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Partisan Conflict and Income Inequality in the United States: A Nonparametric Causality-in-Quantiles Approach[#]

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Abstract

This paper examines the predictive power of a partisan conflict on income inequality. Our study contributes to the existing literature by using the newly introduced nonparametric causality-in-quantile testing approach to examine how political polarization in the United 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 reduction in our measures of income inequality, but this requires that inequality is not exceptionally high.

Keywords: Partisan Conflict; Income Inequality; Quantile Causality.

JEL Codes: C22, O15

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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)

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.

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

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. 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.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

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

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

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

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

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

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

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

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:

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

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:

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

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:

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

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:

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

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

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

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.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.

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

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).

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:

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

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:

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

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:

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

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 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 $W(x_t)$.

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. 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

⁵ In general, the process $\sqrt{T}(\hat{\alpha}(\theta) - \alpha(\theta))$ does not have 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.

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)⁶. More specifically, the income

⁶ 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).

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).

<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) 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.

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.

<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 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 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)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 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.

<Insert Figure 1 here>

<Insert Figure 2 here>

<Insert Figure 3 here>

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

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,⁸ 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.⁹

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, 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,

⁸ All the data are non-stationary at level.

⁹ 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.

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.

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).

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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***

Note: 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.

Table 2: Linear Granger causality tests of the hypothesis that PCI 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-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***

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-percent levels of significance, respectively.

Table 4: Nonlinear Granger Causality Test

Equation for:	$m=2$		$m=3$		$m=4$	
	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 PCI on inequality measures

Equation for:	$H_0: \bar{h}(\theta) \leq 0$ for all θ		$H_0: \bar{h}(\theta) \geq 0$ for all θ		$H_0: \bar{h}(\theta) = 0$ for all θ	
	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-percnet levels of significance, respectively.

Figure 1: Time series plots of the PCI and inequality series

Note: 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.

Figure 2. Tests of Granger causality from PCI to inequality series

Note: Figure plots 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

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