly Journal of Economics* 118, 1-39.

Pontusson, J., Rueda, D. 2008. Inequality as a source of political polarization: A comparative analysis of twelve OECD countries. *Democracy, inequality, and representation*, 312-353.

Rosenthal, H. 2004. Politics, public policy, and inequality: A look back at the twentieth century. *Social Inequality*, 861-92.

Racine, J., Li, Q. 2004. Nonparametric estimation of regression functions with both categorical and continuous data. *Journal of Econometrics*, *119*(1), 99-130.

van der Vaart, A., Wellner, J., 1996. Weak Convergence and Empirical Processes. Springer Series in Statistics.

Table 1: Descriptive statistics

	PConflict	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^{***}

Note: Table reports the descriptive statistics for the Partisan Conflict (PConflict) and inequality series Gini Coefficient (Gini), Atkinson Index (Atkin05), the Relative Mean Deviation (RMeanDev), Theil's entropy Index (Theil) as well as Top 10% (Top10), Top 5% (Top5), Top 1% (Top1), Top 0.5% (Top05), Top 0.1% (Top01), and Top 0.01% (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). *** represents significance at the 1%, level.

Table 2: Linear Granger causality tests of the hypothesis that Partisan Conflict does not Granger cause inequality series

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

Note: 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% 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***

Note: 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% levels of significance, respectively.

Table 4: Nonlinear Granger Causality Test

	m=2		*m*=3		*m*=4	
Equation 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
RMeanDev	-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

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

Table 5: Sign tests for the effect of partisan conflict 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	
Equation 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
RMeanDev	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

Note: 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% levels of significance, respectively.

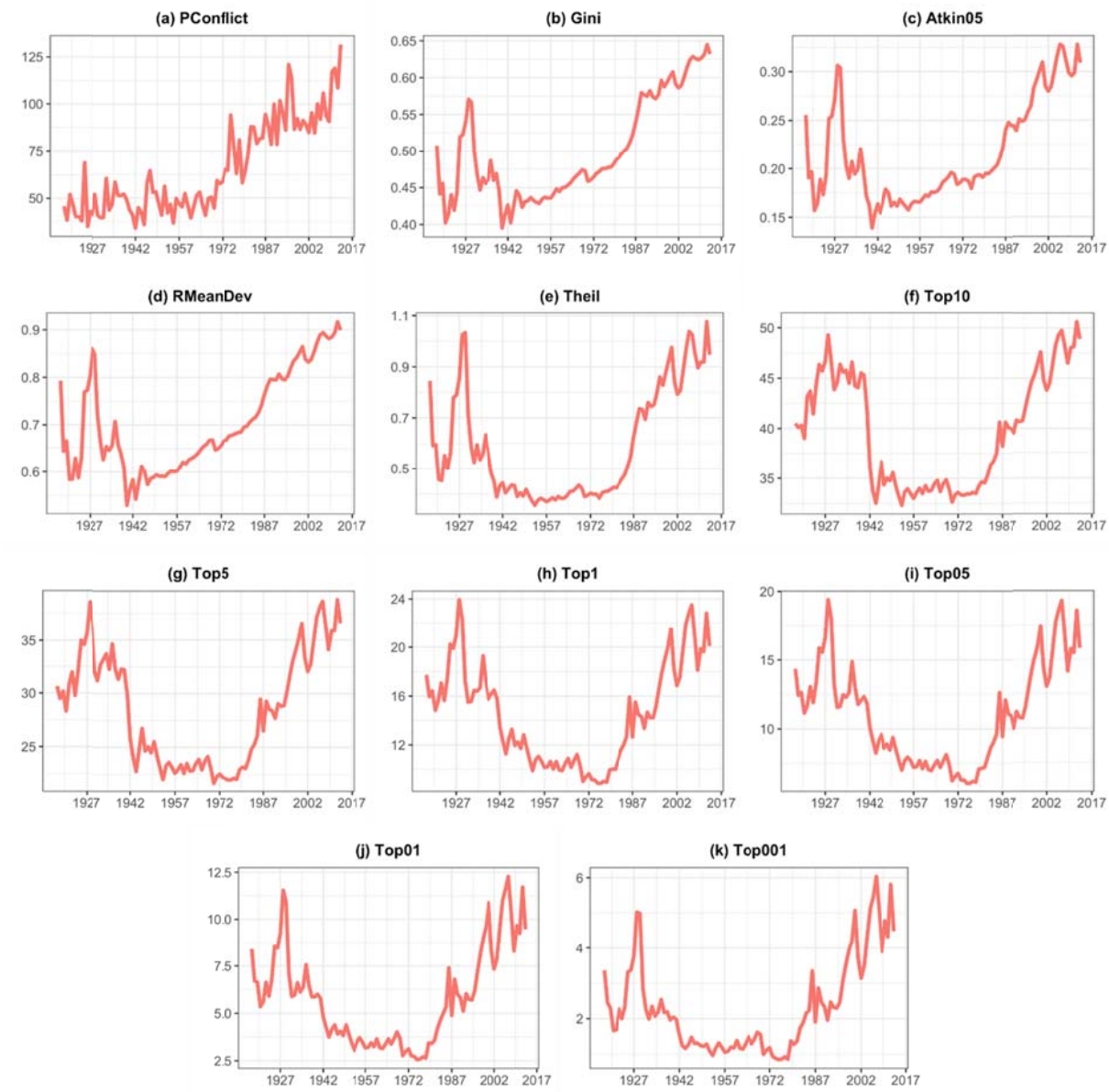

Figure 1: Time series plots of the partisan conflict and inequality series

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

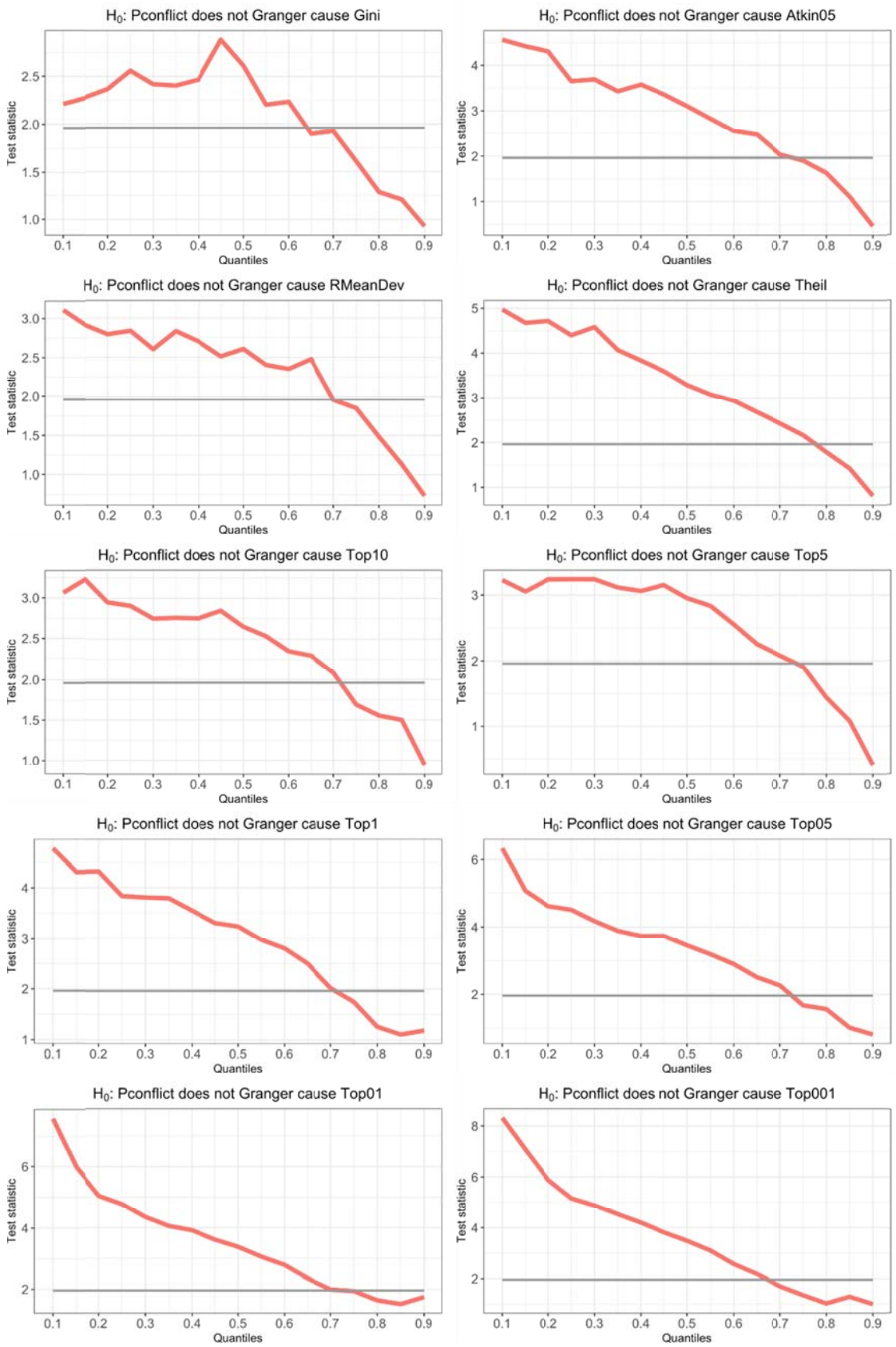

Figure 2. Tests of Granger causality from partisan conflict to inequality series

Note: Figure plots the estimates of the nonparametric causality-in-quantiles tests at various quantiles. Horizontal thin lines represent the 5% value.

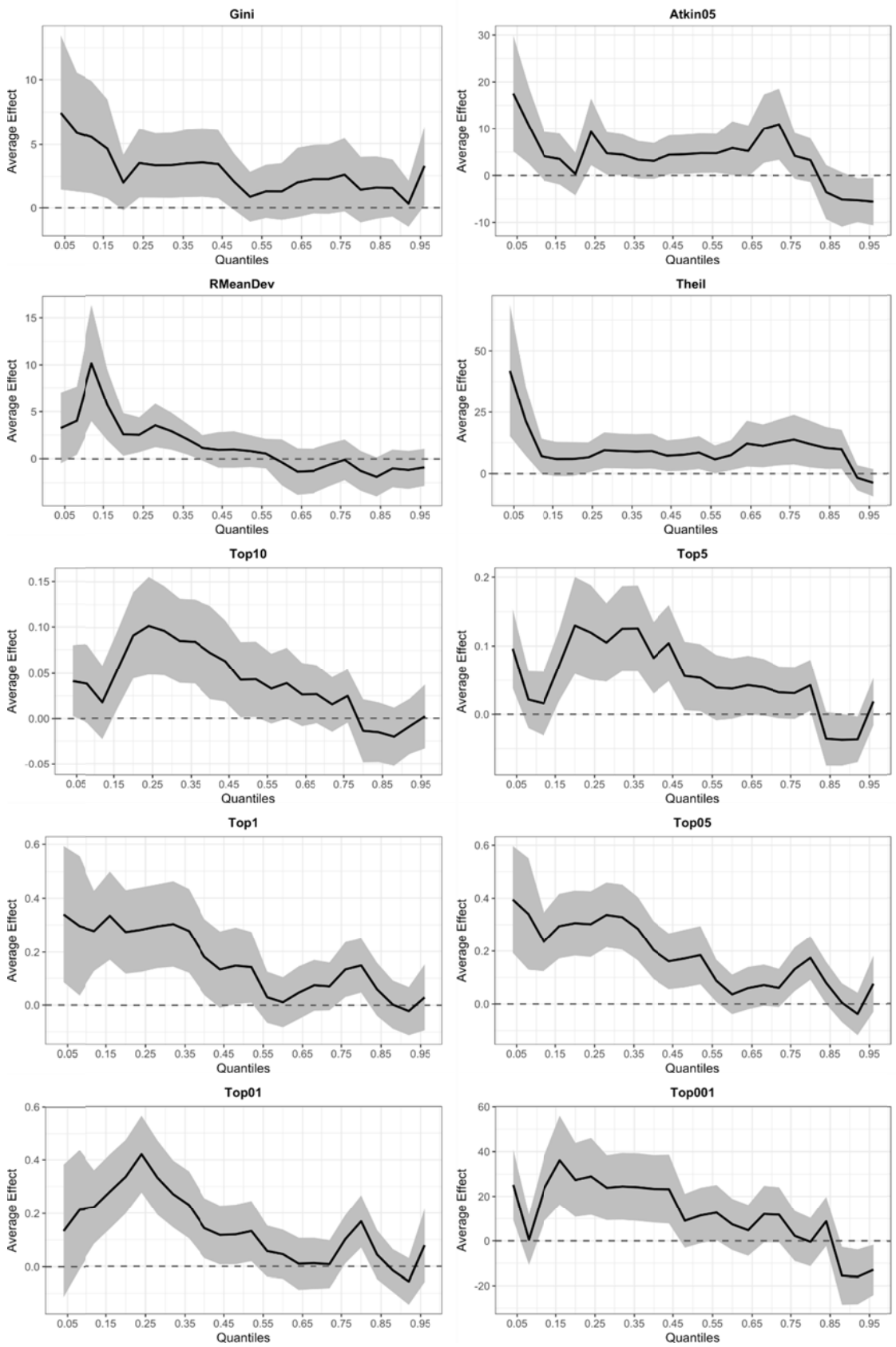

Figure 3: Average derivative estimates for the effect of partisan conflict

Note: Figure plots the estimates of the average derivative estimates. Gray region represents the 95% confidence interval. A dashed horizontal line is drawn at zero.