

POLICY UNCERTAINTY, TARIFF RATE, MONETARY POLICY
AND
INCOME INEQUALITY: AN ASYMMETRIC ANALYSIS

by
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ABSTRACT

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This study offers a contribution to the income inequality literature within the traditional Kuznets model and explores the relationship between income inequality and a set of macroeconomic variables such as policy uncertainty, tariff rate, and monetary policy. By implementing a Nonlinear Autoregressive Distributed Lag (ARDL) model, I aim to identify the possible nonlinear effects of policy uncertainty, tariff rate -as a measure of trade openness-, and monetary policy on income inequality in United States and its 50 states and District of Columbia. The advantage of choosing this methodology is that it helps researchers to explain both long run relationships and short run dynamics. Results from linear model that assume effects are symmetric, do not show any significant links between the set of variables and income inequality. However, the empirical results from nonlinear model that assumes effects are asymmetric reveal that they have nonlinear effects on the U.S income inequality as well as on state level income inequality. Results show that a decline in policy uncertainty will increase U.S. income inequality

in the long run, while an increase in it does not have any significant effect. A contractionary monetary policy (decline in monetary base to GDP ratio) decreases U.S. income inequality in the long run while an expansionary monetary policy will not affect it. Estimates from nonlinear model do not show any link between U.S tariff rate and income inequality. More observation from state-level data show that policy uncertainty, tariff rate, and monetary policy have asymmetric effect on income inequality in many states.

Keywords: Monetary Policy, Monetary Base, Income inequality, Asymmetry, State level data, United States.

To
my parents

TABLE OF CONTENTS

LIST OF TABLES	vi
1. Introduction.....	1
2. Policy Uncertainty and income distribution: Asymmetric evidence from state-level data in the United States	3
2.1 Introduction	4
2.2 Model and Methodology	6
2.2.1 The Linear Model	6
2.2.2 The Nonlinear Model.....	8
2.3. Results	10
2.4 Conclusion.....	30
3. Asymmetric Link between U.S. Tariff Policy and Income Distribution: Evidence from State Level Data.....	32
3.1 Introduction	33
3.2 Model and Methodology	37
4.3.1 The Linear Model	37
4.3.2. The Nonlinear Model.....	37
3.3 Results.....	38
3.4 Conclusion.....	55
4. Asymmetric Link between U.S. Monetary Policy and Income Distribution: Evidence from State Level Data.....	57
4. 1 Introduction	58
4.2 Related Literature.....	60
4.3 Model and Methodology	63
4.3.1 The Linear Model	64
4.3.2. The Nonlinear Model.....	64
4.4 Results.....	65
4.4 Conclusion.....	83
5. Summary and Conclusion.....	85
References.....	94
Appendix: Data Sources	101

LIST OF TABLES

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)	13
Table 2: Full-Information Estimates of Nonlinear ARDL Models (Population).....	27
Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)	42
Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy).....	70
Table 5: Summary Information Estimates of Linear ARDL Model (Average Tariff Rate)	88
Table 6: Summary Information Estimates of Linear ARDL Model (Policy Uncertainty)	90
Table 7: Summary Information Estimates of Linear ARDL Model (Monetary Policy)	92

1. Introduction

Growing inequality has been of much attention among policy makers (e.g., Bernanke, 2015; Draghi, 2016; Piketty, 2014; OECD, 2015). A large literature identified and studied different factors causing income inequality: financial development (Jauch and Watzka, 2016; Seven and Coskun, 2016), technological progress (Bound and Johnson, 1992; Acemoglu, 2002), trade openness and globalization (Feenstra and Hanson, 1999; Furceri and Loungani, 2018; Rojas-Vallejos and Turnovsky, 2017), labor market structure (Jaumotte and Osorio-Buitron, 2015), and monetary policy (Acemoglu and Johnson, 2012; Stiglitz, 2015; Furceri et al. 2018).

This study offers a contribution to the income inequality literature within the traditional Kuznets model. By implementing a Nonlinear Autoregressive distributed lag (NARDL) model, I study the effects of policy uncertainty, average tariff rate and monetary policy on income inequality in the U.S as a whole and in each of the 50 states and District of Columbia. Moreover, I go beyond the literature and study if these effects are asymmetric. NRDL method captures not only long-term relationship and short-term dynamics between these variables but also possible asymmetric associations between them.

This dissertation is organized as follows: The current chapter provides the introduction, background, and motivation for the thesis. Section 2 provides the estimate of the impact policy uncertainty on income inequality. Both the linear and nonlinear ARDL models are estimated for all 50 states of United States and District of Columbia to determine in which state income inequality responds to tariff rate. Section 3 provides both linear and nonlinear results for all states to evaluate distributional effects of the U.S. average tariff rate in each state. And in Section 4, I estimated the impact of monetary policy in income inequality in all states using both the

linear and nonlinear models. And finally, data source information and some summarized table are provided in the Section 5.

2. Policy Uncertainty and income distribution: Asymmetric evidence from state-level data in the United States

2.1 Introduction

The recent literature provides different type of uncertainty shocks measures (Baker et al. 2016; Basu and Bundick, 2017; Bloom, 2009; Caggiano et al. 2014; Caldara et al. 2016; Carriero et al. 2018; Jurado et al. 2015; Mumtaz and Theodoridis, 2018). For instance, Bloom (2009) used the volatility index of the Chicago Board Options Exchange as a measure of uncertainty which is associated with financial market uncertainty. Baker et al. 2016 highlighted the uncertainty as the unanticipated activities of policy makers in the government and central banks. They build policy-related economic uncertainty indexes (EPU) for U.S based on scaled frequency counts of newspaper articles that contain terms relating to the economy, uncertainty, and economic policy¹. All these types of uncertainty measures have a lot in common and they seem to be harmful for economic performance, at least in the short run.

Raising uncertainty can affect the economy through a range of different channels. For example, in the case of financial crisis, negative news will increase uncertainty that will change expectation of future economic activities. It will increase firm's borrowing costs (Christiano et al. 2014). It also will change firm's hiring and investing decision since they are uncertain about future demand. Changing in their decisions about hiring and firing will affect consumer's purchasing decisions (Bernanke, 1983; and Bloom, 2014 and 2009; Bloom et al. 2007). The level of changes in uncertainty is an important determinant of changes in economic activity. While larger changes in uncertainty triggers changes in behavior, the smaller changes may be ignored,

¹ Baker, Bloom and Davis (2013) monthly EPU index for the U.S relies on 10 leading newspapers: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal. They searched the digital archives of each newspaper from January 1985 to obtain a monthly count of articles that contain the following terms: "uncertainty" or "uncertain"; "economic" or "economy"; and one of the following policy terms: "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House" (including variants like "uncertainties," "regulatory," or "the Fed"). An article must contain terms in all three categories pertaining to uncertainty, the economy, and policy.

inducing asymmetric effects. The aggregate effect of uncertainty depends on both size and the sign of the changes (Bloom et al. 2007).

Foerster (2014) provided empirical evidence suggesting that economic uncertainty -presented by VIX- has asymmetric effects. This means increases in uncertainty can make persistent declines in economic activities; however, decrease in it has small or no effect on economic activities. Many studies found that income inequality declines during economic downturns; however, it depends on the compositions of income (Heathcote et al. 2010; Petev et al. 2011; Meyer and Sullivan, 2013; Mumtaz and Theophilopoulou, 2017; and Theophilopoulou, 2018). During recessions that corporate profits and stock prices decline, capital owners who mostly are from top-income households, are more subjected to unpleasant business cycle movements and income inequality could decrease. On the other hand, during economic downturns, if the income share of capital is low in the economy, income inequality could increase because unskilled workers are more exposed to labor market and technological changes.

There are some studies on the links between household income inequality and the emergence of economic crises (for example see Stiglitz, 2012; Van Treeck, 2014); however, there are not many studies on the relationship between income inequality and uncertainty. Among them Fischer et al. (2019) studied the links between macroeconomic uncertainty and household income inequality in the U.S as well as its 50 states and District of Columbia. They used a panel of quarterly data from 1985 to 2017 and found that income inequality decreases in most states while it increases in some states mostly located at Midwest. They find that these differences in the response can be explained by composition of income and fundamentals of labor market. Although they found that the effects of policy uncertainty on income inequality is heterogeneous, they did not consider that the effects can also be asymmetric. Here, we fill in this gap and study

the asymmetric impact of policy uncertainty on income inequality. It means that increase and decrease in policy uncertainty induce different responses in income inequality.

2.2 Model and Methodology²

2.2.1 The Linear Model

Kuznets (1955) argued that economic growth at early stages of development increases income inequality and decreases it only after a threshold level of development which is a result of labor migration from rural to urban areas. This study contributes to the income inequality literature within the traditional Kuznets model. We test the effect of policy uncertainty on income distribution through the Kuznets model following long run model (1):

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma \ln PU_t + \epsilon_t \quad (1)$$

Where Gini index, a well-known measure of income inequality, takes numbers between zero to one that higher amount shows a higher level of inequality. Y is per-capita real personal income or GDP, and explanatory variable PU is U.S. policy uncertainty. All variables are in state level here. If economic development reduces income inequality, an estimate of β should be negative.

To verify Kuznets' hypothesis, we should test the short run effects. We do this following Pesaran et al.'s (2001) bound testing approach. In order to better understand the bounds testing approach, we begin with Engle and Granger (1987) error correction model as follows:

$$\Delta \ln Gini_t = \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_j \Delta \ln PU_{t-j} + \lambda \epsilon_{t-1} + u_t \quad (2)$$

Where in this equation, λ shows the speed of adjustment and its sign determines if the adjustment is toward the long run equilibrium. A negative significant value of λ implies that there is cointegration between measures of inequality and explanatory variables. In (2) short-run effects are judged by the estimate of the coefficients attached to first-differenced variables. Long-run

² This section closely follows Bahmani-Oskooee et al. (2018) and Bahmani-Oskooee and Harvey (2020).

effects are inferred by estimating (1) once cointegration is established. However, this approach imposes a limit on variables that they all require to be cointegrated of the same order and therefore, unit root test for the variables in levels is needed. In case variables are not integrated of the same order, Pesaran et al. (2001) offer an alternative approach known as bounds testing ARDL (Autoregressive Distributive Lag) approach which allows variables to be combination of I(1) and I(0). The error correction model in equation (2) can be rewritten by replacing the lagged value of the error term ϵ_{t-1} with the linear combination of lagged-level variables from equation (1) as follows:

$$\Delta \ln Gini_t = \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_{kj} \Delta \ln PU_{t-j} + \lambda_1 \ln Gini_{t-1} + \lambda_2 \ln Y_{t-1} + \lambda_3 \ln PU_{t-1} + u_t \quad (3)$$

By applying OLS to the above error-correction model, short run and long run effects of exogenous variables on income inequality can be estimated in one step. The short run effects of each variable on Gini are inferred by estimates of coefficients π_i and Γ_j and the long run effects are shown by the estimate of λ_2 and λ_3 normalized on $-\lambda_1$. This could easily be seen by setting the lagged-linear combination of variables in (4) equal to zero as follows:

$$\hat{\lambda}_1 \ln Gini_{t-1} + \hat{\lambda}_2 \ln Y_{t-1} + \hat{\lambda}_3 \ln PU_{t-1} = 0 \quad (4)$$

Or

$$\ln Gini_{t-1} = -\frac{\hat{\lambda}_2}{\hat{\lambda}_1} \ln Y_{t-1} - \frac{\hat{\lambda}_3}{\hat{\lambda}_1} \ln PU_{t-1} \quad (5)$$

To avoid spurious estimates, cointegration between *Gini*, *Y* and *PU* must be established and for this purpose Pesaran et al. (2001) recommend two tests. The first is standard F-test to establish the joint significance of lagged-level variables in equation (3). They provide two sets of critical

values including upper bound that is created by assuming that all variables are I(1) and the lower bound that is created by assuming all variables to be I(0). If the computed F-statistic is smaller than the lower critical bound, the null hypothesis of no cointegration between variable cannot be rejected. And, if F-statistics is larger than upper bound then all the variables are cointegrated and if the F-statistics falls between lower and upper bound, the test result is inconclusive. Pesaran et al. (2001) also show that if variables are a combination of I(1) and I(0), the upper-bound critical value should be used to establish cointegration, so as we mentioned before, there is no need for pre-unit testing. The second test is to use equation (5) and generate the error correction term. Denoting this term by ECM_{t-1} . We have:

$$ECM_{t-1} = \ln Gini_{t-1} + \frac{\hat{\lambda}_2}{\hat{\lambda}_1} \ln Y_{t-1} + \frac{\hat{\lambda}_3}{\hat{\lambda}_1} \ln PU_{t-1} \quad (6)$$

The next step is to rewrite (3) by substituting the lagged level variables by ECM_{t-1} as in (7):

$$\Delta \ln Gini_t = \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_{kj} \Delta \ln PU_{t-j} + \gamma ECM_{t-1} + u_t \quad (7)$$

Then, we estimate equation (7) using the same optimum-lag structure. According to Bahmani-Oskooee and Ardalani (2006), a negative and significant estimated coefficient γ supports adjustment toward the long run equilibrium, which implies a cointegration between the variables. Since the t-test is used to establish significance of γ , the test is known as the t-test for cointegration. Pesaran et al. (2001) tabulate new critical values for this test too.

2.2.2 The Nonlinear Model

Now, we follow Shin et al. (2014) nonlinear autoregressive distributed lag model (NARDL) to test the asymmetric effects of policy uncertainty changes on income inequality. This approach helps to comprise all possible combination of short run and long run (a)symmetry while

maintaining all advantages of a linear ARDL model explained earlier. Following Shin et al. (2014), to separate variable PU increases and decreases, natural logarithm of PU ($\ln PU$) is decomposed to partial sum of positive and negative changes. We use the partial sum concept to generate two new time-series variables POS and NEG as:

$$POS_t = \sum_{j=1}^t \Delta \ln PU_t^+ = \sum_{j=1}^t \max(\Delta \ln PU_j, 0)$$

$$NEG_t = \sum_{j=1}^t \Delta \ln PU_t^- = \sum_{j=1}^t \min(\Delta \ln PU_j, 0)$$

We represent nonlinear long run and Error Correction specifications by replacing $\ln PU$ variable with POS and NEG from equation (1) and (3) as follows:

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma_1 POS_t + \gamma_2 NEG_t + \epsilon_t \quad (8)$$

$$\Delta \ln Gini_t = \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_j^+ \Delta POS_{t-j} + \sum_{j=0}^{n_4} \Gamma_j^- \Delta NEG_{t-j} + \rho_0 \ln Gini_{t-1} + \rho^+ POS_{t-1} + \rho^- NEG_{t-1} + \vartheta_t \quad (9)$$

Shin et al. (2014) label (9) as a nonlinear model that it can be estimated by OLS and Pesaran et al. (2001) approach of testing cointegration using upper bound critical values of F- and the t-test. Equation (9) includes both short run and long run asymmetric effects. The estimates of the coefficients of the first differenced variables reflect the short run effects. Once (9) is estimated, the short run “asymmetric adjustment” can be detected if the number of lags on ΔPOS and ΔNEG were different. Also, if either size or sign of the estimates of Γ_j^+ and Γ_j^- were different, it could be judged as short run “asymmetric effects”. The Wald test can be applied to determine the short run asymmetric impact effects if we can reject the null of $\Sigma \Gamma_j^+ = \Sigma \Gamma_j^-$. The asymmetric

long run impacts of changes in PU on income inequality is judged by applying the Wald test on normalized coefficients of *POS* and *NEG* variables to determine if $\rho^+ / -\rho_0 \neq \rho^- / -\rho_0$.

2.3. Results

Results from linear model show that economic growth has no significant effect on U.S income inequality in the short run while it widens it in the long run. Nonlinear model results show that economic growth will decrease income inequality both in the short run and long run. More observation from the linear model implies that policy uncertainty does not have any significant effect on U.S income inequality. However, nonlinear model that assumes the effect of policy uncertainty is rather asymmetric shows significant effects in the long run. In the long run, a decline in policy uncertainty will increase U.S. income inequality, while an increase in it does not have any significant effect. The cointegration between variables is supported by F test. These results support the idea of asymmetric effects since coefficient of variable *NEG* is negative and significant and coefficient of variable *POS* is insignificant. Cumulative asymmetric effect is also supported by Wald test for the long run model (reported as Wald-L in Panel C). Next, we estimate models for states to see how the results change. From linear model we can see that only in Arkansas, policy uncertainty affects income inequality in the short run. In this state, at least one of $\Delta \ln PU_{t-j}$ lags carry a significant coefficient. This significant coefficient is negative that implies increasing policy uncertainty will reduce income inequality in Arkansas. However, this short run effect will not translate into long run since estimated coefficient attached to $\ln PU_t$ is insignificant.

Next, we estimate nonlinear model that assumes the effects are asymmetric. I find that in the short run, a rise in policy uncertainty will decrease income inequality in Arkansas while a decrease in does not have a significant effect on it. These results are due to the fact that ΔPOS

variables carries at least one negative and significant coefficient but ΔNEG variable does not. The difference in the coefficients attached to ΔPOS and ΔNEG support the asymmetric effects. However, cumulative asymmetric effects are not supported by the Wald test (reported as Wald-S in Panel C). Long run estimates show that only in the case of Alaska, both *POS* or *NEG* carry positive and significant coefficients which imply a raise in policy uncertainty will increase income inequality and a decline in it will reduce it. Although estimates attached to *POS* and *NEG* variables seem different in size, long run asymmetric effects is not supported by Wald test reported as Wald-L in Panel C.

Suspecting that our findings for the United States as a whole could suffer from aggregation bias, we estimated both the linear and nonlinear ARDL models for each state of the United States. From the linear models, we found that policy uncertainty has short-run effects on income inequality measured by GINI in 31 states which lasted into the long run only in eight states of Arizona, Indiana, Maine, Missouri, Nebraska, Pennsylvania, Rhode Island, and Vermont. However, when we estimated the nonlinear ARDL model for each state, the number of states increased substantially.

Indeed, we found short-run effects of either increased policy uncertainty or decreased uncertainty in a total of 41 states. While short-run effects were asymmetric in almost all states, short-run cumulative or impact asymmetric effects were established in 26 states. Short-run asymmetric effects were translated into long-run asymmetric effects in 25 states.

Additional analysis revealed that the results are state-specific. We found that while decreased uncertainty improved income inequality in Colorado, in 20 other states of Delaware, Florida, Hawaii, Iowa, Illinois, Indiana, Massachusetts, Maine, Michigan, Minnesota, Missouri, North Dakota, Nebraska, Oregon, Pennsylvania, Rhode Island, Virginia, Vermont, Wisconsin, and

Wyoming, it worsened income inequality. On the other hand, in 14 states, that is, Delaware, Florida, Hawaii, Iowa, Indiana, Maine, Michigan, Missouri, Nebraska, Oregon, Pennsylvania, Vermont, Wisconsin, and Wyoming, increased uncertainty improved inequality. In these states, most likely more low-income people engaged in more risky business and improved their standard of living or income.

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	U.S.		Alaska		Alabama		Arkansas	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.01(.04)	.19(.71)	.19(.58)	-.00(.01)	-.33(-.98)
$\Delta \text{LnGINI}_{t-2}$.52(2.30)**	.53(2.09)**	.40(1.90)*	.27(1.10)
$\Delta \text{LnGINI}_{t-3}$.32(1.84)*	.33(1.72)*	.30(1.66)*	.23(.73)
ΔLnRGDP	.02(.14)	-.42(1.67)*	.10(.78)		.40(1.83)*	.39(1.50)	1.03(2.93)**	.95(2.11)**
$\Delta \text{LnRGDP}_{t-1}$.61(1.41)		-.08(.50)	.26(1.00)	.22(.58)	.93(2.00)**	.62(.82)
$\Delta \text{LnRGDP}_{t-2}$.70(1.60)			-.19(.66)	-.21(.53)	-.33(.65)	-.63(.78)
$\Delta \text{LnRGDP}_{t-3}$					-.63(2.37)**	-.64(1.91)*	-.84(2.05)**	-1.04(2.04)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.02(1.54)		-.45(0.2)	-.45(.02)	-.01(.70)		.043(1.40)	
ΔLnPU_{t-1}							.01(.17)	
ΔLnPU_{t-2}							-.08(2.33)**	
ΔLnPU_{t-3}							-.06(2.21)**	
ΔLnPU_{t-4}								
ΔPOS_t		-.02(.59)		.03(.48)		-.02(.69)		.05(.82)
ΔPOS_{t-1}		-.017(.50)		-.02(.39)				-.05(.59)
ΔPOS_{t-2}		.070(1.21)						-.13(1.56)
ΔPOS_{t-3}		.049(.95)						-.11(1.66)*
ΔPOS_{t-4}								
ΔNEG_t		-.03(.47)		-.01(.20)		-.00(.09)		
ΔNEG_{t-1}		.06(1.61)		-.11(1.35)				
ΔNEG_{t-2}		.04(.56)		-.08(.96)				
ΔNEG_{t-3}		-.04(.76)		-.08(1.05)				
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-3.35(3.70)**	2.58(2.70)**	26.9(.06)	-8.26(11.88)**	-5.27(4.07)**	-6.15(2.43)**	-8.88(1.58)	-442.37(.05)
LnRGDP_t	.30(3.06)**	-.30(3.28)**	1.49(.07)	.70(.70)	.47 (3.86)**	.54(2.17)**	.76(1.49)	43.28(.05)
LnPU_t	-.075(.92)		-9.22(.07)		-.04(.88)		.09(.71)	
POS_t		.00(.05)		.08(3.29)**		-.048(.95)		9.78(.05)
NEG_t		-.12(4.91)**		.21(7.39)**		-.03(.68)		17.60(.05)
Panel C: Diagnostic Statistics								
F	2.66	6.2**	1.61	1.36	3.73	2.17	4.50*	1.66
$\hat{\rho}_0$ (t-ratio)	-.34(2.35)	-.97(2.90)	-.052(.55)	-.19(.58)	-.42(2.41)	-.45(2.09)	-.29(1.80)	-.01(.05)
LM	.65	3.07*	1.21	.62	1.26	1.50	3.60*	2.40
RESET	1.32	2.05	6.01**	6.35**	.68	.58	.01	5.78**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.25	.28	.012	.00	.58	.51	.60	.56
Wald-S		.03		1.47		.13		.32
Wald-L		10.13**		1.48		.04		.00

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Arizona		California		Colorado		Connecticut	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$.45(1.53)		.53(1.72)**	.46(2.02)**	1.11(4.44)**		.38(1.35)
$\Delta \text{LnGINI}_{t-2}$.38(1.30)		.43(1.81)*		.87(4.51)**		.21(.50)
$\Delta \text{LnGINI}_{t-3}$.07(.33)		.28(1.25)				-.83(1.64)*
$\Delta \text{LnGINI}_{t-4}$.25(1.29)						
ΔLnRGDP_t	-.043(.43)	.10(.76)	-.09(.42)	.02(.09)	.08(.41)	.27(1.18)	.08(.37)	.47(2.24)**
$\Delta \text{LnRGDP}_{t-1}$	-.17(1.88)*		.24(1.07)	.55(2.01)**		1.21(3.64)**	-.30(1.51)	.62(1.31)
$\Delta \text{LnRGDP}_{t-2}$	-.16(1.68)*		-.16(.87)	.00(.01)		.47(2.24)**	-.44(1.92)*	-.46(.94)
$\Delta \text{LnRGDP}_{t-3}$	-.18(1.72)*		-.48(2.80)**	-.29(.94)		.36(1.89)*	-.35(1.90)*	
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.03(2.42)**		-.05(2.07)**		-.02(.85)		-.02(.92)	
ΔLnPU_{t-1}			.04(1.71)*				.07(2.00)*	
ΔLnPU_{t-2}			.10(3.68)**				.06(2.21)**	
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.03(.96)		.01(.25)		.04(1.23)		.02(.45)
ΔPOS_{t-1}				.05(.98)		-.05(1.60)		.10(2.89)**
ΔPOS_{t-2}				.15(3.58)**		.10(2.95)**		.17(3.24)**
ΔPOS_{t-3}						.02(.79)		-.11(1.21)
ΔPOS_{t-4}								
ΔNEG_t		-.02(.64)		-.12(2.22)**		-.04(1.27)		-.05(.98)
ΔNEG_{t-1}		.11(2.41)**				-.06(1.76)*		.19(2.93)**
ΔNEG_{t-2}		.08(1.89)*				-.10(2.08)**		-.02(.38)
ΔNEG_{t-3}		.05(1.34)				-.13(2.45)**		.14(2.75)**
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.02(2.44)**	.99(2.99)**	-6.31(.30)	4.03(2.28)**	-2.34(.96)	.95(3.64)**	7.56(.16)	13.94(.90)
LnRGDP_t	.21(2.38)**	-.15(4.74)**	1.92(.22)	-.44(2.60)**	.21(.79)	-.15(5.90)**	1.12(.29)	-1.3(.95)
LnPU_t	-.15(1.91)*		-3.12(.20)		-.09(.43)		-4.23(.24)	
POS_t		-.03(1.51)		.01(.05)		.10(8.03)**		-.05(.19)
NEG_t		-.11(4.63)**		-.15(1.32)		.03(2.12)**		-.42(.70)
Panel C: Diagnostic Statistics								
F	4.60*	3.70	4.65*	5.02*	1.04	10.72**	3.43	1.32
$\hat{\rho}_0$ (t-ratio)	-.25(2.43)	-1.11(3.20)	-.03(.21)	-.69(1.59)	-.31(1.68)	-.48(1.28)	-.03(.25)	-.27(.68)
LM	.60	2.55	.01	3.32*	2.54	.61	.07	2.35
RESET	.07	.90	.73	9.25**	.19	2.71*	.11	7.56**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.28	.26		.49	.06	.00	.12	.66
Wald-S		4.39**		7.82**		.71		.14
Wald-L		81.44**		10.92**		3.18*		1.18

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Delaware		District of Columbia		Florida		Georgia	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.36(1.92)*	-.28(1.24)	-.39(1.00)		.37(1.03)		.60(1.44)
$\Delta \text{LnGINI}_{t-2}$		-.14(1.20)		-.26(.80)				.61(1.66)*
$\Delta \text{LnGINI}_{t-3}$		-.23(1.97)**		-.34(1.68)*				.40(1.44)
ΔLnRGDP	.09(1.13)	.15(2.74)**	-.35(1.40)	-.15(.59)	-.17(.72)	-.46(1.35)	-.17(1.22)	-.75(2.24)**
$\Delta \text{LnRGDP}_{t-1}$.08(1.11)	.34(6.46)**	-.30(1.11)		-.38(1.85)*	-.09(.22)		.62(1.90)*
$\Delta \text{LnRGDP}_{t-2}$	-.05(.63)	.41(6.91)**	-.34(1.22)		.35(1.69)*	.36(1.59)		.45(.98)
$\Delta \text{LnRGDP}_{t-3}$	-.18(2.11)**	.22(2.82)**			-.56(3.13)**	-.43(1.68)*		-.51(2.60)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.02(1.43)		.08(2.68)**		-.02(1.35)		-.04(2.38)**	
ΔLnPU_{t-1}					-.03(1.52)			
ΔLnPU_{t-2}								
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.01(.71)		.05(.98)		-.03(1.14)		-.04(1.29)
ΔPOS_{t-1}		-.03(2.81)**		-.06(1.46)		-.04(.95)		.05(1.23)
ΔPOS_{t-2}		-.02(1.44)				.03(.44)		.13(2.25)**
ΔPOS_{t-3}		-.04(3.21)**						.10(1.39)
ΔPOS_{t-4}								
ΔNEG_t		-.04(2.40)**		.16(2.32)**		-.05(.83)		-.09(2.33)**
ΔNEG_{t-1}		.12(5.06)**				.08(1.40)		.22(2.89)**
ΔNEG_{t-2}		.06(2.08)**				.04(.82)		.17(1.74)*
ΔNEG_{t-3}		.02(.88)						
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-1.73(1.43)	-.11(.52)	-1.16(2.36)**	3.11(1.78)*	-4.47(4.81)**	1.59(2.75)**	-8.57(.96)	.82(1.97)**
LnRGDP_t	.12(1.15)	-.05(2.54)**	.03(.78)	-.31(2.07)**	.40(4.39)**	-.20(3.65)**	.98(.87)	-.14(3.38)**
LnPU_t	-.04(.74)		.06(2.05)**		-.04(.63)		-.51(.62)	
POS_t		-.02(1.80)*		.11(2.15)**		-.04(3.37)**		-.07(3.56)**
NEG_t		-.07(5.94)**		.03(.64)		-.15(8.36)**		-.17(7.37)**
Panel C: Diagnostic Statistics								
F	.74	16.16**	2.65	1.99	3.89	5.52**	3.43	4.41
$\hat{\rho}_0$ (t-ratio)	-.20(1.40)	-1.63(6.91)**	-.85(2.75)	-.87(1.92)	-.35(3.28)*	-1.02(2.76)	-.14(1.66)	-1.86(2.89)
LM	3.17*	2.57	.01	.25	.26	.45	.01	2.31
RESET	1.90	.05	.46	.63	.25	.28	4.01**	.25
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.18	.88	.64	.71	.39	.35	.23	.41
Wald-S		7.06**		3.23*		.44		.26
Wald-L		195.37**		6.88**		19.24**		161.92**

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Hawaii		Iowa		Idaho		Illinois	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$		-.35(2.25)**		-.21(.22)		.24(.69)		.49(1.36)
$\Delta \text{LnGINI}_{t-2}$				-.03(.05)		.23(.86)		.31(1.32)
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	.41(2.98)**	.64(4.86)**	.26(2.12)**	.29(.69)	.11(.71)	.04(.23)	.21(1.20)	.37(1.75)*
$\Delta \text{LnRGDP}_{t-1}$	-.09(.66)	.08(.67)	.11(1.02)	.53(1.26)		-.11(.55)		.93(2.52)**
$\Delta \text{LnRGDP}_{t-2}$.07(.54)	.45(3.09)**	.21(1.62)	.51(1.09)		-.76(4.08)**		.66(2.05)**
$\Delta \text{LnRGDP}_{t-3}$	-.33(2.59)**	-.22(2.39)**	-.18(1.42)	-.07(.24)		-.42(2.92)**		
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.00(.31)		.01(.56)		-.03(1.37)		-.01(.68)	
ΔLnPU_{t-1}								
ΔLnPU_{t-2}								
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.08(3.31)**		-.01(.25)		.01(.26)		.03(.88)
ΔPOS_{t-1}		.06(3.18)**		.032(.79)		.02(.46)		.06(1.89)*
ΔPOS_{t-2}		-.04(2.10)**		.05(.97)		.04(1.05)		.12(2.67)**
ΔPOS_{t-3}		.02(.74)		.03(.55)		-.08(2.06)**		.03(.99)
ΔPOS_{t-4}								
ΔNEG_t		.04(1.73)*		.01(.09)		.00(.01)		-.07(1.81)*
ΔNEG_{t-1}		.16(4.73)**		.06(.62)		-.04(.54)		.05(1.52)
ΔNEG_{t-2}		.21(4.75)**		.02(.30)		-.21(3.15)**		
ΔNEG_{t-3}		.16(4.28)**				-.18(3.33)**		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-4.22(2.76)**	-1.31(2.17)**	-3.79(1.38)	1.41(2.56)**	-3.90(3.30)**	-4.36(.51)	-3.65(2.06)**	2.85(2.57)**
LnRGDP_t	.34(2.37)**	.07(1.21)	.27(1.24)	-.19(3.57)**	.35(2.97)**	.39(.45)	.34(1.70)*	-.33(3.10)**
LnPU_t	-.02(.67)		.043(.36)		-.06(.81)		-.10(.60)	
POS_t		-.10(3.10)**		-.05(6.46)**		.38(.64)		.01(.48)
NEG_t		-.13(3.42)**		-.12(5.92)**		.63(.57)		-.11(2.52)**
Panel C: Diagnostic Statistics								
F	2.74	13.54**	2.00	6.08**	1.04	11.82**	1.19	4.53*
$\hat{\rho}_0$ (t-ratio)	-.47(2.43)	-.71(3.82)**	-.15(1.04)	-.27(.32)	-.20(1.52)	-.83(2.21)	-.24(1.58)	-1.12(3.22)
LM	.01	4.07**	.32	1.30	.03	.36	1.08	.75
RESET	.11	3.99**	.93	2.52	.09	.24	.01	8.45**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.38	.80	.45	.16	.11	.55	.15	.33
Wald-S		19.65**		.01		5.77**		3.71*
Wald-L		13.37**		.25		.23		25.87**

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Indiana		Kansas		Kentucky		Louisiana	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$	-.08(.38)	-.04(.14)			.38(1.58)			.14(.76)
$\Delta \text{LnGINI}_{t-2}$.24(1.28)	.33(1.56)			.34(1.55)			.09(.47)
$\Delta \text{LnGINI}_{t-3}$.29(1.44)			.34(1.95)*
ΔLnRGDP	-.09(.73)	-.34(1.50)	-.18(.97)	.00(.02)	.00(.02)	.34(1.62)	.41(3.55)**	.39(2.79)**
$\Delta \text{LnRGDP}_{t-1}$	-.02(.16)	-.09(.53)	-.15(.83)	.22(.79)	.33(1.47)	1.38(3.83)**	-.08(.61)	-.23(1.16)
$\Delta \text{LnRGDP}_{t-2}$	-.21(1.74)*	-.15(1.13)	-.31(1.69)*	-.12(.47)	-.05(.21)	.52(2.45)**	.47(3.37)**	.53(2.81)**
$\Delta \text{LnRGDP}_{t-3}$	-.38(3.34)**	-.32(2.57)**	-.57(3.25)**	-.48(2.22)**	-.53(2.54)**			
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.03(2.10)**		-.05(2.95)**		-.01(.23)		-.02(.97)	
ΔLnPU_{t-1}			.03(1.81)*				-.04(2.11)**	
ΔLnPU_{t-2}			.04(1.90)*				-.02(1.10)	
ΔLnPU_{t-3}							-.06(2.66)**	
ΔLnPU_{t-4}								
ΔPOS_t		-.07(2.38)**		-.01(.20)		.15(2.90)**		-.09(2.04)**
ΔPOS_{t-1}		-.03(.78)		.05(1.82)*		.00(.01)		
ΔPOS_{t-2}				.06(1.76)*		.11(2.54)**		
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.01(.30)		-.08(1.64)*		-.10(2.21)**		-.03(.54)
ΔNEG_{t-1}		.10(1.74)*				-.20(3.19)**		
ΔNEG_{t-2}		.07(1.45)				-.28(4.63)**		
ΔNEG_{t-3}						-.18(4.13)**		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.26(3.46)**	-1.81(1.54)	-3.26(5.06)**	2.69(.62)	-2.99(2.04)**	-1.98(.32)	-7.46(4.36)**	-3.53(1.13)
LnRGDP_t	.20(3.12)**	.12(1.02)	.36(4.19)**	-.32(.76)	.24(1.86)*	.19(.30)	.55(3.20)**	.27(.94)
LnPU_t	-.09(1.74)*		-.23(1.63)		-.02(.23)			
POS_t		-.07(2.50)**		-.07(.66)		-.84(1.44)	.22(1.40)	.02(.47)
NEG_t		-.11(3.10)**		-.18(1.60)		-.89(1.58)		-.02(.31)
Panel C: Diagnostic Statistics								
F	4.66*	4.65*	4.21	2.22	2.67	4.42	4.79*	2.68
$\hat{\rho}_0$ (t-ratio)	-.42(2.76)	-.90(2.50)	-.34(2.39)	-.33(1.41)	-.38(2.75)	.20(1.09)	-.33(2.34)	-.51(2.52)
LM	1.96	1.48	.10	.18	2.47	10.54**	.02	1.99
RESET	.32	.05	.16	4.67**	.22	2.71*	1.31	14.34**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.45	.44	.37	.36	.38	.61	.63	.54
Wald-S		4.01**		2.38		17.96**		5.04**
Wald-L		3.36*		1.65		.23		1.19

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Massachusetts		Maryland		Maine		Michigan	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$.49(2.41)**	.54(2.80)**	.17(.71)	.37(1.73)*	.57(2.00)**	.22(.51)		
$\Delta \text{LnGINI}_{t-2}$.43(2.04)**	.59(2.99)**	.42(1.73)*	.44(2.17)**	.30(1.32)	-.24(.44)		
$\Delta \text{LnGINI}_{t-3}$					-.24(1.29)	-.40(1.05)		
ΔLnRGDP_t	.16(.77)	.03(.16)	-.22(1.03)	-.24(1.15)	-.43(1.28)	-.65(1.30)	-.06(.89)	-.14(2.53)**
$\Delta \text{LnRGDP}_{t-1}$.58(2.57)**	-.06(.30)	.47(1.98)**	-.75(2.48)**	-.97(2.09)**	.05(.72)	.08(1.50)
$\Delta \text{LnRGDP}_{t-2}$.24(1.04)	.25(1.15)	.37(1.59)	-.56(1.61)	-1.07(2.38)**	-.08(1.19)	.12(2.02)**
$\Delta \text{LnRGDP}_{t-3}$.43(2.25)**	-.50(2.85)**		-.87(2.75)**	-.63(1.47)	-.27(4.51)**	-.11(1.75)*
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.05(2.07)**		-.03(1.49)		-.06(2.54)**		-.02(2.00)**	
ΔLnPU_{t-1}	-.01(.54)		.01(.54)		.14(3.23)**		-.02(1.21)	
ΔLnPU_{t-2}	.05(2.20)**		.05(2.03)**		.06(2.01)**		-.01(.47)	
ΔLnPU_{t-3}			.02(1.02)		.03(1.20)		-.04(2.93)**	
ΔLnPU_{t-4}								
ΔPOS_t		.00(.12)		.02(.71)		-.06(1.38)		-.06(3.55)**
ΔPOS_{t-1}		-.03(.87)		-.01(.45)		.10(1.61)		
ΔPOS_{t-2}		.09(2.44)**		.06(2.05)**		.02(.30)		
ΔPOS_{t-3}						-.09(1.56)		
ΔPOS_{t-4}								
ΔNEG_t		-.12(2.83)**		-.08(1.99)*		-.10(1.04)		-.00(.13)
ΔNEG_{t-1}						.23(2.91)**		.10(3.33)
ΔNEG_{t-2}						.09(1.43)		.10(3.52)**
ΔNEG_{t-3}						.14(2.72)**		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.38(3.73)**	4.58(2.89)**	-2.15(1.12)	8.40(4.67)**	-3.34(17.28)**	-5.69(3.81)**	-4.27(2.43)**	.44(1.07)
LnRGDP_t	.21(3.08)**	-.50(3.28)**	.35(.78)	-.86(5.02)**	.32(18.57)**	.49(3.38)**	.37(2.09)**	-.10(2.55)**
LnPU_t	-.09(.86)		-.46(.58)		-.14(6.34)**		-.04(.28)	
POS_t		.08(2.21)**		.09(3.26)**		-.16(4.53)**		-.08(4.59)**
NEG_t		-.10(1.75)*		-.12(2.91)**		-.14(4.24)**		-.17(8.83)**
Panel C: Diagnostic Statistics								
F	3.18	6.80**	2.17	4.31	8.42**	9.81**	2.36	8.77**
$\hat{\rho}_0$ (t-ratio)	-.31(1.89)	-.72(3.61)*	-.13(.81)	-.53(3.14)	-1.91(4.90)**	-1.96(4.06)**	-.14(2.11)	-.85(4.29)**
LM	.26	1.93	.22	.01	.80	1.49	2.38	1.15
RESET	4.98**	7.36**	5.08**	.36	1.51	2.36	.10	.45
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.32	.57	.16	.27	.63	.76	.54	.69
Wald-S		4.76**		3.52*		3.86**		16.32**
Wald-L		18.82**		15.52**		.98		220.79**

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Minnesota		Missouri		Mississippi		Montana	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.19(.75)	.47(2.83)**	.14(.86)		.16(.57)
$\Delta \text{LnGINI}_{t-2}$.42(2.19)**	.76(3.89)**		.33(1.19)
$\Delta \text{LnGINI}_{t-3}$.66(2.25)**		
ΔLnRGDP	.13(.97)	.02(.15)	-.09(.46)	-.41(1.69)*	.83(3.31)**	.86(2.69)**	.17(.51)	-1.41(2.19)**
$\Delta \text{LnRGDP}_{t-1}$	-.16(1.23)	.53(2.61)**	-.19(1.06)	-.34(1.86)*		-.09(.32)	.42(1.29)	.88(1.29)
$\Delta \text{LnRGDP}_{t-2}$	-.06(.43)	.42(2.79)**	-.31(1.80)*	-.35(1.96)**		.32(1.11)	.32(.89)	-.02(.03)
$\Delta \text{LnRGDP}_{t-3}$	-.34(2.50)**		-.32(1.84)*	-.21(1.04)		-1.01(3.47)**	-.35(.96)	-1.30(2.51)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.02(1.14)		-.04(2.23)**		.00(.06)		-.02(.78)	
ΔLnPU_{t-1}								
ΔLnPU_{t-2}								
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.00(.20)		-.07(2.53)**		-.16(3.47)**		-.00(.01)
ΔPOS_{t-1}		.01(.43)				-.01(.14)		-.06(1.27)
ΔPOS_{t-2}		.07(2.59)**				-.08(1.81)*		.18(2.64)**
ΔPOS_{t-3}						.07(1.72)*		.06(.92)
ΔPOS_{t-4}								
ΔNEG_t		-.04(1.26)		-.04(1.05)		.18(2.95)**		-.13(1.77)*
ΔNEG_{t-1}		.10(2.98)**		.14(2.36)**				-.07(.57)
ΔNEG_{t-2}				.09(1.73)*				-.13(1.42)
ΔNEG_{t-3}								-.21(2.76)**
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.33(1.75)*	4.36(3.61)**	-3.04(3.13)**	-.89(1.22)	-8.81(3.89)**	-10.65(3.57)**	-3.21(2.04)**	13.20(.56)
LnRGDP_t	-.14(.88)	-.48(4.11)**	.29(3.20)**	.03(.43)	.75(3.51)**	.99(3.34)**	.28(1.90)*	-1.35(.58)
LnPU_t	.23(1.49)		-.12(2.37)**		.11(1.16)		-.05(.57)	
POS_t		-.02(1.02)		-.13(5.73)**		.07(.72)		-.05(.25)
NEG_t		-.18(3.73)**		-.18(7.40)**		.11(.88)		-.29(.56)
Panel C: Diagnostic Statistics								
F	2.45	6.14**	4.53*	4.59*	4.74*	7.21**	.68	1.90
$\hat{\rho}_0$ (t-ratio)	-.18(1.26)	-.75(3.95)**	-.43(3.08)	-1.20(3.53)*	-.29(3.45)*	-.55(4.70)**	-.27(1.38)	-.27(.95)
LM	.08	.26	.11	1.87	1.14	2.14	.61	9.13**
RESET	1.66	.11	.00	.49	1.72	1.54	.20	2.79*
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.21	.46	.31	.41	.57	.74	.17	.30
Wald-S		.10		5.67**		4.63**		8.32**
Wald-L		30.88**		21.65**		.76		.31

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	North Carolina		North Dakota		Nebraska		New Hampshire	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$		-.14(.50)	.29(1.34)	.35(1.95)*	-.44(2.65)**	-.24(.88)		
$\Delta \text{LnGINI}_{t-2}$		-.31(1.24)		.43(2.43)**		.28(1.61)		
$\Delta \text{LnGINI}_{t-3}$.24(1.38)		.28(1.97)**		
ΔLnRGDP	-.21(1.49)	-.39(2.15)**	.23(2.32)**	.26(3.10)**	.44(2.32)**	.64(3.45)**	.10(.67)	.07(.29)
$\Delta \text{LnRGDP}_{t-1}$		-.61(2.05)**	-.26(1.67)*		.82(3.60)**	1.52(5.27)**		
$\Delta \text{LnRGDP}_{t-2}$		-.42(1.81)*	-.13(1.02)		.73(4.55)**	1.24(6.04)**		
$\Delta \text{LnRGDP}_{t-3}$			-.27(2.21)**					
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.04(2.63)**		-.01(.53)		-.03(2.77)**		-.02(.94)	
ΔLnPU_{t-1}	-.03(2.08)**		-.03(1.38)		.02(1.45)			
ΔLnPU_{t-2}			-.05(2.50)**		.04(2.71)**			
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		.06(1.70)*		-.03(1.11)		-.04(2.41)**		-.06(1.46)
ΔPOS_{t-1}		-.10(2.32)**		-.03(.94)		.07(3.48)**		
ΔPOS_{t-2}		-.11(2.14)**		-.05(1.99)**		.10(5.06)**		
ΔPOS_{t-3}		-.08(1.83)*						
ΔPOS_{t-4}								
ΔNEG_t		-.01(.35)		.01(.25)		-.08(3.12)**		.02(.41)
ΔNEG_{t-1}						.14(3.49)**		.06(1.27)
ΔNEG_{t-2}						.10(2.79)**		.10(1.84)*
ΔNEG_{t-3}						.13(3.71)**		.05(.91)
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-3.74(3.64)**	-6.63(2.39)**	-2.48(2.62)**	.56(.71)	-4.20(2.58)**	-1.68(.87)	-1.09(.94)	.09(.05)
LnRGDP_t	.33(3.50)**	.59(2.16)**	.14(2.31)**	-.11(1.48)	.40(2.22)**	.09(.49)	.09(.80)	-.06(.40)
LnPU_t	-.07(1.23)		.11(.77)		-.15(1.74)*		-.08(.67)	
POS_t		-.06(1.16)		.04(1.07)		-.17(2.23)**		-.19(1.54)
NEG_t		-.00(.07)		-.04(1.64)*		-.24(2.74)**		-.26(1.69)*
Panel C: Diagnostic Statistics								
F	2.91	3.46	3.08	4.73*	6.31**	10.25**	2.66	2.12
$\hat{\rho}_0$ (t-ratio)	-.30(2.60)	-.51(2.30)	-.35(1.92)	-.84(4.00)**	-.32(1.53)	-.68(2.24)	-.32(2.25)	-.34(1.83)
LM	.44	.18	.03	.07	.97	1.61	2.11	.92
RESET	4.11**	.34	.68	.37	.22	1.29	1.44	4.89**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.36	.34	.56	.60	.66	.82	.20	.16
Wald-S		4.40**		2.89*		3.46*		3.12*
Wald-L		.75		7.14**		4.68**		2.14

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	New Jersey		New Jersey		Nevada		New York	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$				-.52(1.63)		.24(.93)		
$\Delta \text{LnGINI}_{t-2}$								
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.20(.81)	-.11(.43)	-.20(.92)	-.05(.18)	-.05(.32)	.11(.51)	.24(2.13)**	.21(1.95)*
$\Delta \text{LnRGDP}_{t-1}$	-.20(1.02)		-.28(1.38)	-.48(1.49)	-.59(3.48)**	1.25(2.11)**		.23(1.70)*
$\Delta \text{LnRGDP}_{t-2}$	-.24(1.11)		-.18(.82)	-.22(.66)	.02(.11)	.32(1.56)		.29(2.29)**
$\Delta \text{LnRGDP}_{t-3}$	-.35(2.16)**		-.46(2.37)**	-.43(1.49)	-.56(3.20)**			
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.04(1.83)*		-.07(1.85)*		-.05(1.65)*		-.00(.03)	
ΔLnPU_{t-1}	.04(1.45)							
ΔLnPU_{t-2}	.06(2.62)**							
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.03(1.03)		.00(.00)		.02(.44)		.03(1.12)
ΔPOS_{t-1}		.01(.31)		-.13(1.99)**		.12(1.80)*		-.03(1.45)
ΔPOS_{t-2}		.08(2.69)**		-.10(1.58)		.29(2.70)**		
ΔPOS_{t-3}				-.09(1.43)				
ΔPOS_{t-4}								
ΔNEG_t		-.05(1.38)		.00(.00)		-.10(1.35)		-.01(.27)
ΔNEG_{t-1}		.08(2.14)**		-.18(1.92)*		.31(2.67)**		
ΔNEG_{t-2}				-.17(1.61)				
ΔNEG_{t-3}				-.14(1.68)*				
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-5.3(1.77)*	-69.88(.24)	.18(.12)	-608.80(.01)	.42(.10)	7.27(4.46)**	-3.91(4.39)**	1.88(1.16)
LnRGDP_t	.15(.65)	6.49(.24)	.02(.18)	61.33(.01)	.09(.26)	-.73(4.80)**	.31(3.59)**	-.23(1.49)
LnPU_t	.67(1.37)		-.18(2.37)**		-.39(1.55)		.02(.29)	
POS_t		2.52(.24)		26.83(.01)		-.11(2.08)**		.10(3.67)**
NEG_t		3.84(.24)		53.76(.01)		-.26(3.52)**		-.02(.72)
Panel C: Diagnostic Statistics								
F	3.14	3.15	2.76	3.14	3.22	3.49	2.33	3.19
$\hat{\rho}_0$ (t-ratio)	.15(1.09)	-.01(.09)	-.47(2.73)	-.00(.02)	-.19(2.17)	-.90(2.85)	-.31(2.46)	-.58(3.18)
LM	.38	.24	.71	4.36**	1.49	.03	.01	.77
RESET	.06	.67	.12	2.52	.12	.02	.37	.01
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.16	.20	.17	.30	.30	.42	.18	.27
Wald-S		.09		.47		1.76		.02
Wald-L		.01		.00		32.63**		10.58**

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Ohio		Oklahoma		Oregon		Pennsylvania	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.11(.40)				.19(1.06)		
$\Delta \text{LnGINI}_{t-2}$								
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.04(.33)	-.49(2.66)**	.56(2.52)**	.48(1.73)*	.07(.67)	-.18(1.51)	-.02(.16)	-.11(.80)
$\Delta \text{LnRGDP}_{t-1}$.06(.45)				-.19(1.74)*			
$\Delta \text{LnRGDP}_{t-2}$	-.20(1.66)*							
$\Delta \text{LnRGDP}_{t-3}$	-.34(2.70)**							
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.04(2.76)**		-.03(1.59)		-.02(1.56)		-.02(2.25)**	
ΔLnPU_{t-1}								
ΔLnPU_{t-2}								
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.06(2.10)**		-.03(.83)		-.02(.94)		-.04(2.20)**
ΔPOS_{t-1}		-.04(1.35)						
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.04(1.48)		-.04(.80)		-.01(.52)		-.02(.90)
ΔNEG_{t-1}		.12(1.91)*						.07(2.50)**
ΔNEG_{t-2}		.07(1.24)						.04(1.50)
ΔNEG_{t-3}		-.04(1.02)						
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.78(3.78)**	-.18(.34)	-2.07(1.37)	10.99(.65)	-2.01(5.94)**	-1.11(3.28)**	-3.09(7.51)**	-1.47(2.53)**
LnRGDP_t	.26(3.67)**	-.04(.87)	.18(1.16)	-1.13(.69)	.15(4.81)**	.05(1.49)	.27(6.36)**	.08(1.49)
LnPU_t	-.13(2.47)**		-.07(.98)		-.04(1.36)		-.07(2.09)**	
POS_t		-.07(3.59)**		-.00(.03)		-.02(1.85)*		-.07(5.31)**
NEG_t		-.14(5.44)**		-.27(1.03)		-.05(3.07)**		-.12(6.58)**
Panel C: Diagnostic Statistics								
F	4.40	3.14	.86	.64	3.21	6.35**	6.55**	5.52**
$\hat{\rho}_0$ (t-ratio)	-.34(2.75)	-1.14(2.87)	-.19(1.21)	-.20(1.21)	-.64(2.90)	-1.05(4.24)**	-.58(3.80)*	-1.00(4.51)**
LM	.81	1.83	.20	.09	.01	1.34	2.28	.40
RESET	1.08	.67	.19	.07	1.46	.90	1.22	.17
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.42	.41	.30	.24	.41	.49	.49	.54
Wald-S		2.15		.02		.04		4.44**
Wald-L		37.84**		.21		5.06**		16.00**

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Rhode Island		South Carolina		South Dakota		Tennessee	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$		1.13(3.57)**						.26(.93)
$\Delta \text{LnGINI}_{t-2}$.55(2.95)**						.06(.21)
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.12(1.03)	-.43(4.43)**	-.72(2.09)**	-.73(1.72)*	.12(.70)	.15(.84)	-.33(1.21)	-.52(1.38)
$\Delta \text{LnRGDP}_{t-1}$.37(3.14)**	.15(.44)	.49(1.42)			-.26(1.32)	-.51(1.45)
$\Delta \text{LnRGDP}_{t-2}$.43(4.91)**	-.63(2.07)**	-.43(1.68)*			-.45(2.13)**	-.74(2.04)**
$\Delta \text{LnRGDP}_{t-3}$		-.11(1.12)	-.41(1.60)	-.32(1.27)			-.77(2.88)**	-.88(2.37)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.04(2.58)**		-.04(1.77)*		-.04(2.12)**		-.05(2.24)**	
ΔLnPU_{t-1}			-.05(1.80)*				-.04(1.95)*	
ΔLnPU_{t-2}			-.03(1.09)				-.06(2.89)**	
ΔLnPU_{t-3}			-.06(2.05)**				-.05(2.24)**	
ΔLnPU_{t-4}								
ΔPOS_t		.00(.06)		-.03(.69)		-.06(1.97)**		-.05(1.09)
ΔPOS_{t-1}		.04(1.96)*		-.08(2.21)**				-.06(.99)
ΔPOS_{t-2}		.08(3.63)**						-.08(1.57)
ΔPOS_{t-3}								-.06(1.29)
ΔPOS_{t-4}								
ΔNEG_t		-.06(2.69)**		-.04(1.01)		-.01(.27)		-.07(1.08)
ΔNEG_{t-1}		.10(3.86)**		-.07(1.10)				
ΔNEG_{t-2}		.03(1.63)		-.05(.95)				
ΔNEG_{t-3}		.06(2.96)**		-.15(2.80)**				
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.65(5.22)**	1.21(2.57)**	-3.44(4.14)**	-3.79(.93)	1.76(4.44)**	-3.91(1.60)	-2.10(2.75)**	-4.12(1.60)
LnRGDP_t	.23(4.61)**	-.18(3.87)**	.29(4.02)**	.31(.79)	.14(3.66)**	.33(1.37)	.18(2.52)**	.35(1.40)
LnPU_t	-.08(1.83)*		-.02(.46)		-.06(2.00)**		-.07(1.46)	
POS_t		-.01(.86)		-.02(.18)		-.08(1.90)*		-.01(.14)
NEG_t		-.09(6.13)**		-.03(.17)		-.02(.45)		.02(.22)
Panel C: Diagnostic Statistics								
F	6.52**	8.78**	5.33*	2.81	1.91	1.37	5.08*	3.99
$\hat{\rho}_0$ (t-ratio)	-.47(3.64)*	-1.37(4.85)**	-.60(2.93)	-.38(1.28)	-.44(2.35)	-.43(2.11)	-.61(3.71)*	-.82(2.51)
LM	2.18	2.65	.00	7.93**	.16	.03	.17	.17
RESET	.45	.55	.42	.72	.02	.98	1.65	.08
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.49	.83	.46	.51	.22	.17	.47	.24
Wald-S		.02		1.38		.76		.97
Wald-L		76.76**		.14		.00		.00

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)

	Texas		Utah		Virginia		Vermont	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.48(1.31)		.52(2.34)**		
$\Delta \text{LnGINI}_{t-2}$.26(1.06)		.34(1.78)*		
$\Delta \text{LnGINI}_{t-3}$				-.25(1.13)		-.49(1.96)*		
ΔLnRGDP	.11(.61)	-.00(.01)	-.22(1.01)	-.19(.83)	-.05(.24)	-.21(.96)	-.10(.80)	-.09(.72)
$\Delta \text{LnRGDP}_{t-1}$.15(.72)	.62(2.03)**		.64(2.67)**		-.21(1.23)
$\Delta \text{LnRGDP}_{t-2}$			-.11(.63)	.23(1.10)		1.01(3.79)**		
$\Delta \text{LnRGDP}_{t-3}$			-.48(3.13)**	-.32(1.48)				
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.03(1.71)*		-.05(2.82)**		-.02(.91)		-.03(2.48)**	
ΔLnPU_{t-1}			.02(.98)					
ΔLnPU_{t-2}			.04(1.92)*					
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		-.02(.69)		-.02(.50)		.06(2.19)**		-.06(2.58)**
ΔPOS_{t-1}				.04(1.04)		.01(.35)		
ΔPOS_{t-2}				.08(1.63)		.09(4.35)**		
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.04(1.20)		-.08(1.67)*		-.08(3.01)**		-.01(.21)
ΔNEG_{t-1}				.08(1.78)*		.06(2.13)**		.08(2.00)**
ΔNEG_{t-2}				.06(1.31)				.05(1.21)
ΔNEG_{t-3}				.04(1.00)				
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-3.16(3.07)**	.52(.34)	-1.26(1.78)*	1.15(1.40)	-3.21(1.13)	7.29(3.77)**	-2.49(6.56)**	-3.58(3.36)**
LnRGDP_t	.27(2.60)**	-.10(.69)	.13(2.53)**	-.17(2.11)**	.31(.90)	-.76(4.10)**	.21(5.67)**	.29(2.78)**
LnPU_t	-.04(.79)		-.14(1.32)		-.14(.47)		-.07(2.62)**	
POS_t		-.03(1.16)		-.02(.90)		.07(3.17)**		-.10(5.34)**
NEG_t		-.10(2.40)**		-.11(2.80)**		-.12(2.50)**		-.09(3.35)**
Panel C: Diagnostic Statistics								
F	1.01	2.05	4.31	3.11	1.46	11.65**	7.29**	4.40
$\hat{\rho}_0$ (t-ratio)	-.24(1.65)	-.48(2.74)	-.39(2.45)	-1.43(2.29)	-.22(1.56)	-.80(3.96)**	-.58(4.18)**	-.94(3.95)**
LM	2.36	3.10*	3.33*	2.01	.79	.63	.29	1.57
RESET	.49	.35	8.93**	1.59	.04	2.26	.97	.00
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.14	.24	.44	.57	.03	.66	.48	.42
Wald-S		6.39**		18.80**		7.57**		3.99**
Wald-L		7.37**		.00		23.73**		.15

Table 1: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Policy Uncertainty)								
	Washington		Wisconsin		West Virginia		Wyoming	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.12(.31)		.15(.52)	-.60(2.98)**	.30(.86)
$\Delta \text{LnGINI}_{t-2}$.37(1.26)	-.37(2.05)**	-.68(2.69)**
$\Delta \text{LnGINI}_{t-3}$								-.76(2.77)**
ΔLnRGDP	.13(.56)	-.09(.47)	-.21(1.36)	-.20(.97)	-.10(.24)	.32(.45)	-.11(1.04)	-.40(3.16)**
$\Delta \text{LnRGDP}_{t-1}$.08(.44)	.40(2.14)**	-.13(.90)	.10(.23)		.20(.24)	-.21(2.05)**	.15(1.28)
$\Delta \text{LnRGDP}_{t-2}$.20(.87)	.27(1.23)	.02(.18)	.45(1.39)		-1.34(1.74)*		-.19(1.56)
$\Delta \text{LnRGDP}_{t-3}$	-.42(1.50)	-.41(1.42)	-.41(2.95)**			-1.06(2.33)**		
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnPU_t	-.02(.54)		-.03(2.26)**		-.05(1.72)*		-.03(1.90)*	
ΔLnPU_{t-1}	.02(.43)							
ΔLnPU_{t-2}	.06(1.58)							
ΔLnPU_{t-3}								
ΔLnPU_{t-4}								
ΔPOS_t		.03(.67)		-.05(1.45)		-.03(.32)		.04(1.06)
ΔPOS_{t-1}		.07(1.20)		.00(.13)				.09(2.53)**
ΔPOS_{t-2}		.13(2.17)**		.01(.24)				.09(3.16)**
ΔPOS_{t-3}				.03(.77)				
ΔPOS_{t-4}								
ΔNEG_t		-.10(1.25)		.00(.02)		-.05(.64)		-.03(.78)
ΔNEG_{t-1}				.12(2.04)**		.08(.65)		.28(4.13)**
ΔNEG_{t-2}				.08(1.62)		-1.14(1.41)		.09(1.91)*
ΔNEG_{t-3}						-1.10(1.10)		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-2.60(.92)	710.39(.02)	-1.49(1.73)*	2.66(6.41)**	3.92(1.38)	-1.10(.34)	-1.14(.18)	3.58(8.10)**
LnRGDP_t	.31(.58)	-.67.79(.02)	.14(1.92)*	-.32(7.92)**	.42(1.50)	.05(.16)	.42(.52)	-.38(9.32)**
LnPU_t	-.28(.22)		-.11(1.84)*		-.23(1.64)*		-.81(.36)	
POS_t		-3.31(.02)		-.03(3.77)**		-.07(.51)		-.05(3.91)**
NEG_t		-16.94(.02)		-.16(11.40)**		-.08(.54)		-.16(9.25)**
Panel C: Diagnostic Statistics								
F	1.01	2.12	3.94	9.73**	2.14	2.52	2.30	7.57**
$\hat{\rho}_0$ (t-ratio)	-.12(.36)	.00(.01)	-.27(2.34)	-1.12(2.68)	-.25(2.02)	-.57(2.42)	-.14(.93)	-2.36(3.98)**
LM	.94	.00	.19	.06	2.07	7.18**	1.91	1.84
RESET	2.71*	.50	.16	.88	.49	7.36**	.03	2.67
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.25	.39	.29	.24	.13	.17	.35	.69
Wald-S		2.42		1.95		.30		1.09
Wald-L		.00		15.11**		.14		179.10**

Notes:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables (k=2), the upper bound critical value of the F test is 4.47 (5.47). These come from Narayan (2005, p. 1988) for our small sample size
3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when k=2 and these come from Banerjee et al (1989, p. 276). In the nonlinear model where k=3, these critical values change to -3.46 (-3.91).

4. LM is Lagrange Multiplier test of residual serial correlation. It is distributed as χ^2 with one degree of freedom (first order). Its critical value at 10% (5%) significance level is 2.70 (3.84). These critical values are also used for Wald tests since they also have a χ^2 distribution with one degree of freedom.
5. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom.

Finally, some sensitivity analysis and robustness check has been conducted to determine if the findings are sensitive to alternative uncertainty measures. We tried the macro policy uncertainty measure and the volatility index of stock market (VIX) index. The outcome was not significantly different than the results obtained by using the policy uncertainty measure. In addition, to control for population size, each state's population was added to the model as another exogenous variable. The results for the nonlinear models are reported in Table 2. As can be seen, 13 additional states in which income inequality responds asymmetrically to changes in policy uncertainty were added to the list of 21. These 13 states are Alabama, Arkansas, Arizona, California, District of Columbia, North Carolina, New Mexico, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, and Washington.

Table 2: Full-Information Estimates of Nonlinear ARDL Models (Population)								
	U.S.	Alaska	Alabama	Arkansas	Arizona	California	Colorado	Connecticut
Panel B: Long-Run Estimates								
Constant	.22(.15)	2.29(.29)	-3.49(4.56)**	-22.55(1.46)	1.48(3.86)**	8.02(2.32)**	.41(.72)	7.80(2.70)**
LnRGDP _t	-.16(2.50)**	-.08(.13)	.70(6.96)**	3.00(1.46)	-.22(4.42)**	-.65(5.44)**	-.09(1.41)	-1.56(1.68)*
LnPop _t	.14(.43)	2.95(1.14)	-3.09(7.83)**	-10.08(1.55)	.21(1.80)*	-.53(.56)	-.02(.13)	7.09(.81)
POS _t	.03(1.77)*	-.79(1.09)	-.05(2.44)**	.01(.11)	-.09(3.13)**	.04(.78)	.06(2.52)**	-.20(.83)
NEG _t	-.06(2.14)**	-.48(.71)	-.26(7.77)**	-.67(1.91)*	-.11(3.61)**	-.23(2.50)**	-.00(.00)	-.27(2.44)**
Panel C: Diagnostic Statistics								
F	6.01**	1.89	6.86**	4.65*	4.35*	7.71**	6.10**	3.36
$\hat{\rho}_0$ (t-ratio)	-1.49(3.72)*	-.47(1.50)	-.84(4.66)**	-.37(2.04)	-1.33(4.23)**	-.37(1.39)	-1.20(3.36)	-.46(3.10)
LM	2.65	2.75*	15.79**	4.43**	1.68	.01	.92	1.83
RESET	.01	.43	4.24**	4.40**	1.01	.37	4.16**	.11
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.60	.19	.75	.56	.45	.48	.54	.36
Wald-S	.22	.12	4.66**	1.82	7.03**	.38	.27	2.63
Wald-L	8.17**	.23	46.04**	5.85**	.29	1.82	5.04**	.04
	Delaware	District of Columbia	Florida	Georgia	Hawaii	Iowa	Idaho	Illinois
Panel B: Long-Run Estimates								
Constant	.57(1.81)*	9.18(3.98)**	.29(.61)	-1.57(1.78)*	-1.64(3.68)**	1.36(3.11)**	-.30(.28)	.86(1.30)
LnRGDP _t	-.09(3.30)**	-.86(4.19)**	.01(.13)	.31(1.91)*	.10(2.36)**	-.13(3.64)**	-.03(.29)	-.44(1.50)
LnPop _t	.54(5.86)**	-.59(3.33)**	-.36(2.28)**	-1.20(2.46)**	-.16(.90)	-.62(2.75)**	-.42(1.99)*	1.27(1.07)
POS _t	-.02(1.77)*	.16(4.39)**	-.03(1.73)*	-.05(1.83)*	-.01(.61)	.01(1.14)	-.00(.02)	.02(.92)
NEG _t	.01(.67)	-.03(.68)	-.19(6.43)**	-.34(3.81)**	-.05(1.93)*	-.08(3.67)**	-.17(5.78)**	-.06(2.74)**
Panel C: Diagnostic Statistics								
F	7.47**	10.82**	4.80*	3.47	6.73**	12.21**	4.04	7.83**
$\hat{\rho}_0$ (t-ratio)	-.88(5.61)**	1.59(6.93)**	-.90(4.10)*	-.63(2.75)	-1.16(5.07)**	-1.41(5.11)**	-.69(2.19)	-.81(4.45)**
LM	8.98**	1.07	1.00	1.57	3.23*	2.46	8.79**	5.45**
RESET	4.89**	.08	.55	.31	.10	8.10**	3.66*	4.05**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.71	.74	.45	.38	.64	.82	.27	.62
Wald-S	.44	.47	7.27**	4.28**	1.71	6.78**	1.56	5.20**
Wald-L	1.64	17.04**	6.12**	4.07**	2.10	33.88**	0.21	9.16**
	Indiana	Kansas	Kentucky	Louisiana	Massachusetts	Maryland	Maine	Michigan
Panel B: Long-Run Estimates								
Constant	.05(.10)	-2.95(1.53)	-3.96(.93)	-3.36(2.20)**	-2.30(1.79)*	3.05(.95)	1.73(1.29)	1.04(.94)
LnRGDP _t	.42(1.98)**	.36(1.58)	1.23(1.26)	.50(3.78)**	-.26(2.64)**	-.34(1.22)	-.28(2.01)**	-.01(.04)
LnPop _t	-2.94(2.46)**	1.52(2.34)**	-7.26(1.40)	-1.77(7.33)**	2.46(3.74)**	-.08(.07)	2.62(4.20)**	-.68(.68)
POS _t	-.06(2.32)**	.03(1.22)	.13(.75)	.01(.43)	-.05(1.44)	.01(.22)	-.13(7.75)**	-.06(1.47)
NEG _t	-.27(4.34)**	-.06(1.82)*	-.35(1.91)*	-.04(1.22)	-.06(1.31)	-.10(.85)	-.12(4.54)**	-.12(2.57)**
Panel C: Diagnostic Statistics								
F	10.93**	3.14	1.10	4.31*	2.21	1.37	6.67**	4.21*
$\hat{\rho}_0$ (t-ratio)	-1.19(4.97)**	-.55(3.23)	-.27(1.58)	-.63(2.31)	-.25(1.41)	-.14(.88)	-.82(4.76)**	-.30(2.19)
LM	2.75*	1.15	.16	.77	.88	.21	1.70	1.80
RESET	1.13	8.28**	.94	.02	7.85**	.00	1.24	.60
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.69	.39	.28	.21	.28	.05	.52	.39
Wald-S	17.32**	.41	.09	.04	.18	.03	.02	.73
Wald-L	31.35**	7.11**	2.38	1.70	.47	.58	.92	2.69

Table 2: Full-Information Estimates of Nonlinear ARDL Models (Population)							
	Minnesota	Missouri	Mississippi	Montana	North Carolina	North Dakota	Nebraska
Panel B: Long-Run Estimates							
Constant	2.15(1.32)	.12(.18)	-22.87(2.13)**	-9.51(2.74)**	-1.58(3.58)**	.06(.02)	-2.61(2.46)**
LnRGDP _t	-.23(1.08)	.11(.82)	2.66(2.04)**	.85(2.53)**	.29(4.48)**	-.05(.23)	.24(2.12)**
LnPop _t	-.26(.27)	-1.15(1.55)	-4.83(1.42)	-1.37(2.76)**	-1.12(5.47)**	.47(1.17)	-1.08(2.77)**
POS _t	-.02(.56)	-.07(3.03)**	-.22(1.20)	-.06(1.82)*	-.04(2.08)**	-.08(1.81)*	-.03(1.85)*
NEG _t	-.14(1.61)	-.20(4.76)**	-.22(1.44)	-.09(1.48)	-.27(9.32)**	-.14(2.61)**	-.09(3.49)**
Panel C: Diagnostic Statistics							
F	2.90	4.45*	2.07	2.28	6.83**	2.08	4.42*
$\hat{\rho}_0$ (t-ratio)	-.41(1.93)	-.42(2.50)	-.19(1.69)	-.67(3.09)	-1.02(4.72)**	-.53(3.06)	-1.03(3.15)
LM	2.44	1.16	1.74	.42	4.29**	.05	3.76*
RESET	.99	5.34**	3.62*	.31	.02	.58	.36
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.27	.40	.39	.24	.66	.35	.40
Wald-S	.04	.50	.04	.67	10.29**	.00	2.68
Wald-L	2.51	.08	.04	.07	49.85**	.98	5.94**
Panel B: Long-Run Estimates							
Constant	-7.80(2.84)**	3.60(1.15)	-4.88(3.42)**	-7.80(2.84)**	.91(.25)	1.91(2.36)**	.63(.30)
LnRGDP _t	.73(2.64)**	-1.01(2.14)**	.52(3.05)**	.73(2.64)**	-.13(.63)	.08(1.15)	.17(.83)
LnPop _t	-3.11(2.85)**	3.21(2.28)**	-2.5(3.29)**	-3.11(2.85)**	-.02(.02)	-1.43(2.62)**	-2.61(9.08)**
POS _t	-.06(1.23)	-.16(1.66)	.05(1.05)	-.06(1.24)	.05(1.41)	-.09(5.86)**	-.04(1.89)*
NEG _t	-.20(2.75)**	-.17(1.50)	-.24(5.10)**	-.20(2.75)**	-.05(1.08)	-.17(8.38)**	-.29(6.45)**
Panel C: Diagnostic Statistics							
F	3.86	2.70	5.54**	3.61	2.97	5.77**	4.62*
$\hat{\rho}_0$ (t-ratio)	-.52(3.00)	-.28(1.54)	-1.03(3.97)*	-.63(3.52)	-.40(2.55)	-1.13(4.65)**	-1.01(4.46)**
LM	.41	1.54	.22	.19	3.63*	.55	1.61
RESET	1.79	.85	1.24	.03	4.89**	1.27	.12
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.40	.14	.35	.35	.28	.58	.66
Wald-S	4.30**	3.06*	1.79	1.30	.54	11.37**	10.04**
Wald-L	9.20**	.16	12.69**	.11	3.21*	69.84**	25.25**
Panel B: Long-Run Estimates							
Constant	-1.33(3.03)**	3.24(2.38)**	-2.40(2.54)**	-4.52(1.34)	-.22(.42)	-3.16(4.11)**	1.24(1.00)
LnRGDP _t	.13(2.68)**	.00(.01)	.17(1.88)*	1.03(1.37)	-.07(1.48)	.56(4.51)**	-.22(1.30)
LnPop _t	-.57(4.45)**	1.06(1.78)*	-.77(2.44)**	-5.47(1.45)	-1.12(5.58)**	-2.04(5.03)**	.24(.56)
POS _t	-.03(2.11)**	-.06(6.07)**	-.05(3.87)**	.18(.85)	-.04(3.09)**	-.07(2.47)**	-.11(1.98)*
NEG _t	-.12(5.88)**	-.08(3.90)**	-.10(4.43)**	-.59(1.98)**	-.20(9.42)**	-.33(9.01)**	-.16(2.87)**
Panel C: Diagnostic Statistics							
F	9.09**	8.86**	8.07**	9.04**	5.36**	6.70**	2.69
$\hat{\rho}_0$ (t-ratio)	-.93(4.46)**	-1.53(5.81)**	-.65(3.95)*	-.53(1.55)	-1.25(3.84)*	-1.02(4.63)**	-.44(2.48)
LM	2.57	.71	1.07	19.21**	6.15**	1.90	1.79
RESET	.18	.04	.29	.27	.97	3.40*	.12
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.71	.69	.64	.77	.41	.67	.49
Wald-S	6.85**	6.68**	3.70*	12.83***	7.62**	14.17**	2.62
Wald-L	19.70**	1.89	1.81	2.49	27.76**	39.62**	.04

Table 2: Full-Information Estimates of Nonlinear ARDL Models (Population)							
	Utah	Virginia	Vermont	Washington	Wisconsin	West Virginia	Wyoming
Panel B: Long-Run Estimates							
Constant	-4.09(.62)	6.79(2.90)**	-4.66(3.67)**	8.49(1.60)	.48(1.30)	19.16(1.69)	3.18(5.11)**
LnRGDP _t	.49(.57)	-.76(4.18)**	.38(3.27)**	-.91(1.81)*	-.03(.37)	-.47(1.27)	-.32(5.40)**
LnPop _t	-3.21(.69)	.28(.63)	-.35(1.35)	.36(1.26)	-.52(1.69)	-26.32(1.47)	.35(1.70)*
POS _t	.47(.77)	.05(2.02)**	-.11(5.90)**	.07(1.84)*	-.05(4.50)**	.15(.61)	-.08(4.47)**
NEG _t	-.20(.75)	-.13(1.64)	-.10(4.09)**	-.07(.77)	-.15(8.09)**	-.51(2.57)**	-.15(4.83)**
Panel C: Diagnostic Statistics							
F	10.50**	11.42**	4.40**	6.24**	4.75**	2.17	3.32
$\hat{\rho}_0$ (t-ratio)	-.37(.84)	-.60(3.31)	-1.03(4.37)**	-.56(3.08)	-.92(4.24)**	-.27(1.18)	-.92(3.63)
LM	3.08*	.22	2.40	2.66	1.81	3.47*	1.05
RESET	1.70	8.74**	2.36	.37	.10	.00	1.13
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.76	.86	.48	.56	.47	.26	.33
Wald-S	.95	.26	4.21**	1.79	8.63**	2.56	2.37
Wald-L	.56	4.72**	.21	2.14	21.26**	1.70	4.44**

Notes:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are three exogenous variables (k=3), the upper bound critical value of the F test is 4.15 (5.02). These come from Narayan (2005, p. 1988) for our small sample size
3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.68 (-4.18) In the nonlinear model where k=4 and these come from Banerjee et al (1989, p. 276).
4. LM is Lagrange Multiplier test of residual serial correlation. It is distributed as χ^2 with one degree of freedom (first order). Its critical value at 10% (5%) significance level is 2.70 (3.84). These critical values are also used for Wald tests since they also have a χ^2 distribution with one degree of freedom.
5. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom.

2.4 Conclusion

This study uses a measure of uncertainty that captures most uncertain economic or political events that is constructed for more than 20 countries using popular newspapers from each country. By collecting the volume of the news associated with an uncertain situation, the Policy Uncertainty Group constructs an index that truly reflects uncertain events at a given time. Our goal in this paper, for the first time, is to assess the effects of policy uncertainty which is said to be a relatively more comprehensive measure of uncertainty on GINI in the United States as a whole, and in each state of the United States. individually using time-series data.

Result from linear model implies that policy uncertainty does not have any significant effect on U.S income inequality. However, nonlinear model that assumes the effect of policy uncertainty is rather asymmetric shows that a decline in policy uncertainty will increase U.S. income inequality, while an increase in it does not have any significant effect.

By implementing the linear model on state- level data, we found that in Arkansas, policy uncertainty affects income inequality in the short run. However, this short run effect will not translate into long run.

Next, I estimate nonlinear model that assumes the effects are asymmetric. Results show that a rise in policy uncertainty will decrease income inequality in Arkansas while a decrease in does not have a significant effect on it. The difference in the coefficients attached to ΔPOS and ΔNEG support the asymmetric effects. Long run estimates show that only in the case of Alaska, a raise in policy uncertainty will increase income inequality and a decline in it will reduce it. Although estimates attached to POS and NEG variables seem different in size, long run asymmetric effects is not supported by Wald test reported as Wald-L in Panel C.

Finally, each state's population was added to the model as another exogenous variable. In this scenario, income inequality responds asymmetrically to changes in policy uncertainty in 13 additional states of Alabama, Arkansas, Arizona, California, District of Columbia, North Carolina, New Mexico, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, and Washington.

3. Asymmetric Link between U.S. Tariff Policy and Income Distribution: Evidence from State Level Data

3.1 Introduction

We can classify studies on distributional consequences of tariff rate into two groups. First group studies the effects using a sample of different countries, and the second group studies the regional effects in one country. From the first group, Murakami (2018) attempted to identify the channels thorough which globalization has affected income inequality in Latin American countries. He classified these channels into four groups: Stolper–Samuelson effects, within-industry skill-biased technological change, offshoring from developed countries, and technology or quality upgrading of high-productivity firms. His finding shows that increase in the relative supply of skilled workers in Mexico is the main reason of inequality reduction in the 2000s. However, this decrease in inequality in South American countries such as Brazil and Chile can be explained by the Stolper–Samuelson effect. Rojas-Vallejos and Turnovsky (2015) establish two hypotheses concerning the links between tariffs and inequality. First, a reduction in tariff rates will increase income inequality. And second, more rapidly tariff reduction stimulates more increase in income inequality both in short run and long run. They test these hypotheses empirically in Rojas-Vallejos and Turnovsky (2017) using a panel data of 37 countries over 27 years. Their findings show that tariff cuts will increase income inequality in short run; however, this effect in the long run is less conclusive. They also study the effect of tariff rate changes on income shares by quantiles and their results show that the most adversely affected agents are in lowest quantile while the agents in second richest quantile benefit the most. Their empirical evidence supports the idea that the initial level of tariff rate and speed of its changes affect the income inequality. Finally, they show that tariff reduction increases aggregate output which suggests a short run tradeoff between increase in economic activity and higher inequality.

Jaumotte et al. (2013) used a panel data of 51 countries from 1981 to 2003 to study the relationship between financial and trade globalization and income inequality. Their results show that the technological progress has a larger effect on income inequality than globalization. The reason is that globalization can affect income inequality through different channels which offset each other's effects: Raising trade will reduce income inequality; however, foreign direct investment will increase it. They also show that both financial globalization and technological progress increase the demand for skills and education. Income have increased across all sectors of the population in all countries in their sample, however, countries with higher level of education and skills shows excessive rise in income. Reuveny and Li (2003) over a sample of 69 countries during a period of 37 years from 1960 to 1996 show that trade openness and democracy reduce income inequality. However, foreign direct investments increase income inequality, and financial capital does not affect it. In this study, the income inequality is measured with Gini coefficient and openness is measured with trade flows, foreign direct investment inflows, and financial capital inflows. Asteriou et al. (2014) over a panel of the EU-27 countries from 1995 to 2009 found that trade openness improves income inequality. However, financial globalization through FDI, stock market capitalization and capital account openness worsen it. Among these factors, FDI shows the highest contribution to inequality stem. Edwards (1997) found no evidence connecting trade openness and liberalization to increases in income inequality in a sample of 70 developing countries over the period of 1980 to 1999. Bin Grace Li, et al. (2018) studied the city and individual-level datasets for about 162 cities and 60,000 urban households in China over the period 2002 to 2009 following China's entry of WTO. They show that urban areas that experienced greater degree of trade openness also experienced greater increases in both output and income inequality. The city level data shows that trade openness stimulate

growth but also increase inequality and the household level data provide more detailed analysis into the issue. It shows that higher income and higher educated group benefit more from the same trade openness, implying a heterogeneous impact on individuals as well as a continuous rise in inequality in the urban areas.

From the studies on state-level data in one country, Wan et al. (2007) use a panel of 29 regions in China over 15 years (1987–2001) and show that a positive and substantial share of regional inequality is due to globalization and the share rises over time. However, domestic capital is the largest contributor to regional inequality. They also show that economic reform characterized by privatization has an increasingly significant impact on regional inequality; while the impacts of education, location, urbanization, and dependency ratio on regional inequality have been decline. Castilho et al. (2012) using detailed microdata from 1987 to 2005 on Brazilian states find that states subjected to more tariff cuts had experienced smaller decreases in household poverty and inequality. They also find that trade liberalization contributes to inequality increases in urban areas while it may be associated with inequality declines in rural areas. Zakaria et al. (2016) used a panel data of 40 years for the period of 1973 to 2012 for China and the South Asian Association for Regional Cooperation countries. Their empirical finding show that trade liberalization policies widen income inequality in studied countries. Per capita income growth can increase income inequality, while education, financial development, financial openness, democracy, and government size can reduce inequality. Rivas (2007) tested the hypothesis that a region's ability to benefit from trade openness depends on its critical endowments. And the geographic distribution of region's endowments can affect the range of inequality reduction. They tested this hypothesis in Mexico, using statistical analysis of an original sub-national dataset from 1940 to 2000. Their results show that trade openness benefits more the regions with

lower levels of education and also regions with higher levels of income and infrastructure; so, it will decrease income inequality through the former effect and increase it through the latter. This latter effect is stronger than the former one, so the overall effect of trade openness is to increase regional inequality. Székely and Sámano (2012) assembled a database on within country income distribution indicators which are estimated from household surveys for the years 1980 to 2010 in Latin America. They conclude that the greater trade openness is associated with the rises in inequality in the region. Moreover, they find that trade openness contributed with other factors to the increase in inequality during the 1980s and 1990s. However, it did not lead to further rises in inequality, because of offsetting effect of some other factors such as greater education levels across the population. Jalil (2012) using Auto Regressive Distributed Lag (ARDL) estimator found that Kuznets curve fits the relationship between openness and equality in China. His empirical results show that income inequality rises with the increase in openness and then starts fall after a critical point. However, he did not consider that the effects can be asymmetric. Here, I use Nonlinear Auto Regressive Distributed Lag method within the traditional Kuznets model and explores the asymmetric links between tariff rate and income inequality in U.S. and in each state.

3.2 Model and Methodology³

The linear and nonlinear model are discussed in detail in part 2.2. The only difference is that here, the main explanatory variable is U.S. average tariff rate.

4.3.1 The Linear Model

I test the effect of tariff rate on income distribution through the Kuznets model following long run model (1):

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma \ln TR_t + \epsilon_t \quad (1)$$

Where Gini index is a measure of income inequality, Y is per-capita real personal income or GDP, and TR is U.S average tariff rate. All variables are in state level here. If economic development reduces income inequality, an estimate of β should be negative. The error correction model can be rewritten by as follows:

$$\begin{aligned} \Delta \ln Gini_t = & \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_{kj} \Delta \ln TR_{t-j} + \lambda_1 \ln Gini_{t-1} + \\ & \lambda_2 \ln Y_{t-1} + \lambda_3 \ln TR_{t-1} + u_t \end{aligned} \quad (2)$$

By applying OLS to the above error-correction model, short run and long run effects of exogenous variables on income inequality can be estimated in one step.

4.3.2. The Nonlinear Model

Again, we use the partial sum concept to generate two new time-series variables POS and NEG as:

$$\begin{aligned} POS_t &= \sum_{j=1}^t \Delta \ln TR_t^+ = \sum_{j=1}^t \max(\Delta \ln TR_j, 0) \\ NEG_t &= \sum_{j=1}^t \Delta \ln TR_t^- = \sum_{j=1}^t \min(\Delta \ln TR_j, 0) \end{aligned}$$

³ This section closely follows Bahmani-Oskooee et al. (2018) and Bahmani-Oskooee and Harvey (2020).

We represent nonlinear long run and Error Correction specifications by replacing *lnTR* variable with *POS* and *NEG* from equation (1) and (3) as follows:

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma_1 POS_t + \gamma_2 NEG_t + \epsilon_t \quad (3)$$

$$\begin{aligned} \Delta \ln Gini_t = & \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_j^+ \Delta POS_{t-j} + \\ & \sum_{j=0}^{n_4} \Gamma_j^- \Delta NEG_{t-j} + \rho_0 \ln Gini_{t-1} + \rho^+ POS_{t-1} + \rho^- NEG_{t-1} + \vartheta_t \end{aligned} \quad (4)$$

3.3 Results

In this chapter, the Linear and Nonlinear model results, which is identified by L-ARDL and NL-RDL respectively, are reported in Table 1. Panel A represent the short run and Panel A represent the long run outcomes for U.S. as a whole and for 50 states of US as well as Discrete of Colombia. The annual data is covered a long period from 1917 to 2015⁴. The maximum number of four lags is imposed on each first-differenced variable and Akaike's information criterion is applied to select an optimum model.

Several additional diagnostic statistics are also reported (panel C). An insignificant Lagrange Multiplier test (LM) supporting the fact that there is no autocorrelation between residuals. An insignificant Ramsey's RESET test is also that supports the fact that there is no model misspecification. Following the literature, we also applied the CUSUM and CUSUMSQ tests to determine the stability of all estimated coefficients. These tests are reported as *QS* and *QS*² respectively where an assigned "S" value shows the coefficients are stable and "US" indicates estimated coefficients are unstable. And finally, reported adjuster *R*² shows the goodness of fit.

⁴ Appendix is provided for more information about the data.

Results from both linear and nonlinear models show that economic growth widens U.S income inequality in the short run and reduce it after one lag (Table 1- Panel A). However, it increases income inequality in the long run (Table 1- Panel B). From both linear and nonlinear model, we did not find any significant links between tariff rate and aggregate Gini index. However, state-level data provide different results. Estimates of the linear model indicate that tariff cuts will increase income inequality in Alaska, Connecticut, Delaware, Nevada, and Washington in and decrease it in North Carolina in the short run. These results come from negative and significant coefficient of $\Delta LnTR$ in the first five states and positive and significant coefficient of $\Delta LnTR$ in North Carolina. In the long run, $LnTR$ estimated coefficient is positive and significant in the case of Alaska, Iowa, and Utah; implying that a reduction in tariff rate reduces income inequality in these states. Cointegration between variables is supported by F and t-test in this state (Panel B). So, the study of linear model show that average tariff rate has significant short-run effect on income inequality in six states and significant long-run effect in three states. Next, we estimate nonlinear model to see if tariff rate changes have asymmetric effects.

Short run estimates of nonlinear model show that either ΔPOS or ΔNEG carry at least one lagged significant coefficient in following 22 states: Alaska, Arizona, Arkansas, Connecticut, Delaware, District of Columbia, Hawaii, Iowa, Kentucky, Louisiana, Maine, Missouri, North Carolina, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Dakota, Virginia, Washington, and West Virginia. The short run effects are asymmetric since the estimated coefficient of ΔPOS_{t-j} at any given lag order j , is different from the one of ΔNEG_{t-j} . This increase in the number of states from six (linear models) to 22 (nonlinear models) must be attributed to the nonlinear adjustment of the tariff rate. However, Wald test results for the short-run (Wald-S in Panel C) is significant only for 20 states: Alabama, Alaska, Arizona, Arkansas,

Delaware, District of Columbia, Iowa, Maine, Michigan, Missouri, Mississippi, North Carolina, New Hampshire, New Mexico, Oklahoma, Oregon, Pennsylvania, Rhode Island, Tennessee, and West Virginia. A significant Wald test rejects the hypothesis that the sum of the coefficients attached to ΔPOS_{t-j} is equal to the sum attached to ΔNEG_{t-j} . It shows the cumulative asymmetric effects of tariff changes on income inequality in above mentioned states. These short run effects last into long run in 12 states of Alaska, Arizona, Connecticut, District of Columbia, Iowa, Idaho, Illinois, Indiana, New Hampshire, New Jersey, Pennsylvania, and Utah since either the POS or the NEG variables carries a significant coefficient. Cointegration in these states is supported by either the F or t-test.

This increase in the number of states that are affected in the long run from three (linear model) to twelve, must be attributed to nonlinear adjustment of the tariff rate. Clearly, our findings are state specific. For example, consider the case of Iowa and Alaska. The linear model shows a significant and positive relationship between average tariff rate and income inequality in these states. This implies that tariff cuts will reduce inequality in the long run. However, the nonlinear model predicts that while a decreased tariff rate will reduce inequality, an increased tariff rate will have no long run effects in these states. Or consider the case of Arizona. The linear model implies that tariff rate does not have any significant distributional effect in the long run. However, nonlinear estimates show that increase in tariff rate (POS variable) will increase income inequality in this state. In this case, the NEG variable is insignificant, implying that tariff cuts have not long run effects on income inequality in Arizona. The long run asymmetric effects are supported by the Wald test) not just in Arizona but also in Indiana, District of Columbia, Idaho, and Pennsylvania.

Furthermore, estimated coefficient of NEG variable in non-linear model implies that a tariff reduction will increase income inequality in Idaho and will reduce it in Alaska, Connecticut, Iowa, Illinois, Indiana, New Hampshire, New Jersey, Ohio, Pennsylvania, and Utah. On the other hand, estimated coefficient of POS variable implies that an increase in tariff rate will increase income inequality in Arizona, District of Columbia, and Idaho and will decrease it in West Virginia.

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	U.S.		Alabama		Alaska		Arizona	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}$								
$\Delta \ln \text{GINI}_{t-1}$	-.00(.01)	-.01(.13)			.24(1.76)*	.26(2.14)**	-.16(1.35)	
$\Delta \ln \text{GINI}_{t-2}$	-.22(2.08)**	-.23(2.17)**			.17(1.30)		-.14(1.37)	
$\Delta \ln \text{GINI}_{t-3}$								
$\Delta \ln \text{RGDP}$	-.01(.51)	-.01(.35)	.02(1.08)	.02(.98)	-.02(.15)	.04(.68)	.04(2.14)**	.04(2.01)**
$\Delta \ln \text{RGDP}_{t-1}$	-.02(1.08)	-.02(1.07)			-.12(1.92)*	-.13(2.14)**		-.06(2.85)**
$\Delta \ln \text{RGDP}_{t-2}$.06(2.71)**	.05(2.43)**			.12(2.16)**	.14(2.43)**		
$\Delta \ln \text{RGDP}_{t-3}$	-.06(3.38)**	-.06(3.33)**			-.16(3.26)**	-.20(3.69)**		
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{TR}_t$.00(.15)		-.01(.24)		-.017(.36)		.03(1.48)	
$\Delta \ln \text{TR}_{t-1}$					-.08(1.63)			
$\Delta \ln \text{TR}_{t-2}$.07(1.45)			
$\Delta \ln \text{TR}_{t-3}$					-.10(1.85)*			
$\Delta \ln \text{TR}_{t-4}$								
ΔPOS_t		-.04(.88)		-.07(1.28)		-.10(.97)		.00(.03)
ΔPOS_{t-1}						-.06(.53)		-.09(1.93)*
ΔPOS_{t-2}						-.06(.57)		-.10(2.21)**
ΔPOS_{t-3}						-.35(3.26)**		
ΔPOS_{t-4}								
ΔNEG_t		.02(1.01)		.02(.73)		.05(.76)		.02(.69)
ΔNEG_{t-1}						-.05(.76)		
ΔNEG_{t-2}						.15(2.27)**		
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.12(.69)	.22(3.62)**	.29(1.77)*	.30(5.85)**	-.70(2.93)**	-.06(.52)	.28(2.53)**	.34(10.62)**
$\ln \text{RGDP}_t$.05(3.17)**	.08(3.10)**	.03(2.02)**	.05(1.68)*	.12(5.69)**	.15(5.52)**	.03(3.47)**	.01(.85)
$\ln \text{TR}_t$.05(1.02)		.01(.19)		.23(4.45)**		.00(.00)	
POS_t		-.07(.83)		-.09(.77)		-.02(.10)		.08(1.73)*
NEG_t		.06(1.55)		.03(.57)		.21(5.27)**		-.02(.86)
Panel C: Diagnostic Statistics								
F	5.25**	4.13	3.50	2.43	5.13**	5.22**	3.27	6.88**
$\hat{\rho}_0$ (t-ratio)	-.14(2.98)	-.16(3.17)	-.19(3.09)	-.19(3.04)	-.34(3.79)**	-.40(4.33)**	-.29(2.96)	-.46(5.23)**
LM	.00	.00	.00	.29	.30	.73	1.72	1.52
RESET	.39	1.96	1.53	2.52	.38	.01	2.83*	1.04
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.20	.20	.12	.11	.35	.42	.19	.28
Wald-S		.10		3.93**		5.29**		4.51**
Wald-L		.06		.21		1.53		4.05**

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Arkansas		California		Colorado		Connecticut	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$								
$\Delta \text{LnGINI}_{t-2}$								
$\Delta \text{LnGINI}_{t-3}$								
$\Delta \text{LnGINI}_{t-4}$								
ΔLnRGDP	.05(2.84)**	.05(2.75)**	.03(1.10)	.03(1.10)	.07(3.31)**	.08(3.49)**	.00(.03)	-.01(.38)
$\Delta \text{LnRGDP}_{t-1}$			-.11(3.76)**	-.11(3.70)**	-.05(2.60)**	-.06(2.76)**	-.08(2.77)**	-.07(2.42)**
$\Delta \text{LnRGDP}_{t-2}$.09(3.25)**	.09(3.13)**			.06(2.13)**	.05(1.71)*
$\Delta \text{LnRGDP}_{t-3}$			-.07(3.17)**	-.07(3.16)**			-.07(3.29)**	-.08(3.45)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	.02(.67)		-.00(.26)		.03(1.19)		.01(.43)	
ΔLnTR_{t-1}							-.04(1.89)*	
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		-.11(1.93)*		-.00(.09)		.03(.59)		-.04(.68)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.07(2.18)**		-.00(.07)		.03(.91)		.03(1.05)
ΔNEG_{t-1}								-.06(1.91)*
ΔNEG_{t-2}								-.05(1.44)
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.39(3.05)**	.39(7.64)**	.12(.75)	.18(2.67)**	.17(1.25)	.26(5.24)**	.00(.02)	.14(1.69)*
LnRGDP_t	.02(1.89)*	.03(1.03)	.05(3.96)**	.07(2.59)**	.04(3.29)**	.06(2.50)**	.06(3.42)**	.08(2.57)**
LnTR_t	-.01(.35)		.03(.81)		.04(1.07)		.07(1.27)	
POS_t		-.14(1.10)		-.02(.24)		-.03(.38)		.06(.44)
NEG_t		-.03(.59)		.04(1.03)		.06(1.43)		.10(1.79)*
Panel C: Diagnostic Statistics								
F	2.94	2.52	4.95*	3.66	3.67	3.03	6.14**	5.10**
$\hat{\rho}_0$ (t-ratio)	-.21(2.97)	-.20(2.89)	-.18(3.50)*	-.19(3.39)	-.21(3.10)	-.24(3.24)	-.15(3.68)**	-.17(3.63)*
LM	.05	.88	.38	.37	.03	.01	.04	.16
RESET	.95	1.85	1.40	1.44	2.30	1.29	1.82	3.52*
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.15	.18	.22	.20	.21	.20	.23	.24
Wald-S		5.80**		.00		.00		.11
Wald-L		.75		.20		1.13		.00

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Delaware		District of Columbia		Florida		Georgia	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$			-.27(2.54)**	-.22(1.94)*			-.36(2.93)**	-.39(3.07)**
$\Delta \text{LnGINI}_{t-2}$							-.28(2.62)**	-.30(2.75)**
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.01(.30)	-.02(.64)	.12(3.15)**	.07(1.81)*	-.01(.33)	-.00(.18)	.03(1.68)*	.04(1.85)*
$\Delta \text{LnRGDP}_{t-1}$	-.10(3.28)**	-.11(3.48)**	-.05(1.69)*	-.08(2.50)**	-.05(1.75)*	-.05(1.79)*		
$\Delta \text{LnRGDP}_{t-2}$.08(3.11)**	.08(2.91)**		
$\Delta \text{LnRGDP}_{t-3}$					-.08(3.96)**	-.08(3.84)**		
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.03(.84)		.03(1.31)		.01(.45)		.01(.66)	
ΔLnTR_{t-1}	-.06(1.95)*							
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		-.17(2.18)**		.03(.40)		-.05(.81)		-.03(.46)
ΔPOS_{t-1}		-.15(2.25)**		-.09(1.69)*				
ΔPOS_{t-2}				-.12(2.20)**				
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.02(.43)		.01(.32)		.03(1.20)		.04(1.15)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.33(.95)	.60(3.85)**	.10(1.02)	.25(6.92)**	-.02(.05)	.24(1.84)*	.12(.34)	.24(1.87)*
LnRGDP_t	.02(.79)	.02(.30)	.05(5.95)**	.03(2.02)**	.07(1.86)*	.11(1.77)*	.05(1.47)	.09(1.12)
LnTR_t	.06(.70)		.04(1.51)		.11(.99)		.06(.57)	
POS_t		-.08(.43)		.12(2.62)**		-.08(.38)		-.08(.36)
NEG_t		.00(.03)		.02(.78)		.14(1.25)		.36(.70)
Panel C: Diagnostic Statistics								
F	4.34*	3.15	4.25*	4.65*	2.44	1.81	1.34	1.03
$\hat{\rho}_0$ (t-ratio)	-.14(3.19)	-.15(3.24)	-.37(3.48)*	-.47(4.21)**	-.08(2.06)	-.08(2.20)	-.07(1.16)	-.07(1.07)
LM	1.34	.71	.04	1.20	.14	.00	.89	.33
RESET	.03	.86	.21	.45	.43	.26	8.76**	6.96**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.15	.18	.31	.36	.15	.15	.14	.12
Wald-S		8.40**		3.00*		1.25		.73
Wald-L		.30		4.92**		.81		.35

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Hawaii		Iowa		Idaho		Illinois	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}$								
$\Delta \ln \text{GINI}_{t-1}$					-.24(2.05)**		-.05(.47)	-.04(.38)
$\Delta \ln \text{GINI}_{t-2}$					-.24(2.28)**		-.27(2.68)**	-.27(2.67)**
$\Delta \ln \text{GINI}_{t-3}$								
$\Delta \ln \text{RGDP}$.06(1.80)*	.07(1.89)*	.01(1.22)	.01(1.02)	.02(1.05)	.01(.62)	.00(.01)	.00(.11)
$\Delta \ln \text{RGDP}_{t-1}$	-.01(.23)	-.02(.47)					-.01(.59)	-.01(.61)
$\Delta \ln \text{RGDP}_{t-2}$	-.03(.89)	-.04(1.03)					.06(3.13)**	.05(2.81)**
$\Delta \ln \text{RGDP}_{t-3}$	-.08(2.61)**	-.08(2.56)**					-.07(4.48)**	-.07(4.49)**
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{TR}_t$.03(1.46)		.02(.82)		-.01(.57)		.02(1.33)	
$\Delta \ln \text{TR}_{t-1}$								
$\Delta \ln \text{TR}_{t-2}$								
$\Delta \ln \text{TR}_{t-3}$								
$\Delta \ln \text{TR}_{t-4}$								
ΔPOS_t		-.01(.21)		-.06(1.26)		-.00(.08)		.00(.06)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.06(1.80)*		.05(1.74)*		-.04(1.00)		.04(1.53)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.24(2.38)**	.34(6.18)**	.16(3.19)**	.27(13.22)**	.30(3.33)**	.27(12.81)**	-.01(.04)	.15(2.00)**
$\ln \text{RGDP}_t$.03(3.62)**	.04(2.78)**	.04(8.77)**	.04(4.34)**	.03(4.19)**	.01(1.18)	.06(3.37)**	.09(3.04)**
$\ln \text{TR}_t$.03(1.27)		.05(3.41)**		-.02(.72)		.07(1.39)	
POS_t		-.05(.55)		.03(.87)		.07(2.12)**		-.03(.36)
NEG_t		.02(1.08)		.05(3.16)**		-.04(2.16)**		.09(1.82)*
Panel C: Diagnostic Statistics								
F	4.34*	3.46	10.95**	8.32**	3.53	8.59**	6.02**	4.82*
$\hat{\rho}_0$ (t-ratio)	-.32(3.50)*	-.33(3.55)*	-.53(5.70)**	-.54(5.64)**	-.36(3.20)	-.62(5.83)**	-.13(3.00)	-.15(3.23)
LM	.48	.57	.02	.21	.12	.86	.44	.22
RESET	.84	.54	.22	.18	.75	.21	.83	.20
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.25	.25	.27	.28	.28	.29	.31	.31
Wald-S		.10		2.87*		.14		.37
Wald-L		.59		.11		8.76**		2.00

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Indiana		Kansas		Kentucky		Louisiana	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}$								
$\Delta \ln \text{GINI}_{t-1}$	-.00(.03)	.00(.00)	-.12(1.13)	-.16(1.43)	.11(1.03)			
$\Delta \ln \text{GINI}_{t-2}$	-.12(1.10)	-.12(1.11)	-.23(2.22)**	-.25(2.40)**				
$\Delta \ln \text{GINI}_{t-3}$.21(1.95)*	.24(2.20)**						
$\Delta \ln \text{RGDP}$	-.00(.16)	.00(.01)	-.02(1.29)	-.02(1.11)	-.02(1.23)	-.02(.97)	.02(.85)	-.00(.01)
$\Delta \ln \text{RGDP}_{t-1}$.00(.05)	.00(.05)						
$\Delta \ln \text{RGDP}_{t-2}$.01(.56)	.00(.11)						
$\Delta \ln \text{RGDP}_{t-3}$	-.04(2.98)**	-.05(3.20)**						
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{TR}_t$.01(.49)		-.02(.87)		-.02(1.01)		-.01(.58)	
$\Delta \ln \text{TR}_{t-1}$								
$\Delta \ln \text{TR}_{t-2}$								
$\Delta \ln \text{TR}_{t-3}$								
$\Delta \ln \text{TR}_{t-4}$								
ΔPOS_t		-.00(.10)		-.07(1.31)		-.10(1.77)*		-.04(.53)
ΔPOS_{t-1}								-.02(.28)
ΔPOS_{t-2}								-.10(1.80)*
ΔPOS_{t-3}								.13(2.43)**
ΔPOS_{t-4}								
ΔNEG_t		.03(1.04)		.01(.30)		.00(.07)		-.02(.45)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.15(1.12)	.21(4.27)**	.32(4.21)**	.30(9.76)**	.30(2.51)**	.31(7.46)**	.31(2.07)**	.30(4.87)**
$\ln \text{RGDP}_t$.04(3.42)**	.07(3.12)**	.03(4.07)**	.05(2.75)**	.03(2.69)**	.05(2.04)**	.03(2.35)**	.04(1.11)
$\ln \text{TR}_t$.04(1.05)		.00(.13)		.01(.36)		-.00(.02)	
POS_t		-.07(1.00)		-.06(1.13)		-.07(.82)		-.04(.37)
NEG_t		.06(1.74)*		.02(.85)		.03(.85)		-.00(.05)
Panel C: Diagnostic Statistics								
F	3.99	3.69	6.06**	4.64*	7.95**	6.11**	3.97	2.36
$\hat{\rho}_0$ (t-ratio)	-.17(3.23)	-.20(3.57)*	-.38(4.08)**	-.38(4.04)**	-.27(3.91)**	-.30(4.57)**	-.24(3.41)*	-.22(3.03)
LM	.16	.02	.16	.04	.85	1.06	.45	1.73
RESET	8.90**	15.56**	.44	.37	.69	2.95*	.77	1.31
QS(QS ²)	US(S)	S(S)	US(S)	S(S)	S(S)	S(S)	S(S)	US(S)
Adjusted R ²	.13	.14	.25	.24	.12	.25	.11	.11
Wald-S		.26		1.26		1.87		0.00
Wald-L		2.85*		.56		.70		.07

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Massachusetts		Maryland		Maine		Michigan	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$					-.14(1.38)	-.16(1.59)		
$\Delta \text{LnGINI}_{t-2}$								
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP_t	.03(1.01)	.03(.97)	-.01(.40)	-.01(.49)	-.05(1.90)*	-.05(1.65)*	-.03(1.45)	-.02(1.14)
$\Delta \text{LnRGDP}_{t-1}$	-.09(3.35)**	-.09(3.27)**		-.03(1.14)			-.00(.21)	-.01(.33)
$\Delta \text{LnRGDP}_{t-2}$.08(2.99)**	.08(2.85)**		.04(1.91)*			.05(2.65)**	.05(2.52)**
$\Delta \text{LnRGDP}_{t-3}$	-.09(3.89)**	-.09(3.92)**		-.04(2.45)**			-.06(3.81)**	-.06(3.81)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	.01(.40)		-.02(.98)		-.04(1.37)		.00(.01)	
ΔLnTR_{t-1}								
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		.04(.73)		-.06(1.23)		-.20(2.56)**		-.09(1.53)
ΔPOS_{t-1}				.06(1.50)				
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.00(.03)		-.01(.22)		.03(.68)		.04(1.20)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.15(1.02)	.23(4.33)**	.13(.87)	.29(5.92)**	.20(1.32)	.31(5.91)**	.19(1.13)	.21(2.98)**
LnRGDP_t	.05(3.80)**	.06(2.56)**	.04(3.10)**	.03(1.59)	.04(2.56)**	.06(2.63)**	.04(2.70)**	.06(2.04)**
LnTR_t	.04(1.02)		.05(1.17)		.05(1.12)		.02(.46)	
POS_t		-.00(.05)		.05(.71)		-.11(1.26)		-.06(.57)
NEG_t		.04(1.18)		.03(.96)		.06(1.41)		.04(.81)
Panel C: Diagnostic Statistics								
F	5.84**	4.48*	12.03**	3.46	5.72**	4.14	4.10	3.32
$\hat{\rho}_0$ (t-ratio)	-.19(3.69)**	-.20(3.60)*	-.27(5.43)**	-.20(3.10)	-.31(3.95)**	-.32(3.98)**	-.17(3.26)*	-.19(3.44)
LM	.00	.03	.68	.26	.23	1.55	.73	1.91
RESET	.37	.78	7.79**	.00	4.81**	5.77**	6.96**	11.79**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.25	.24	.34	.15	.20	.23	.21	.22
Wald-S		.31		.03		4.91**		2.92*
Wald-L		.37		.12		2.18		.45

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Minnesota		Missouri		Mississippi		Montana	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}_t$.01(.64)							
$\Delta \ln \text{GINI}_{t-1}$.17(1.58)			
$\Delta \ln \text{GINI}_{t-2}$.17(1.54)			
$\Delta \ln \text{GINI}_{t-3}$								
$\Delta \ln \text{RGDP}_t$.00(.21)	.02(.95)	.01(.67)	.04(2.06)**	.05(3.03)**	.03(1.71)*	.03(1.34)
$\Delta \ln \text{RGDP}_{t-1}$								
$\Delta \ln \text{RGDP}_{t-2}$								
$\Delta \ln \text{RGDP}_{t-3}$								
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{TR}_t$	-.00(.18)		-.02(.95)		.01(.21)		.00(.07)	
$\Delta \ln \text{TR}_{t-1}$								
$\Delta \ln \text{TR}_{t-2}$								
$\Delta \ln \text{TR}_{t-3}$								
$\Delta \ln \text{TR}_{t-4}$								
ΔPOS_t		-.03(.57)		-.11(2.28)**		-.10(1.60)		.00(.04)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.00(.06)		.02(.68)		.07(1.83)*		-.00(.06)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.22(1.91)*	.29(6.59)**	.27(1.43)	.30(3.83)**	.43(2.79)**	.35(5.48)**	.17(1.80)*	.21(4.90)**
$\ln \text{RGDP}_t$.03(3.48)**	.03(1.63)	.03(1.84)*	.04(1.19)	.02(1.30)	.08(1.68)*	.05(5.32)**	.05(2.49)**
$\ln \text{TR}_t$.03(.94)		.01(.27)		-.03(.59)		.01(.58)	
POS_t		.03(.40)		-.05(.39)		-.28(1.49)		.01(.22)
NEG_t		.03(.82)		.02(.34)		.03(.40)		.02(.50)
Panel C: Diagnostic Statistics								
F	7.60**	5.76**	4.34*	2.82	3.31	2.08	7.40**	5.51**
$\hat{\rho}_0$ (t-ratio)	-.28(4.46)**	-.26(3.99)**	-.17(3.17)	-.16(2.91)	-.20(3.14)	-.15(2.55)	-.42(4.70)**	-.41(4.50)**
LM	.35	.05	.41	.17	.01	2.22	.09	.05
RESET	1.10	.83	3.03*	1.38	4.18**	1.41	.26	.09
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.26	.26	.20	.23	.12	.13	.21	.19
Wald-S		.21		4.06**		4.01**		.00
Wald-L		.83		.01		1.70		.25

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	North Carolina		North Dakota		Nebraska		New Hampshire	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.18(1.48)	.17(1.40)			-.20(1.98)**	-.21(2.02)**
$\Delta \text{LnGINI}_{t-2}$			25(2.32)**	.24(2.12)**				
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	.01(.33)	.02(.94)	-.00(.26)	-.00(.10)	.00(.20)	-.00(.16)	.03(1.24)	.04(1.36)
$\Delta \text{LnRGDP}_{t-1}$							-.06(2.41)**	-.07(2.50)**
$\Delta \text{LnRGDP}_{t-2}$								
$\Delta \text{LnRGDP}_{t-3}$								
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.02(1.27)		-.00(.11)		.00(.06)		-.01(.20)	
ΔLnTR_{t-1}	.01(.49)							
ΔLnTR_{t-2}	-.02(1.27)							
ΔLnTR_{t-3}	.05(2.89)**							
ΔLnTR_{t-4}								
ΔPOS_t		-.11(2.12)**		-.08(1.20)		-.05(.89)		-.09(1.54)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.01(.33)		.02(.59)		.02(.65)		.03(.98)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.46(2.29)**	.42(6.44)**	.26(5.33)**	.29(15.91)**	.26(4.96)**	.31(14.34)**	.09(.57)	.24(4.92)**
LnRGDP_t	.02(.95)	.04(1.13)	.03(7.58)**	.03(2.95)**	.03(6.86)**	.03(3.01)**	.05(3.44)**	.07(3.37)**
LnTR_t	-.04(.73)		.01(.85)		.02(1.22)		.07(1.58)	
POS_t		-.24(1.43)		.01(.32)		.01(.43)		-.06(.72)
NEG_t		-.05(.94)		.01(.65)		.02(1.04)		.08(2.16)**
Panel C: Diagnostic Statistics								
F	3.86	3.50	9.29**	6.93**	10.18**	8.04**	5.41**	3.73
$\hat{\rho}_0$ (t-ratio)	-.11(2.64)	-.13(2.90)	-.64(5.23)**	-.64(5.10)**	-.54(5.51)**	-.55(5.60)**	-.24(3.59)*	-.26(3.55)*
LM	.00	.32	.18	.17	.08	.02	.48	1.06
RESET	.24	1.34	.53	.89	1.54	2.84*	.15	.11
QS(QS ²)	US(S)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.12	.12	.25	.25	.24	.24	.19	.20
Wald-S		6.16**		1.31		.89		14.68**
Wald-L		1.12		.04		.18		.92

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	New Jersey		New Mexico		Nevada		New York	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}_t$								
$\Delta \ln \text{GINI}_{t-1}$			-.21(1.67)*	-.16(1.14)	-.16(1.56)	-.18(1.67)*	-.08(.67)	-.08(.68)
$\Delta \ln \text{GINI}_{t-2}$			-.13(1.19)	-.08(.64)			-.27(2.50)**	-.27(2.44)**
$\Delta \ln \text{GINI}_{t-3}$.17(1.61)				
$\Delta \ln \text{RGDP}_t$	-.02(.76)	-.02(.67)	.03(1.10)	-.01(.31)	.05(1.92)*	.04(1.48)	.00(.09)	.01(.22)
$\Delta \ln \text{RGDP}_{t-1}$	-.03(1.24)	-.03(1.25)			-.08(3.04)**	-.07(2.75)**	-.04(1.27)	-.04(1.27)
$\Delta \ln \text{RGDP}_{t-2}$.04(1.65)*	.04(1.58)					.06(1.93)*	.05(1.70)*
$\Delta \ln \text{RGDP}_{t-3}$	-.06(2.89)**	-.06(2.80)**					-.07(2.78)**	-.07(2.80)**
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{TR}_t$	-.01(.59)		-.04(1.13)		.02(.72)		.02(.92)	
$\Delta \ln \text{TR}_{t-1}$					-.07(2.27)**			
$\Delta \ln \text{TR}_{t-2}$								
$\Delta \ln \text{TR}_{t-3}$								
$\Delta \ln \text{TR}_{t-4}$								
ΔPOS_t		-.03(.68)		-.13(1.68)*		-.04(.59)		-.01(.23)
ΔPOS_{t-1}				-.08(1.15)				
ΔPOS_{t-2}				-.14(2.29)**				
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.00(.07)		-.01(.13)		.05(1.07)		.04(1.31)
ΔNEG_{t-1}						-.08(2.01)**		
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.04(.29)	.18(3.15)**	.32(3.31)**	.35(9.93)**	.16(.73)	.23(2.21)**	-.12(.37)	.09(.75)
$\ln \text{RGDP}_t$.06(4.17)**	.07(2.87)**	.03(3.32)**	.00(.19)	.05(2.56)**	.04(.97)	.08(2.67)**	.11(2.87)**
$\ln \text{TR}_t$.06(1.49)		-.01(.28)		.03(.47)		.09(1.15)	
POS_t		.01(.11)		.07(1.12)		.08(.55)		-.08(.56)
NEG_t		.07(1.67)*		-.04(1.26)		.02(.37)		.10(1.55)
Panel C: Diagnostic Statistics								
F	6.26**	4.47*	3.94	3.75	3.95	2.92	6.26**	4.92*
$\hat{\rho}_0$ (t-ratio)	-.18(3.81)**	-.19(3.57)*	-.35(2.97)	-.47(3.72)*	-.21(3.10)	-.20(2.96)	-.10(2.59)	-.13(2.85)
LM	.15	.19	.87	1.29	.00	.30	.22	.18
RESET	2.40	2.02	.45	1.02	7.72**	10.74**	.54	.06
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	US(S)	US(S)	S(S)	S(S)
Adjusted R ²	.15	.13	.25	.30	.20	.18	.21	.21
Wald-S		.26		6.06**		.01		.52
Wald-L		.03		1.40		.38		2.04

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Ohio		Oklahoma		Oregon		Pennsylvania	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.12(1.14)	.11(1.02)			-.22(2.05)**	-.30(2.40)**	-.09(.81)	-.09(.80)
$\Delta \text{LnGINI}_{t-2}$	-.20(1.92)*	-.20(1.89)*				-.15(1.34)	-.17(1.66)*	-.17(1.69)*
$\Delta \text{LnGINI}_{t-3}$.16(1.58)	.22(2.23)**
ΔLnRGDP	-.02(1.22)	-.02(.96)	.01(.50)	-.00(.15)	.03(2.11)**	.04(1.98)**	.02(.63)	.03(1.07)
$\Delta \text{LnRGDP}_{t-1}$.00(.12)	.00(.04)				-.02(1.29)	-.07(2.77)**	-.07(2.91)**
$\Delta \text{LnRGDP}_{t-2}$.03(1.79)*	.03(1.52)					.07(2.98)**	.06(2.41)**
$\Delta \text{LnRGDP}_{t-3}$	-.05(2.99)**	-.05(2.97)**					-.06(3.10)**	-.06(3.17)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.00(.03)		-.04(1.48)		.01(.53)		.00(.22)	
ΔLnTR_{t-1}								
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		-.05(.99)		-.15(2.53)**		-.01(.21)		-.09(1.87)*
ΔPOS_{t-1}						-.10(2.41)**		
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.02(.91)		.01(.16)		.03(1.07)		.05(1.96)**
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.08(.41)	.19(2.91)**	.36(2.88)**	.36(7.59)**	.20(2.06)**	.27(6.94)**	.06(.32)	.18(3.22)**
LnRGDP_t	.05(2.87)**	.08(2.91)**	.03(2.30)**	.01(.51)	.04(4.16)**	.04(2.12)**	.05(3.14)**	.09(4.16)**
LnTR_t	.06(1.19)		-.01(.28)		.02(.76)		.06(1.20)	
POS_t		-.07(.77)		.02(.24)		-.00(.06)		-.12(1.60)
NEG_t		.08(1.75)*		-.03(.64)		.01(.34)		.08(2.26)**
Panel C: Diagnostic Statistics								
F	4.32*	3.36	4.98*	4.31*	3.29	3.22	4.70*	.36
$\hat{\rho}_0$ (t-ratio)	-.15(3.01)	-.17(3.18)	-.26(3.68)**	-.28(3.90)*	-.27(3.05)	-.27(2.88)	-.15(3.20)	-.20(3.65)*
LM	.79	1.26	.34	.00	.82	.05	.00	.01
RESET	7.54**	11.69**	.53	.09	.00	.05	10.11**	12.83**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	US(S)	S(S)	S(S)
Adjusted R ²	.16	.16	.24	.27	.20	.23	.32	.36
Wald-S		1.32		4.07**		3.38*		5.22**
Wald-L		1.47		.02		.60		4.83**

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Rhode Island		South Carolina		South Dakota		Tennessee	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$								-16(1.36)
$\Delta \text{LnGINI}_{t-2}$								-14(1.35)
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.02(.78)	.00(.03)	.03(1.99)**	.02(1.34)	.00(.29)	-.01(.86)	.03(1.77)*	.05(2.21)**
$\Delta \text{LnRGDP}_{t-1}$		-.04(1.75)*						
$\Delta \text{LnRGDP}_{t-2}$								
$\Delta \text{LnRGDP}_{t-3}$								
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.02(.71)		.01(.31)		-.01(.30)		.01(.42)	
ΔLnTR_{t-1}								
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		-.14(2.63)**		-.04(.75)		-.02(.21)		-.05(.88)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.03(1.06)		.02(.63)		.01(.37)		.04(1.40)
ΔNEG_{t-1}						.02(.57)		.04(1.56)
ΔNEG_{t-2}						.05(1.55)		
ΔNEG_{t-3}						-.07(2.01)**		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.14(.73)	.26(4.50)**	.21(.88)	.28(3.86)**	.18(2.37)**	.27(9.32)**	.32(2.19)**	.32(5.14)**
LnRGDP_t	.04(2.52)**	.06(2.61)**	.04(1.77)*	.05(1.20)	.04(6.31)**	.05(2.77)**	.03(2.15)**	.09(1.86)*
LnTR_t	.05(.97)		.03(.51)		.04(1.63)		.00(.06)	
POS_t		-.08(.86)		-.03(.19)		.03(.50)		-.28(1.48)
NEG_t		.05(1.29)		.05(.62)		.04(1.55)		.04(.68)
Panel C: Diagnostic Statistics								
F	7.90**	4.32*	3.32	2.55	7.77**	5.64**	4.05	2.10
$\hat{\rho}_0$ (t-ratio)	-.21(4.41)**	-.22(3.82)*	-.16(2.85)	-.15(2.74)	-.48(4.81)**	-.47(4.67)**	-.22(3.30)*	-.14(2.03)
LM	.02	.99	.18	.01	.25	.74	.06	.05
RESET	.27	1.93	11.87**	10.49**	.50	.21	6.87**	1.16
QS(QS ²)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.21	.17	.14	.15	.20	.23	.17	.10
Wald-S		5.97**		.72		.07		2.98*
Wald-L		1.60		.85		.00		1.51

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Texas		Utah		Virginia		Vermont	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.18(1.71)*	.19(1.76)*	-.12(1.04)	-.14(1.10)
$\Delta \text{LnGINI}_{t-2}$								
$\Delta \text{LnGINI}_{t-3}$								
ΔLnRGDP	-.03(1.37)	-.03(1.29)	-.01(.52)	-.01(.84)	.03(1.76)*	.02(1.13)	.01(.51)	.01(.37)
$\Delta \text{LnRGDP}_{t-1}$.00(.09)	-.00(.01)			-.04(2.77)**	-.05(2.98)**		
$\Delta \text{LnRGDP}_{t-2}$	-.01(.52)	-.01(.48)				.03(1.61)		
$\Delta \text{LnRGDP}_{t-3}$	-.03(1.53)	-.03(1.63)						
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.01(.30)		.01(.49)		-.00(.26)		-.03(1.32)	
ΔLnTR_{t-1}								
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		.02(.27)		-.06(1.17)		-.04(.89)		-.05(.88)
ΔPOS_{t-1}						.03(.79)		
ΔPOS_{t-2}						-.04(1.23)		
ΔPOS_{t-3}						.09(2.84)**		
ΔPOS_{t-4}								
ΔNEG_t		-.01(.31)		.03(1.29)		.00(.06)		-.02(.65)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.25(3.08)**	.30(9.73)**	.08(.70)	.20(4.51)**	.30(3.24)**	.31(5.46)**	.30(2.95)**	.29(7.55)**
LnRGDP_t	.04(5.45)**	.05(3.03)**	.05(5.02)**	.06(2.79)**	.03(3.39)**	.03(1.06)	.03(3.09)**	.04(2.07)**
LnTR_t	.02(.96)		.05(1.77)*		.01(.43)		.00(.05)	
POS_t		-.02(.28)		.02(.24)		.01(.09)		-.04(.66)
NEG_t		.03(1.21)		.06(1.78)*		.01(.14)		.01(.37)
Panel C: Diagnostic Statistics								
F	6.80**	17.40**	8.47**	6.05**	4.15	1.72	4.52*	3.20
$\hat{\rho}_0$ (t-ratio)	-.33(4.49)**	-.32(4.29)**	-.27(4.75)**	-.27(4.66)**	-.20(3.29)*	-.15(2.21)	-.34(3.57)*	-.34(3.46)*
LM	3.30*	3.36*	1.40	.48	.16	.00	.27	.87
RESET	1.16	1.54	1.61	5.20**	.08	.02	2.97*	2.88*
QS(QS ²)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.14	.13	.21	.22	.14	.17	.21	.19
Wald-S		.11		2.08		.25		.14
Wald-L		.31		.01		1.08		.05

Table 3: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Tariff Rate)								
	Washington		Wisconsin		West Virginia		Wyoming	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$							-.43(3.52)**	-.39(3.39)**
$\Delta \text{LnGINI}_{t-2}$							-.39(3.36)**	-.37(3.45)**
$\Delta \text{LnGINI}_{t-3}$							-.03(.30)	
ΔLnRGDP	.04(1.68)*	.04(1.76)*	.01(.67)	.00(.01)	.02(1.20)	.02(1.21)	.01(.40)	.03(1.28)
$\Delta \text{LnRGDP}_{t-1}$	-.10(3.64)**	-.10(3.74)**		-.03(1.23)			-.05(2.26)**	-.03(1.64)*
$\Delta \text{LnRGDP}_{t-2}$.07(2.69)**	.08(2.89)**		.04(1.73)*				
$\Delta \text{LnRGDP}_{t-3}$	-.06(3.09)**	-.06(3.10)**		-.04(2.50)**				
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnTR_t	-.02(1.08)		.00(.14)		-.00(.19)		-.01(.51)	
ΔLnTR_{t-1}	-.03(1.66)*							
ΔLnTR_{t-2}								
ΔLnTR_{t-3}								
ΔLnTR_{t-4}								
ΔPOS_t		-.04(.79)		-.05(1.14)		-.14(2.41)**		-.01(.17)
ΔPOS_{t-1}		-.10(1.98)**						
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.03(1.07)		.02(.95)		.04(1.31)		-.01(.38)
ΔNEG_{t-1}						.06(1.96)**		
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	.18(1.98)**	.03(6.98)**	.17(1.13)	.26(5.94)**	.23(1.25)	.27(4.13)**	-.06(.22)	.16(1.78)*
LnRGDP_t	.04(5.04)**	.02(1.44)	.04(2.85)**	.05(2.67)**	.03(1.93)*	.08(2.16)**	.07(2.79)**	.07(1.88)*
LnTR_t	.01(.57)		.03(.79)		.02(.32)		.09(1.25)	
POS_t		.02(.43)		-.04(.57)		-.25(1.68)*		.09(.72)
NEG_t		-.02(.59)		.04(1.32)		.03(.62)		.11(1.36)
Panel C: Diagnostic Statistics								
F	6.27**	5.02*	5.79**	3.47	3.81	2.94	2.65	2.01
$\hat{\rho}_0$ (t-ratio)	-.29(4.21)**	-.31(4.27)**	-.18(3.63)*	-.22(3.50)*	-.20(3.26)*	-.19(3.18)	-.18(2.19)	-.18(2.07)
LM	.41	.23	.52	2.29	1.70	.06	.45	1.80
RESET	3.67*	2.82*	.99	3.27*	2.49	3.25*	1.88	3.07*
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.25	.25	.20	.11	.14	.16	.34	.26
Wald-S		1.53		1.62		8.27**		.00
Wald-L		.58		.68		1.94		.26

Notes:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables (k=2), the upper bound critical value of the F test is 4.25 (5.04). These come from Narayan (2005, p. 1988) for our sample size.

3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when $k=2$ and these come from Banerjee et al (1989, p. 276). In the nonlinear model where $k=3$, these critical values change to -3.46 (-3.91).
4. LM is Lagrange Multiplier test of residual serial correlation. It is distributed as χ^2 with one degree of freedom (first order). Its critical value at 10% (5%) significance level is 2.70 (3.84). These critical values are also used for Wald tests since they also have a χ^2 distribution with one degree of freedom.
5. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom.

3.4 Conclusion

Heckscher-Ohlin (H-O) model predicts that trade openness should help a country's abundant factor. That means, in a capital abundant country, if the owners of capital benefit more from free trade, income inequality will increase. Similarly, in a labor abundant country, if labor gain from free trade, income inequality will reduce. Studies on the distributional effect of trade openness provided mixed and sometimes opposite results. However, they did not consider that the effects can be asymmetric. Here, I use Nonlinear Auto Regressive Distributed Lag method within the traditional Kuznets model and explores the asymmetric links between tariff rate and income inequality in U.S. and in each state.

Both linear and nonlinear model did not provide any significant links between tariff rate and aggregate Gini index. However, estimates of the linear model on state-level data, indicate that tariff cuts will increase income inequality in Alaska, Connecticut, Delaware, Nevada, and Washington in and decrease it in North Carolina in the short run. In the long run, a reduction in tariff rate reduces income inequality in the case of Alaska, Iowa, and Utah. Cointegration between variables is supported by F and t-test in this state. So, the study of linear model show that average tariff rate has significant short-run effect on income inequality in six states and significant long-run effect in three states.

Next, we estimate nonlinear model to see if tariff rate changes have asymmetric effects. Short run estimates of nonlinear model show significant results in 22 states of Alaska, Arizona, Arkansas, Connecticut, Delaware, District of Columbia, Hawaii, Iowa, Kentucky, Louisiana, Maine, Missouri, North Carolina, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Dakota, Virginia, Washington, and West Virginia. These effects are asymmetric since the estimated coefficient of ΔPOS_{t-j} at any given lag order j , is different from the one of ΔNEG_{t-j} . This increase in the number of states from six (linear models) to 22 (nonlinear models) must be attributed to the nonlinear adjustment of the tariff rate. These short run effects last into long run in 12 states of Alaska, Arizona, Connecticut, District of Columbia, Iowa, Idaho, Illinois, Indiana, New Hampshire, New Jersey, Pennsylvania, and Utah. Cointegration in these states is supported by either the F or t-test. This increase in the number of states that are affected in the long run from three (linear model) to twelve, must be attributed to nonlinear adjustment of the tariff rate.

**4. Asymmetric Link between U.S. Monetary Policy and Income Distribution:
Evidence from State Level Data**

4. 1 Introduction

Monetary policy is a fundamental tool to manage the economy. During booms when aggregate demand leads to an upward pressure on prices, central banks may implement a contractionary monetary policy and increase interest rates to control the activities. During busts when the level of economic activities and pressure on prices is lower, central banks may implement an expansionary monetary policy and cut interest rates to stimulate economic activity. However, it is debatable if monetary policy has a negative effect on the economy like widening income inequality. Studies on the distributional effects of monetary policy yield mixed results. While some studies report that contractionary monetary policy reduces income inequality (Coibion et al. 2017; Mumtaz et al. 2017; Furceri et al. 2018), others state the opposite (Cloyne et al. 2016 and 2020; Inui et al. 2017). Some suggest that the expansionary monetary policy pursued by many advanced economies after the Great Recession has negatively affected income and wealth distribution (Stiglitz, 2015); however, Draghi (2016) suggests the opposite. Some studies provide evidence of equalizing effects of unconventional, accommodative monetary policy in different countries (Montecino and Epstein, 2015; Casiraghi et al. 2018; Lenza and Slacalek, 2018). Some studies even report different conclusions for the same country. For instance, Saiki and Frost (2014) show that quantitative easing widens income inequality in Japan, while Inui et al. (2017) find an equalizing effect for Japan.

One possible explanation of these different results, and also one of the difficulties in the study of this topic, is the possibility of different transmission channels through which monetary policy can affect income inequality. Coibion et al. (2012) identified five transmission channels that appear in recent literature (e.g., Saiki and Frost, 2014; Davtyan, 2017). These channels are: the income composition channel that refers to the heterogeneity in the primary type of income across

households such as business, financial, labor and transfer income; the financial segmentation channel refers to the composition of the asset portfolio; portfolio channel refers to the structure of owned assets; the savings redistribution channel describes the effects of unexpected inflation on nominal contracts; and the earnings heterogeneity channel describes the impacts of business cycle fluctuations on labor income. An expansionary monetary policy increases income inequality through the first three transmission channels and decreases it through the last two. Therefore, the total distributional effect of monetary policy is ambiguous (O'Farrell et al. 2016; Davtyan, K. 2017). Nakajima (2015) classified these five channels into groups: inflation and income. He combined three channels from Coibion et al. (2012) —financial segmentation, portfolio composition, and savings redistribution channels— into a single inflation channel and considered the other two channels —income composition and earnings heterogeneity channels— as the income channel. These aggregated channels are followed by the literature. For example, Davtyan (2017) used prices and real outputs as monetary policy distributive channels and employed the federal fund rates as a monetary policy tool. Bernanke and Mihov (1998), Christiano et al. (1994), Peersman and Smets (2001), and Uhlig (2005) also implemented prices, real outputs, and federal fund rates in their studies on the distributional effects of monetary policy.

In fact, a variety of studies followed different variables and approaches to analyze the distributional effect of monetary policy. The next section reviews the related studies and discusses the contribution of this paper to the literature.

4.2 Related Literature

Studies on the distributional effects of monetary policy yield mixed results. Li and Zou (2002), using cross-country panel data, found that inflation can increase the income share of the rich and reduce it for middle- and low-income households. In other words, they found that inflation worsens income inequality and economic growth. Albanesi (2007) also found a direct relation between equilibrium inflation and income inequality in cross-country data. Based on a political economy model, she found that distributional conflict is one of the consequences of monetary and fiscal policies. Her results are consistent with Erosa and Ventura (2000) who argue that at equilibrium, low-income households, which hold a big share of cash and so are more vulnerable to inflation.

Kang et al. (2013) used a Panel System GMM estimation for household and province-level data of Korea. They found that higher real interest rate is associated with higher poverty while it does not have any significant effect on income distribution. However, inflation reduces poverty rate and improves income inequality only in the short term and has no significant effects on inequality in the long term. They also found that GDP growth reduces income inequality and poverty.

Mumtaz et al. (2017) found that contractionary monetary policy shocks increase earnings, consumption, and income inequality in the UK. Their findings show that contractionary policy has a big negative impact on low-income households. They also found that quantitative easing may increase inequality over the Great Recession. They construct inequality measures survey data, which exclude one percent of the top and the bottom of their distributions. However, the variation in top one percent of income is a major part of income inequality dynamics in the UK

(Atkinson et al. 2011; Leigh, 2007) as well as in the US (Atkinson, 2007; Kenworthy and Smeeding, 2013) since income inequality behavior is similar in both countries.

Furceri et. al. (2018) built a measure of unexpected policy changes using fluctuations in short term interest rate which is orthogonal to unexpected changes in growth and inflation news. Based on panel data of 149 countries from 1970 to 2010, they found that a contractionary monetary policy has an equalizing effect in the short term and midterm. The effect is different depending on the state of the business cycle and the type of shocks, where during expansions the effect of a positive monetary policy shock is large. Their findings also show that the effect is asymmetric. That is, the effect of a contractionary monetary policy is higher than the effect of an expansionary monetary policy in absolute values.

Samarina and Nguyen (2019) found that monetary policy can have distributional effects through macroeconomic and financial channels. They considered the macroeconomic channel through wages and employment, and the financial channel through asset prices and returns. They found that an expansionary monetary policy raises wages and employment in euro area countries, so it reduces income inequality through the macroeconomic channel. However, the financial channel may worsen income inequality and it may have more wealth rather than income effects.

Cravino et.al, (2020) studied the distributional effect of monetary policy through the price channel. They showed that high-income households use more sticky-price goods than middle-income households; so, they experience less volatility in inflation. They showed that for high-income households the estimated impulse responses of consumer price indices to a monetary policy shock are about one third smaller than those for middle-income households. This implies that monetary policy shocks can affect income distribution through relative prices of the goods consumed by households at different spots on the income distribution. Bulir (2001) using cross-

country data found that the level of development and employment, fiscal redistribution, and price stability can lessen income inequality. He found that the impact of price stability on income inequality is nonlinear and can be observed after some lag periods. At a hyperinflationary level, a reduction in inflation can reduce income inequality significantly; while at a lower level of inflation, the effect of the same level of inflation reduction on Gini coefficient is negligible. His results show that a reduction in inflation can cause a decline in Gini coefficient directly, and also indirectly through increasing money demand and protecting the real value of fiscal transfers.

Romer and Romer (1999) using time series data studied the short-run and the long-run impacts of monetary policy on poverty and income inequality. They show that cyclical economic booms created by an expansionary monetary policy is associated with an enhanced condition for the poor in the short run. However, in the long-run, low inflation and stable aggregate demand growth is associated with a permanent improvement in well-being of the poor. Their findings showed a statistically significant and quantitatively large relationship in both the short-run and long-run.

Saiki and Frost (2014) using a vector auto regressive (VAR) model on government's household survey data show that an increase in the monetary base widens income inequality in Japan, mostly through the portfolio channel. Since it increases asset prices disproportional to economic fundamentals like wages and employment, the rich who hold these assets benefit more. Villarreal (2014) using incomplete market models showed that contractionary monetary policy affects income inequality, consumption, and wealth in Mexico. He found that unanticipated increases in the nominal interest rate was associated with a short-run reduction of household income inequality and the effect disperses after two years. He showed that under an inflation targeting regime, a contractionary monetary policy shock reduced income inequality in Mexico. However,

Coibion et al. (2012) found the opposite results for the United States. Villarreal (2014) suggested the existence of threshold effects as a possible explanation of these different results. Because of the different levels of financial access and development in the United States and Mexico, benefits of inflation stabilization in Mexico are higher than its costs, whereas the opposite occurs in the United States. Coibion et al. (2012) found that a contractionary monetary policy systematically widens inequality in labor earnings, total income and particularly in consumption and expenditures in the U.S. They used the consumer expenditure survey which does not include the top one percent of the income distribution. However, Davtyan (2017) found the opposite. Using quarterly and annual data, he showed that a contractionary monetary policy reduces the Gini index in the U.S. Considering the mixed findings, my paper aims to study the distributional consequences of monetary policy from a different approach. Using “monetary base to GDP” as a measure of monetary policy, on a long data period from 1918 to 2015, I study the asymmetric effects of monetary policy on income inequality in the U.S and in each state.

The remainder of the paper is structured as follows: section 3 provides the econometric framework and method adopted and section 4 describes the empirical findings. The last section summarizes and concludes the paper. A summary of the dataset and variables used are provided in the Appendix.

4.3 Model and Methodology⁵

The linear and nonlinear model are discussed in detail in part 2.2. The only difference is that here, the main explanatory variable is monetary policy measures by U.S. monetary base to GDP represented by MB.

⁵ This section closely follows Bahmani-Oskooee et al. (2018) and Bahmani-Oskooee and Harvey (2020).

4.3.1 The Linear Model

I test the effect of policy uncertainty on income distribution through the Kuznets model following long run model (1):

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma \ln MB_t + \epsilon_t \quad (1)$$

Where Gini index is a measure of income inequality, Y is per-capita real personal income or GDP, and PU is U.S. policy uncertainty. All variables are in state level here. If economic development reduces income inequality, an estimate of β should be negative.

The error correction model can be rewritten by as follows:

$$\begin{aligned} \Delta \ln Gini_t = & \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_{kj} \Delta \ln MB_{t-j} + \lambda_1 \ln Gini_{t-1} + \\ & \lambda_2 \ln Y_{t-1} + \lambda_3 \ln MB_{t-1} + u_t \end{aligned} \quad (2)$$

By applying OLS to the above error-correction model, short run and long run effects of exogenous variables on income inequality can be estimated in one step.

4.3.2. The Nonlinear Model

Again, we use the partial sum concept to generate two new time-series variables POS and NEG as:

$$\begin{aligned} POS_t &= \sum_{j=1}^t \Delta \ln MB_t^+ = \sum_{j=1}^t \max(\Delta \ln MB_j, 0) \\ NEG_t &= \sum_{j=1}^t \Delta \ln MB_t^- = \sum_{j=1}^t \min(\Delta \ln MB_j, 0) \end{aligned}$$

We represent nonlinear long run and Error Correction specifications by replacing $\ln MB$ variable with POS and NEG from equation (1) and (3) as follows:

$$\ln Gini_t = \alpha + \beta \ln Y_t + \gamma_1 POS_t + \gamma_2 NEG_t + \epsilon_t \quad (3)$$

$$\Delta \ln Gini_t = \alpha + \sum_{j=1}^{n_1} \phi_j \Delta \ln Gini_{t-j} + \sum_{j=0}^{n_2} \pi_j \Delta \ln Y_{t-j} + \sum_{j=0}^{n_3} \Gamma_j^+ \Delta POS_{t-j} + \sum_{j=0}^{n_4} \Gamma_j^- \Delta NEG_{t-j} + \rho_0 \ln Gini_{t-1} + \rho^+ POS_{t-1} + \rho^- NEG_{t-1} + \vartheta_t \quad (4)$$

4.4 Results

Linear and Nonlinear model, which are identified by L-ARDL and NL-ARDL respectively, are estimated for the U.S. as a whole as well as for each state. The annual data covers a long period from 1918 to 2015⁶. Since the data are annual, the maximum number of four lags is imposed on each first-differenced variable and Akaike's information criterion is applied to select the optimum model. The results of optimum model are reported in Table 1 in the short-run (panel A) and long-run (panel B). Several additional diagnostic statistics are also reported (panel C).

Estimates of the linear and nonlinear models show that economic growth reduces U.S. income inequality in the short-run and increases it in the long-run. These results come from negative and significant coefficient of $\Delta LRGDP$ and positive significant coefficient of $\ln RGDP_t$. Estimates from linear model that assumes the effects are symmetric, show no significant link between monetary policy and U.S income inequality in both the short-run and long-run. However, from nonlinear model, it is found that a contractionary monetary policy (decline in monetary base to GDP ratio) decreases U.S. income inequality and an expansionary monetary policy does not affect it in the long run. These results inferred by positive and significant coefficient of NEG and insignificant coefficient of POS . Cointegration between variables is supported by both F and t-tests. A significant value of the Wald test supports the asymmetric result in the long run.

Several additional diagnostic statistics are also reported (panel C). An insignificant Lagrange Multiplier test (LM) supports the fact that there is no autocorrelation between residuals. An insignificant Ramsey's RESET test also supports the fact there is no model misspecification.

⁶ Appendix is provided for more information about the data.

Following the literature, CUSUM and CUSUMSQ tests are also applied to determine the stability of all estimated coefficients. These tests are reported as QS and QS^2 respectively where an assigned “S” value shows the coefficients are stable and “US” indicates the estimated coefficients are unstable. And finally, reported Adjusted R^2 shows the goodness of fit.

Let us now consider estimates from each state and see if the state level data follow the same pattern as the U.S. as a whole. Estimates of the linear model indicate that $\Delta LnMB_{t-j}$ carries at least one significant coefficient in the 21 states. Among these states, significant coefficients of $\Delta LnMB_{t-j}$ are negative in nine states including Alabama, Arizona, Kentucky, North Dakota, New Mexico, South Carolina, Tennessee, Vermont, West Virginia, and in District of Columbia. And they are positive in seven states including Connecticut, Delaware, Indiana, Louisiana, Minnesota, New York, and Texas. This implies that an expansionary monetary policy reduces income inequality in the first group and widens it in the second one. In addition, results from the same model for four states including Massachusetts, Maine, Ohio, and Washington indicate that an expansionary monetary policy reduces income inequality first and increases it later since a negative coefficient is followed by positive one. These short-run effects translate into the long-run significant effects (Cointegrated) only in four states: Iowa, Minnesota, Montana, and Wyoming, since $LnMB$ carries a significant coefficient in these states. The results are supported by both F and t-tests for cointegration in Iowa, Minnesota, and Wyoming.

So, the linear model provides evidence of short-run effects of monetary base in 21 states and long-run effects in 4 states. Now, let us move to the non-linear model that assumes asymmetric effects and see if it provides different results.

Short-run outcomes from nonlinear model in Panel A show that ΔPOS or ΔNEG carry at least one lagged significant coefficient in 24 states including Alaska, Arkansas, Colorado,

Connecticut, Delaware, District of Columbia, Georgia, Kentucky, Louisiana, Massachusetts, Maine, North Carolina, New Hampshire, New Mexico, New York, Ohio, Oregon, Rhode Island, South Carolina, Tennessee, Texas, Vermont, Washington, and West Virginia. The increase in number of the states in the short run from 21 in linear model to 24 in nonlinear model, must be ascribed by the asymmetric effects of monetary policy. Since the estimated coefficient of ΔPOS is different than the estimated coefficient of ΔNEG in these states, the short-run effects seem to be asymmetric. However, the cumulative asymmetric effect is supported by the Wald test (Wald-S in Panel C) only in 11 states including Alaska, Arkansas, Colorado, Connecticut, Massachusetts, New Hampshire, New York, Oregon, Rhode Island, Vermont, and Washington. In these states, a significant value of the Wald-S rejects the hypothesis that the sum of the coefficients attached to ΔPOS_{t-j} is equal to the sum attached to ΔNEG_{t-j} and supports the idea of asymmetric effects in these states.

The significant and sometimes insignificant short-run effects last into the long-run significant effects (cointegrated) in 34 states including Alaska, Alabama, Arkansas, California, Colorado, Connecticut, Delaware, Discrete of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, Montana, North Carolina, North Dakota, New Hampshire, New Jersey, New York, Ohio, Oklahoma, Pennsylvania, Rhode island, South Dakota, Tennessee, Vermont, and Wisconsin. In these states, the estimated coefficient of POS or NEG , and in some cases both, are significant. The cointegration -except for the case of North Carolina and New Jersey - is supported by either the F or t-test (Panel C). The increase in the number of states with long-run effects from 4 (in the linear model), to 34 states (in the non-linear model) must be attributed by the nonlinear adjustment of monetary base.

The results are different for each state. For example, in the case of Alabama, the linear model predicts that an expansionary monetary policy reduces income inequality in the short run since the coefficient attached to $\Delta \ln MB_t$ is negative and significant. However, monetary policy does not have any significant effect on Gini in the long-run, and this is also the case in nonlinear short run. By contrast, a contractionary monetary policy reduces income inequality in Alabama in the long run. Different from the case of Alabama, in Colorado, the linear model does not show any link between monetary policy and Gini in both the short-run and long-run. However, nonlinear results show that a contractionary monetary policy decreases Gini in both the short-run and long-run while an expansionary monetary policy does not change it at all. In the case of New York, however, the linear model predicts a direct relationship between monetary policy and income inequality in the short run; that is a decline in monetary base to GDP ratio reduces Gini and vice versa. However, it does not predict any significant relationship in the long run. Considering asymmetric effects in nonlinear model, a contractionary monetary policy decreases New York income inequality in both the short-run and long-run; however, an expansionary monetary policy does not have any significant effect on income inequality in this state. This long-run asymmetric effect is supported by the Wald test (Wald L, Panel C) not only in New York, but also in Alabama, California, Colorado, Connecticut, Delaware, Discreet of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Louisiana, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, North Carolina, North Dakota, New Hampshire, New Jersey, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Dakota, Tennessee, Vermont, Wisconsin, and West Virginia. More observations from the nonlinear model in the long-run reveal that a contractionary monetary policy increases Gini in Idaho, Montana, North Dakota, and South Dakota and decrease it in Alabama, Arkansas, California, Colorado, Connecticut, Delaware, Florida,

Georgia, Illinois, Indiana, Kentucky, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, North Carolina, New Hampshire, New Jersey, New York, Ohio, Oklahoma, Pennsylvania, Tennessee, Vermont, and Wisconsin. These results are confirmed by the negative significant estimate attached to *NEG* in the first group and positive significant estimate in the second one. In addition, any changes in monetary base will reduce income inequality in Rhode Island and raise it in Idaho. On the other hand, an expansionary monetary policy decreases income inequality in Alaska, District of Columbia, and Rhode Island and increases it in Arkansas and Idaho. This is confirmed by the negative significant coefficient *POS* in the first three states and the negative coefficient in the last two states.

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	U.S.		AK		AL		AR	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.26(2.28)**	.32(3.21)**		.05(.35)	.03(.24)			-.05(.44)
$\Delta \text{LnGINI}_{t-2}$		-.04(.45)		.38(2.57)**				.05(.47)
$\Delta \text{LnGINI}_{t-3}$.25(2.98)**						.14(1.48)
ΔLnRGDP	-.01(.27)	.01(.21)	-.07(.81)	-.09(1.04)	.02(.41)	.07(1.74)*	.12(2.73)**	.14(3.21)**
$\Delta \text{LnRGDP}_{t-1}$	-.13(3.19)**	-.08(1.83)*			-.10(2.63)**	-.06(1.49)	-.12(3.46)**	-.10(2.27)**
$\Delta \text{LnRGDP}_{t-2}$.18(4.40)**	.11(2.61)**			.09(2.47)**	.10(2.78)**	.08(2.44)**	.04(1.38)
$\Delta \text{LnRGDP}_{t-3}$	-.15(4.00)**	-.14(4.07)**			-.05(1.45)			
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.05(1.10)		.01(.20)		-.09(1.69)*		-.02(.39)	
ΔLnMB_{t-1}								
ΔLnMB_{t-2}								
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		-.03(.69)		-.06(.90)		-.06(1.13)		-.01(.26)
ΔPOS_{t-1}								-.14(2.27)**
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.04(.38)		1.41(2.59)**		-.04(.28)		.20(1.48)
ΔNEG_{t-1}				.78(1.61)		.16(1.35)		
ΔNEG_{t-2}						.15(1.27)		
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.92(6.20)**	-1.01(42.52)**	-1(3.25)**	-1.35(1.10)	-1.02(8.27)**	-.97(20.84)**	-1.11(16.45)**	-1.04(34.85)**
LnRGDP_t	.05(5.89)**	.10(10.26)**	.08(2.38)**	.02(.13)	.05(7.09)**	.09(6.85)**	.05(12.60)**	.08(5.81)**
LnMB_t	-.03(.46)		-.16(1.29)		-.00(.03)		.03(1.03)	
POS_t		-.01(.28)		-.13(2.20)**		-.02(.72)		.07(1.80)*
NEG_t		.18(5.09)**		-.43(.39)		.17(3.14)**		.15(2.44)**
Panel C: Diagnostic Statistics								
F	3.07	10.10**	2.08	4.19	3.22	5.39*	5.20*	5.41*
$\hat{\rho}_0$ (t-ratio)	-.15(2.84)	-.36(5.69)**	-.16(2.24)	-.28(3.74)*	-.22(3.03)	-.23(3.74)*	-.28(3.95)**	-.34(3.56)*
LM	.34	1.11	.22	.00	.09	2.02	2.00	.85
RESET	.13	3.40*	.82	.40	.16	1.11	.51	1.93
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.24	.43	.02	.19	.19	.29	.24	.32
Wald-S		.36		10.80**		2.50		4.25**
Wald-L		36.06**		.09		7.85**		1.40

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	AZ		CA		CO		CT	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$	-.15(1.59)	-.05(.43)		.16(1.57)			.17(1.58)	.17(1.69)*
$\Delta \text{LnGINI}_{t-2}$.24(2.80)**	.27(2.81)**		.11(1.04)				
$\Delta \text{LnGINI}_{t-3}$.20(2.08)**				
$\Delta \text{LnGINI}_{t-4}$								
ΔLnRGDP	.39(6.15)**	.30(4.13)**	.04(.79)	.07(1.44)	.04(.87)	.10(1.98)**	-.11(2.04)**	-.03(.52)
$\Delta \text{LnRGDP}_{t-1}$	-.46(8.11)**	-.32(6.27)**	-.14(2.89)**	-.14(2.97)**	-.11(2.37)**	-.05(1.07)	.07(1.30)	.04(.82)
$\Delta \text{LnRGDP}_{t-2}$.11(2.31)**	.07(1.55)	.10(2.13)**	.11(2.70)**	.08(1.88)*	.06(1.55)
$\Delta \text{LnRGDP}_{t-3}$			-.06(1.49)	-.08(2.10)**	-.09(2.27)**		-.11(2.82)**	-.11(2.99)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	.08(1.17)		-.05(.94)		-.02(.35)		-.07(1.14)	
ΔLnMB_{t-1}	-.24(3.44)**						.18(2.88)**	
ΔLnMB_{t-2}	-.13(2.27)**							
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		.03(.33)		-.01(.19)		.04(.71)		-.04(.62)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.00(.02)		-.01(.10)		.03(.23)		.16(1.22)
ΔNEG_{t-1}						.30(2.49)**		.34(2.66)**
ΔNEG_{t-2}						.16(1.28)		
ΔNEG_{t-3}						.32(2.89)**		
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-1.3(15.42)**	1.19(48.75)**	-1.04(5.23)**	-1.17(34.32)**	-1.01(12.24)**	-.91(19.20)**	-.62(2.18)**	-.97(17.01)**
LnRGDP_t	.07(14.17)**	.07(6.91)**	.07(5.81)**	.12(9.66)**	.05(9.53)**	.07(5.81)**	.04(2.62)**	.12(7.95)**
LnMB_t	.04(1.12)		-.05(.66)		.01(.19)		-.14(1.28)	
POS_t		-.00(.18)		-.02(.71)		.02(.75)		-.02(.57)
NEG_t		.01(.21)		.15(3.43)**		.14(3.21)**		.26(4.38)**
Panel C: Diagnostic Statistics								
F	13.88**	11.60**	2.23	6.44**	7.39**	6.77**	3.91	6.97**
$\hat{\rho}_0$ (t-ratio)	-.29(4.08)**	-.37(4.31)**	-.13(2.41)	-.34(4.79)**	-.32(4.68)**	-.38(4.90)**	-.13(2.93)	-.29(5.09)**
LM	1.27	.56	.88	2.26	1.24	4.36**	.03	1.59
RESET	.39	1.10	.00	17.01**	1.04	6.64**	1.47	.04
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	US(S)	S(S)	US(S)	S(S)
Adjusted R ²	.50	.40	.11	.23	.21	.30	.13	.27
Wald-S		.02		.00		8.32**		8.57**
Wald-L		1.62		20.92**		8.67**		33.04**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	DE		DC		FL		GA	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}$								
$\Delta \ln \text{GINI}_{t-1}$.31(2.94)**	.19(2.12)**	-.10(.88)	-.13(1.19)	.16(1.47)	.04(.41)	.04(.28)	
$\Delta \ln \text{GINI}_{t-2}$.40(4.28)**	.25(3.07)**	.20(2.13)**	.20(2.00)**	.06(.56)	-.02(.18)	.10(.87)	
$\Delta \ln \text{GINI}_{t-3}$.11(1.39)		.14(1.54)	.27(2.81)**	.23(2.61)**	.33(3.20)**	
$\Delta \ln \text{RGDP}$.01(.18)	-.02(.44)	.08(1.25)	.15(2.39)**	.09(3.95)**	.10(4.87)**	.06(1.42)	.06(1.34)
$\Delta \ln \text{RGDP}_{t-1}$		-.04(.64)	-.24(4.04)**	-.22(4.11)**	-.03(1.26)		-.08(2.26)**	-.08(1.67)*
$\Delta \ln \text{RGDP}_{t-2}$.07(1.37)	.03(.58)					.13(2.99)**
$\Delta \ln \text{RGDP}_{t-3}$		-.14(3.15)**						-.11(3.04)**
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{MB}_t$.17(2.35)**		-.12(2.24)**		.06(1.31)		-.01(.15)	
$\Delta \ln \text{MB}_{t-1}$.06(.89)							
$\Delta \ln \text{MB}_{t-2}$								
$\Delta \ln \text{MB}_{t-3}$								
$\Delta \ln \text{MB}_{t-4}$								
ΔPOS_t		-.04(.60)		-.06(1.00)		.00(.03)		.02(.41)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.37(2.85)**		-.25(1.84)*		.16(1.50)		-.19(1.62)
ΔNEG_{t-1}		.32(2.40)**				.15(1.52)		.10(.88)
ΔNEG_{t-2}		-.26(1.91)*						.14(1.26)
ΔNEG_{t-3}		-.30(2.27)**						-.22(1.97)**
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.45(2.51)**	-.55(7.66)**	-1.05(6.40)**	-1.17(23.67)**	-1.10(6.93)**	-.90(14.76)**	-1.13(14.47)**	-1.03(28.93)**
$\ln \text{RGDP}_t$	-.02(2.29)**	.07(3.61)**	.07(6.44)**	.08(6.35)**	.05(5.07)**	.11(5.37)**	.05(12.16)**	.08(6.85)**
$\ln \text{MB}_t$	-.00(.06)		-.04(.69)		.07(1.16)		.05(1.60)	
POS_t		.02(.41)		-.09(2.54)**		.04(.96)		.04(1.40)
NEG_t		.31(5.18)**		-.03(.52)		.29(4.21)**		.14(3.39)**
Panel C: Diagnostic Statistics								
F	9.27**	11.58**	4.28	3.84	3.46	6.41**	4.23	6.30**
$\hat{\rho}_0$ (t-ratio)	-.26(5.13)**	-.29(6.07)**	-.29(3.73)**	-.31(3.60)*	-.17(3.04)	-.21(3.93)**	-.31(3.45)*	-.30(4.25)**
LM	.36	4.78**	.31	.98	.07	.04	.12	7.06**
RESET	6.13**	1.21	1.62	.47	4.16**	.02	8.30**	1.45
QS(QS ²)	S(S)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.292	.53	.32	.34	.23	.35	.19	.27
Wald-S		.29		1.46		4.25**		.59
Wald-L		23.15**		3.39*		11.11**		7.85**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	HI		IA		ID		IL	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$					-.42(3.62)**	-.08(.54)	.12(1.01)	.24(2.23)**
$\Delta \text{LnGINI}_{t-2}$					-.20(1.94)*	-.07(.56)	-.07(.68)	.04(.36)
$\Delta \text{LnGINI}_{t-3}$.16(1.70)*	.30(3.09)**	.39(4.07)**
ΔLnRGDP	.09(1.34)	.08(1.02)	.04(1.40)	.04(1.20)	.08(1.71)*	.06(1.57)	.05(.91)	.06(1.16)
$\Delta \text{LnRGDP}_{t-1}$	-.02(.23)	-.03(.48)	.03(1.27)	.03(1.15)			-.13(2.47)**	-.12(2.29)**
$\Delta \text{LnRGDP}_{t-2}$	-.06(.90)	-.06(.91)	-.02(.69)	-.02(.71)			.13(2.59)**	.12(2.55)**
$\Delta \text{LnRGDP}_{t-3}$	-.16(2.55)**	-.17(2.44)**	-.07(2.82)**	-.07(2.66)**			-.15(3.46)**	-.17(4.43)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	.02(.49)		-.03(.56)		-.01(.21)		-.05(.94)	
ΔLnMB_{t-1}								
ΔLnMB_{t-2}								
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		.03(.71)		-.04(.63)		.03(.46)		-.02(.38)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.25(1.04)		.01(.07)		-.05(.32)		.01(.06)
ΔNEG_{t-1}								.09(.77)
ΔNEG_{t-2}								.13(1.15)
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.91(10.10)**	-1.24(2.16)**	-.99(10.78)**	-.1.06(32.28)**	-1.27(8.64)**	-1.36(64.92)**	-.93(4.94)**	-1.02(32.81)**
LnRGDP_t	.04(6.33)**	.01(.12)	.05(1.07)	.05(4.11)**	.08(8.84)**	.05(6.98)**	.05(4.87)**	.11(12.71)**
LnMB_t	-.03(1.00)		-.03(8.54)**		-.01(.17)		-.04(.49)	
POS_t		-.03(.99)		-.04(1.30)		.03(1.98)**		-.01(.40)
NEG_t		-.29(.53)		-.02(.31)		-.12(4.67)**		.22(7.51)**
Panel C: Diagnostic Statistics								
F	4.62*	3.57	5.53*	4.09	1.05	4.65*	2.56	8.98**
$\hat{\rho}_0$ (t-ratio)	-.32(3.44)*	-.32(3.08)	-.29(4.02)**	-.29(3.99)**	-.14(1.71)	-.59(3.95)**	-.14(2.43)	-.40(5.67)**
LM	.13	.37	1.24	1.31	.13	.08	1.18	4.70**
RESET	3.28*	1.95	.33	.30	.78	.57	.64	1.47
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.24	.23	.21	.19	.19	.34	.25	.43
Wald-S		1.31		.08		.20		1.67
Wald-L		.00		.06		28.52**		43.64**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	IN		KS		KY		LA	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
ΔLnGINI _{t-1}	.34(3.42)**	.27(2.91)**	-.20(2.00)**	-.22(1.99)**			.11(.98)	
ΔLnGINI _{t-2}	.04(.37)	-.02(.24)	-.19(2.05)**	-.20(2.01)**			.02(.23)	
ΔLnGINI _{t-3}	.22(2.49)**	.22(2.54)**					.22(2.28)**	
ΔLnRGDP	-.06(1.61)	-.01(.20)	-.02(.47)	-.02(.35)	-.08(1.93)*	-.06(1.35)	-.00(.02)	.05(.94)
ΔLnRGDP _{t-1}	-.03(.75)	-.02(.61)	-.01(.37)	-.01(.33)				
ΔLnRGDP _{t-2}	.09(2.35)**	.04(1.51)	.07(2.18)**	.08(2.20)**				
ΔLnRGDP _{t-3}	-.12(4.46)**	-.12(4.50)**						
ΔLnRGDP _{t-4}								
ΔLnMB_t	-.06(1.25)		.00(.05)		-.11(2.08)**		-.06(1.17)	
ΔLnMB _{t-1}	.01(.21)						.08(1.59)	
ΔLnMB _{t-2}	.10(2.12)**						-.03(.68)	
ΔLnMB _{t-3}							.12(2.67)**	
ΔLnMB _{t-4}								
ΔPOS_t		-.01(.30)		-.00(.01)		-.12(1.90)*		-.01(.23)
ΔPOS _{t-1}								-.03(.48)
ΔPOS _{t-2}								-.13(2.43)**
ΔPOS _{t-3}								.13(2.44)**
ΔPOS _{t-4}								
ΔNEG_t		-.08(.72)		.00(.01)		-.09(.66)		-.16(1.35)
ΔNEG _{t-1}								.32(2.96)**
ΔNEG _{t-2}								
ΔNEG _{t-3}								
ΔNEG _{t-4}								
Panel B: Long-Run Estimates								
Constant	-.98(9.03)**	1.10(36.03)**	1.08(12.77)**	-1.06(31.55)**	-.90(7.35)**	-.99(29.51)**	1.00(10.83)**	1.05(25.68)**
LnRGDP _t	.05(7.62)**	.09(7.16)**	.05(10.49)**	.07(4.83)**	.04(6.11)**	.09(6.48)**	.06(10.73)**	.09(6.46)**
LnMB _t	-.04(.91)		.01(.24)		-.05(.92)		-.03(.79)	
POS _t		-.03(1.06)		-.00(.02)		-.05(1.51)		-.01(.18)
NEG _t		.12(2.48)**		.07(1.30)		.12(2.19)**		.10(1.49)
Panel C: Diagnostic Statistics								
F	8.52**	10.26**	3.48	2.60	5.00*	3.83	4.65*	4.59*
$\hat{\rho}_0$ (t-ratio)	-.26(4.92)**	-.31(5.96)**	-.26(3.09)	-.25(2.57)	-.23(3.69)**	-.25(3.79)*	-.35(3.60)*	-.31(4.18)**
LM	2.70*	1.57	.00	.11	.97	.43	2.31	1.68
RESET	.01	1.41	.28	.01	.16	.15	.32	1.73
QS(QS ²)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.33	.40	.24	.22	.14	.13	.21	.30
Wald-S		7.11**		.00		.03		.90
Wald-L		12.43**		.18		2.26		5.15**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	MA		MD		ME		MI	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.15(1.23)	.25(2.33)**	-.04(.41)	.02(.20)	-.08(.68)			.18(1.58)
$\Delta \text{LnGINI}_{t-2}$.26(2.89)**	.34(3.77)**				-.09(.91)
$\Delta \text{LnGINI}_{t-3}$.22(2.49)**
ΔLnRGDP	-.05(.71)	-.01(.18)	-.05(1.13)	-.02(.43)	-.08(1.10)	-.02(.35)	.02(.49)	.02(.42)
$\Delta \text{LnRGDP}_{t-1}$	-.14(2.24)**	-.10(2.22)**			-.20(2.53)**	-.13(1.85)*	-.05(1.15)	-.02(.37)
$\Delta \text{LnRGDP}_{t-2}$.30(5.16)**	.24(5.30)**			.18(2.32)**	.17(2.52)**	.16(3.98)**	.10(2.42)**
$\Delta \text{LnRGDP}_{t-3}$	-.19(4.10)**	-.22(5.24)**			-.08(1.46)	-.10(1.95)*	-.09(2.53)**	-.10(2.52)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.12(2.19)**		-.07(1.50)		-.07(.92)		-.04(.59)	
ΔLnMB_{t-1}	.11(1.83)*				-.17(2.13)**			
ΔLnMB_{t-2}	.08(1.56)				.13(1.74)*			
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		-.05(.98)		-.05(.88)		-.08(1.05)		-.05(.73)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.09(.77)		-.10(.81)		.13(.74)		.19(1.30)
ΔNEG_{t-1}		.34(3.03)**		.14(1.42)		-.19(1.16)		
ΔNEG_{t-2}						.36(2.13)**		
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.62(1.75)*	-.99(22.80)**	-.87(4.45)**	-.97(21.73)**	-.89(5.37)**	-.88(14.81)**	-.75(1.75)*	-1.10(25.23)**
LnRGDP_t	.05(2.26)**	.11(8.86)**	.04(3.15)**	.09(6.61)**	.04(3.72)**	.08(5.25)**	.05(2.14)**	.13(7.45)**
LnMB_t	-.17(1.17)		-.04(.58)		-.02(.30)		-.16(.90)	
POS_t		-.04(1.34)		-.04(1.32)		-.04(.99)		-.05(1.30)
NEG_t		.19(3.99)**		.16(3.39)**		.15(2.64)**		.24(4.00)**
Panel C: Diagnostic Statistics								
F	2.42	7.44**	2.60	4.20	3.83	4.83*	1.12	4.83*
$\hat{\rho}_0$ (t-ratio)	-.13(2.55)	-.33(5.27)**	-.13(2.53)	-.26(3.94)**	-.21(2.75)	-.33(4.30)**	-.08(1.49)	-.31(3.71)*
LM	2.45	.00	1.22	.00	1.11	3.08*	.01	7.50**
RESET	3.08*	.40	.00	.28	2.82*	8.63**	.25	4.64**
QS(QS ²)	US(S)	S(S)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.31	.45	.14	.21	.19	.24	.18	.34
Wald-S		3.45*		.33		1.48		2.04
Wald-L		37.90**		12.45**		8.06**		22.94**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	MN		MO		MS		MT	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$.33(3.05)**	.19(1.76)*	.26(2.26)**	.29(2.59)**	-.18(1.49)	-.18(1.45)		.03(.26)
$\Delta \text{LnGINI}_{t-2}$.13(1.34)	.05(.48)	.09(.79)	.11(1.03)	.25(2.56)**	.26(2.54)**		-.01(.07)
$\Delta \text{LnGINI}_{t-3}$.33(3.56)**	.27(3.09)**	.30(2.81)**	.37(3.75)**				.19(2.19)**
ΔLnRGDP_t	-.04(.95)	.04(.94)	.04(.79)	.08(1.49)	.09(2.50)**	.10(2.40)**	-.02(.44)	.00(.10)
$\Delta \text{LnRGDP}_{t-1}$			-.12(2.25)**	-.10(2.07)**				
$\Delta \text{LnRGDP}_{t-2}$.07(1.33)	.05(1.06)				
$\Delta \text{LnRGDP}_{t-3}$			-.12(2.96)**	-.12(3.07)**				
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.03(.60)		-.01(.13)		-.01(.23)		-.07(1.12)	
ΔLnMB_{t-1}	.08(1.95)*							
ΔLnMB_{t-2}	.01(.20)							
ΔLnMB_{t-3}	.11(2.67)**							
ΔLnMB_{t-4}								
ΔPOS_t		-.01(.12)		.00(.07)		.00(.01)		-.04(.63)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.03(.25)		.07(.62)		-.05(.37)		-.15(1.08)
ΔNEG_{t-1}								
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.84(10.16)**	-1.00(35.68)**	-.97(11.78)**	-.98(46.77)**	-1.08(10.60)**	-1.01(21.21)**	-1.16(15.02)**	-1.28(39.59)**
LnRGDP_t	.03(7.73)**	.07(6.95)**	.04(8.88)**	.08(9.15)**	.05(9.30)**	.07(3.52)**	.08(16.54)**	.07(5.48)**
LnMB_t	-.06(1.75)*		.01(.20)		.03(.84)		-.05(1.74)*	
POS_t		-.02(.73)		.00(.09)		-.02(.32)		-.02(.78)
NEG_t		.11(2.63)**		.15(4.46)**		.06(.76)		-.09(2.17)**
Panel C: Diagnostic Statistics								
F	9.22**	6.99**	4.71*	8.07**	3.04	5.26*	3.45	7.94**
$\hat{\rho}_0$ (t-ratio)	-.37(5.21)**	-.32(4.8)**	-.29(3.62)*	-.43(5.19)**	-.28(2.93)	-.28(2.87)	-.23(3.20)	-.44(5.05)**
LM	.03	1.04	.25	4.65**	2.87*	2.23	.02	1.31
RESET	7.20**	.28	1.16	.46	2.86*	4.19**	.07	.01
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.23	.22	.23	.36	.29	.28	.07	.29
Wald-S		.07		.26		.10		.46
Wald-L		8.45**		18.26**		.25		1.21

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	NC		ND		NE		NH	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$.15(1.80)*	-.07(.75)		-.16(1.80)*			
$\Delta \text{LnGINI}_{t-2}$.11(.98)	.05(.57)					
$\Delta \text{LnGINI}_{t-3}$			-.12(1.25)					
ΔLnRGDP	.02(.73)	.04(.91)	-.02(.68)	-.02(.96)	.01(.49)	-.00(.03)	-.06(1.14)	-.00(.03)
$\Delta \text{LnRGDP}_{t-1}$.03(1.52)	.04(1.74)*			-.14(2.84)**	-.08(1.50)
$\Delta \text{LnRGDP}_{t-2}$.07(3.27)**	.03(1.50)			.08(1.63)	.11(1.99)**
$\Delta \text{LnRGDP}_{t-3}$							-.12(2.83)**	-.14(3.32)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.01(.20)		-.07(1.67)*		-.03(.62)		-.06(1.02)	
ΔLnMB_{t-1}								
ΔLnMB_{t-2}								
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		.01(.15)		-.05(.88)		-.01(.15)		-.02(.38)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.01(.08)		-.01(.07)		-.02(.14)		-.01(.08)
ΔNEG_{t-1}		.20(2.0)**						.30(2.15)**
ΔNEG_{t-2}								.16(1.11)
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.85(3.55)**	-.89(23.30)**	-1.07(13.18)**	-1.17(49.80)**	-1.04(18.39)**	-1.07(47.66)**	-.94(8.91)**	-.95(20.06)**
LnRGDP_t	.04(3.18)**	.08(6.16)**	.06(11.47)**	.03(3.42)**	.05(15.82)**	.04(5.28)**	.05(7.50)**	.07(6.29)**
LnMB_t	-.05(.51)		-.04(1.11)		-.02(.71)		-.03(.63)	
POS_t		.00(.15)		-.00(.15)		-.01(.40)		-.02(.61)
NEG_t		.18(3.75)**		-.13(3.58)**		-.05(1.46)		.12(2.50)**
Panel C: Diagnostic Statistics								
F	1.69	2.42	4.50*	5.40*	8.43**	10.64**	6.62**	7.44**
$\hat{\rho}_0$ (t-ratio)	-.09(1.78)	-.18(2.87)	-.28(4.75)**	-.36(4.48)**	-.36(5.92)**	-.44(6.30)**	-.28(4.33)**	-.37(5.39)**
LM	1.70	1.63	.57	1.09	1.20	.15	.25	1.63
RESET	.22	2.44	1.50	5.44**	.40	.39	.10	.01
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.03	.08	.28	.21	.29	.29	.20	.29
Wald-S		1.33		.07		.00		3.47**
Wald-L		3.39**		14.13**		4.14**		8.44**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	NJ		NM		NV		NY	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$			-.27(2.76)**	-.28(2.30)**	-.25(2.49)**	-.26(2.47)**	.03(.31)	
$\Delta \text{LnGINI}_{t-2}$			-.18(1.81)*	-.18(1.64)*			-.27(2.61)**	
$\Delta \text{LnGINI}_{t-3}$.12(1.57)	.12(1.47)				
ΔLnRGDP_t	-.08(1.58)	-.02(.53)	.03(.66)	.04(.65)	-.05(.82)	-.04(.59)	.08(1.31)	.12(2.36)**
$\Delta \text{LnRGDP}_{t-1}$.03(.48)	-.08(1.46)
$\Delta \text{LnRGDP}_{t-2}$.17(3.14)**	.14(2.81)**
$\Delta \text{LnRGDP}_{t-3}$							-.13(2.85)**	-.12(2.82)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.04(.83)		-.05(.85)		-.04(.57)		-.02(.45)	
ΔLnMB_{t-1}			-.09(1.77)*				.14(2.58)**	
ΔLnMB_{t-2}								
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		-.06(.98)		-.04(.54)		-.05(.62)		-.01(.24)
ΔPOS_{t-1}				-.15(2.15)**				
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.02(.14)		-.04(.28)		-.05(.24)		.01(.12)
ΔNEG_{t-1}						.20(1.22)		.30(2.77)**
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.96(3.37)**	-1.12(23.10)**	-1.14(11.90)**	-1.13(23.00)**	-1.23(8.30)**	-1.14(12.35)**	2.92(.15)	-1.00(24.27)**
LnRGDP_t	.06(3.42)**	.12(7.56)**	.07(12.43)**	.06(3.27)**	.07(8.08)**	.10(3.50)**	.03(.13)	.13(10.96)**
LnMB_t	-.06(.57)		.00(.03)		.03(.48)		-2.20(.20)	
POS_t		-.05(1.19)		.03(.66)		.00(.06)		.00(.10)
NEG_t		.21(3.37)**		.00(.03)		.11(1.23)		.32(7.51)**
Panel C: Diagnostic Statistics								
F	5.02*	3.09	7.21**	5.42*	2.73	1.69	1.45	5.36*
$\hat{\rho}_0$ (t-ratio)	-.15(3.37)*	-.19(3.26)	-.35(4.58)**	-.35(3.29)	-.17(2.73)	-.16(2.31)	-.01(.21)	-.25(3.96)**
LM	1.06	1.13	.01	.06	.02	.00	.01	.00
RESET	3.24*	.94	.13	.09	4.39**	3.56*	.08	.80
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.10	.06	.37	.37	.15	.12	.21	.31
Wald-S		.07		.56		.63		4.05**
Wald-L		10.09**		.00		.08		41.97**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	OH		OK		OR		PA	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$.39(3.40)**	.43(4.14)**	.20(1.72)*					.13(1.20)
$\Delta \text{LnGINI}_{t-2}$		-.03(.27)	.01(.07)					.00(.05)
$\Delta \text{LnGINI}_{t-3}$.13(1.55)	.38(3.75)**					.25(2.97)**
ΔLnRGDP_t	-.14(2.94)**	-.10(2.19)**	.12(2.81)**	.18(4.15)**	.05(1.14)	.06(1.26)	.03(.50)	.06(1.08)
$\Delta \text{LnRGDP}_{t-1}$.02(.56)	.05(1.22)	-.10(2.50)**	-.10(2.85)**	-.11(2.69)**	-.07(1.51)	-.18(4.18)**	-.14(2.99)**
$\Delta \text{LnRGDP}_{t-2}$.13(3.23)**	.05(1.36)	.07(1.80)*	.07(2.02)**	.13(3.15)**	.13(3.21)**	.23(5.08)**	.13(2.66)**
$\Delta \text{LnRGDP}_{t-3}$	-.14(4.53)**	-.14(4.36)**	-.11(3.07)**	-.03(.87)	-.10(3.04)**	-.10(3.10)**	-.13(3.51)**	-.11(2.79)**
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.11(2.32)**		.01(.24)		-.04(.82)		-.07(1.45)	
ΔLnMB_{t-1}	.07(1.30)							
ΔLnMB_{t-2}	.09(1.77)*							
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		-.04(.71)		-.03(.40)		-.00(.06)		-.06(1.19)
ΔPOS_{t-1}								
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.12(1.02)		.02(.14)		-.15(1.24)		.17(1.42)
ΔNEG_{t-1}		.22(2.04)**				.19(1.73)*		
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.79(4.49)**	-1.04(28.84)**	-.97(11.74)**	-1.00(36.31)**	-1.16(22.19)**	-1.16(39.86)**	-.68(1.87)*	-1.04(35.78)**
LnRGDP_t	.04(3.64)**	.10(8.73)**	.05(10.13)**	.09(6.73)**	.06(18.35)**	.07(8.64)**	.05(2.70)**	.12(10.37)**
LnMB_t	-.08(1.23)		-.02(.60)		.00(.08)		-.17(1.08)	
POS_t		-.03(.98)		-.04(1.52)		-.00(.18)		-.03(1.13)
NEG_t		.17(4.21)**		.10(2.19)**		.04(1.30)		.23(5.52)**
Panel C: Diagnostic Statistics								
F	4.90*	8.08**	5.48**	6.06**	9.09**	7.31**	1.75	7.53**
$\hat{\rho}_0$ (t-ratio)	-.17(3.56)*	-.35(5.45)**	-.36(3.98)**	-.27(3.61)*	-.43(5.20)**	-.44(5.36)**	-.08(1.71)	-.33(4.89)**
LM	.01	.31	8.26**	.55	3.56*	3.76*	.37	.51
RESET	.00	1.95	12.62**	8.87**	1.89	1.42	.14	4.23**
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.28	.41	.37	.33	.30	.32	.29	.45
Wald-S		.73		.07		4.01**		2.94*
Wald-L		29.66**		6.18**		1.84		45.94**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	RI		SC		SD		TN	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
$\Delta \ln \text{GINI}$								
$\Delta \ln \text{GINI}_{t-1}$				-0.15(1.35)				.21(1.72)*
$\Delta \ln \text{GINI}_{t-2}$.01(.10)				.17(1.47)
$\Delta \ln \text{GINI}_{t-3}$				-.27(2.53)**				.16(1.49)
$\Delta \ln \text{RGDP}$	-.11(1.94)*	-.07(1.18)	.08(3.15)**	.14(2.84)**	-.01(.53)	-.02(.79)	.04(1.00)	.02(.38)
$\Delta \ln \text{RGDP}_{t-1}$			-.09(3.75)**	-.10(2.51)**	.04(1.89)*	.03(1.30)	-.13(3.13)**	-.10(2.14)**
$\Delta \ln \text{RGDP}_{t-2}$.02(.85)	.01(.58)	.11(2.64)**	.12(2.57)**
$\Delta \ln \text{RGDP}_{t-3}$.05(2.63)**	.05(2.25)**	-.08(2.22)**	-.14(3.54)**
$\Delta \ln \text{RGDP}_{t-4}$								
$\Delta \ln \text{MB}_t$	-.06(1.03)		-.07(1.67)*		-.04(.79)		-.09(1.90)*	
$\Delta \ln \text{MB}_{t-1}$								
$\Delta \ln \text{MB}_{t-2}$								
$\Delta \ln \text{MB}_{t-3}$								
$\Delta \ln \text{MB}_{t-4}$								
ΔPOS_t		-.09(1.38)		-.03(.62)		-.02(.39)		-.05(.93)
ΔPOS_{t-1}				-.16(2.83)**				
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		.03(.19)		-.09(.72)		-.01(.06)		-.22(1.77)*
ΔNEG_{t-1}		.22(1.88)*		.02(1.66)*				.21(1.73)*
ΔNEG_{t-2}				.02(.15)				.07(.60)
ΔNEG_{t-3}				-.22(2.18)**				-.25(2.12)**
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.74(2.27)**	-.93(17.69)**	-1.03(7.55)**	-1.00(5.09)**	-1.03(9.99)**	-1.14(35.23)**	-1.04(8.11)**	-1.02(28.50)**
$\ln \text{RGDP}_t$.04(2.11)**	.10(7.10)**	.05(7.06)**	.19(1.18)	.06(9.40)**	.04(2.81)**	.05(6.80)**	.07(7.15)**
$\ln \text{MB}_t$	-.12(.87)		-.02(.35)		-.04(1.13)		.01(.24)	
POS_t		-.06(1.64)*		-.02(.11)		-.02(.54)		.00(.02)
NEG_t		.21(4.03)**		.49(.94)		-.14(2.73)**		.10(2.54)**
Panel C: Diagnostic Statistics								
F	5.82**	4.07	2.67	1.96	6.12**	5.60**	3.11	5.07*
$\hat{\rho}_0$ (t-ratio)	-.15(3.53)*	-.26(3.87)*	-.16(2.68)	-.08(.90)	-.27(4.21)**	-.37(4.55)**	-.20(2.93)	-.39(4.06)**
LM	.33	1.10	1.58	.83	2.28	.93	.07	12.91**
RESET	.07	1.89	4.48**	8.68**	2.27	2.35	.03	.15
QS(QS ²)	US(S)	S(S)	US(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.12	.13	.26	.38	.21	.23	.20	.33
Wald-S		3.30*		.14		.01		.16
Wald-L		14.19**		.76		5.62**		7.28**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)

	TX		UT		VA		VT	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI								
$\Delta \text{LnGINI}_{t-1}$	-.04(.36)		.18(2.05)**	.20(2.03)**	.42(4.72)**	.40(4.42)**	-.12(.97)	-.03(.23)
$\Delta \text{LnGINI}_{t-2}$	-.04(.41)				.16(1.81)*	.15(1.63)	-.00(.04)	.07(.69)
$\Delta \text{LnGINI}_{t-3}$.19(2.28)**	.20(2.36)**	.19(2.14)**	.25(2.86)**
ΔLnRGDP	-.02(.49)	.02(.50)	-.12(3.05)**	-.12(2.75)**	-.01(.34)	.01(.21)	-.01(.19)	.02(.42)
$\Delta \text{LnRGDP}_{t-1}$		-.02(.41)			-.13(4.66)**	-.12(4.30)**		
$\Delta \text{LnRGDP}_{t-2}$.06(1.78)*			.09(3.38)**	.10(3.38)**		
$\Delta \text{LnRGDP}_{t-3}$		-.09(2.88)**			-.11(4.49)**	-.10(4.10)**		
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.07(1.53)		-.05(.98)		-.02(.59)		-.09(1.84)*	
ΔLnMB_{t-1}	.02(.52)							
ΔLnMB_{t-2}	.01(.22)							
ΔLnMB_{t-3}	.07(1.72)*							
ΔLnMB_{t-4}								
ΔPOS_t		-.01(.13)		-.08(1.27)		-.02(.64)		-.06(1.01)
ΔPOS_{t-1}								-.09(1.51)
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.19(1.75)*		.04(.28)		.01(.19)		-.12(.98)
ΔNEG_{t-1}		.22(2.17)**		.00(.00)				.33(3.05)**
ΔNEG_{t-2}		.13(1.29)						
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-.98(12.05)**	-1.02(27.39)**	-1.08(12.03)**	1.09(22.1)**	-1.05(24.18)**	-1.02(56.7)**	-1.11(11.93)**	-1.05(34.14)**
LnRGDP_t	.06(13.14)**	.07(6.62)**	.06(11.43)**	.08(5.20)**	.05(18.37)**	.05(7.01)**	.05(8.88)**	.08(8.11)**
LnMB_t	-.03(1.02)		-.03(.81)		.02(.93)		.01(.33)	
POS_t		-.01(.47)		-.04(.98)		.01(.77)		.02(.71)
NEG_t		.04(.91)		.06(1.07)		.04(1.31)		.12(2.94)**
Panel C: Diagnostic Statistics								
F	7.30**	6.15**	6.88**	4.76*	12.86**	9.87**	3.26	5.12*
$\hat{\rho}_0$ (t-ratio)	-.26 (3.63)*	-.29(4.76)**	-.24(4.43)**	-.24(4.28)**	-.37(6.17)**	-.37(6.20)**	-.31(3.04)	-.45(4.20)**
LM	.61	3.98**	.15	.73	2.14	1.84	.52	1.45
RESET	1.47	1.74	3.62*	4.71**	.02	.09	2.78*	.03
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	US(S)	S(S)	S(S)	S(S)
Adjusted R ²	.17	.27	.20	.18	.42	.42	.20	.33
Wald-S		.76		.36		.16		3.52*
Wald-L		.69		.00		1.42		9.14**

Table 4: Full-Information Estimates of Both Linear and Nonlinear ARDL Models (Monetary Policy)								
	WA		WI		WV		WY	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
ΔLnGINI_t								
$\Delta \text{LnGINI}_{t-1}$.26(2.27)**				-0.16(1.91)*	
$\Delta \text{LnGINI}_{t-2}$							-0.28(3.92)**	
$\Delta \text{LnGINI}_{t-3}$.10(1.53)	
ΔLnRGDP_t	-.14(2.93)**	-.12(2.44)**	-.10(2.46)**	-.04(.91)	-.07(1.80)*	-.02(.44)	.02(.53)	-.17(3.29)**
$\Delta \text{LnRGDP}_{t-1}$.08(1.58)	.10(2.20)**	.02(.58)	.00(.04)	-.04(1.30)	-.06(1.81)*		
$\Delta \text{LnRGDP}_{t-2}$.07(1.36)	.03(.74)	.06(1.85)*	.08(2.44)**	-.04(.99)	.03(1.08)		
$\Delta \text{LnRGDP}_{t-3}$	-.07(1.99)**	-.07(2.02)**	-.10(3.18)**	-.08(2.69)**	-.07(2.48)**	-.07(2.46)**		
$\Delta \text{LnRGDP}_{t-4}$								
ΔLnMB_t	-.16(2.76)**		-.05(1.27)		-.14(2.67)**		-.04(.66)	
ΔLnMB_{t-1}	.13(2.00)**							
ΔLnMB_{t-2}	.08(1.38)							
ΔLnMB_{t-3}								
ΔLnMB_{t-4}								
ΔPOS_t		-.09(1.50)		-.06(1.21)		-.10(1.66)*		-.06(.75)
ΔPOS_{t-1}						-.11(1.71)*		
ΔPOS_{t-2}								
ΔPOS_{t-3}								
ΔPOS_{t-4}								
ΔNEG_t		-.23(1.60)		-.01(.14)		-.05(.38)		-.27(1.46)
ΔNEG_{t-1}		.48(3.62)**						
ΔNEG_{t-2}								
ΔNEG_{t-3}								
ΔNEG_{t-4}								
Panel B: Long-Run Estimates								
Constant	-1.19(13.57)**	-1.22(28.16)**	-.95(8.66)**	-1.04(34.06)**	-1.03(8.14)**	-1.08(23.79)**	-1.26(13.20)**	-1.20(24.28)**
LnRGDP_t	.07(12.80)**	.07(5.59)**	.05(7.20)**	.08(7.17)**	.06(6.91)**	.09(4.87)**	.08(.60)	.08(4.96)**
LnMB_t	-.02(.74)		-.03(.68)		-.03(.56)		.02(13.40)**	
POS_t		.00(.01)		-.03(1.17)		.01(.20)		.01(.24)
NEG_t		-.00(.01)		.11(2.39)**		.14(1.66)		.03(.43)
Panel C: Diagnostic Statistics								
F	9.53**	8.02**	3.59	5.46*	4.71*	5.42*	5.17*	3.27
$\hat{\rho}_0$ (t-ratio)	-.42(5.25)**	-.42(5.51)**	-.19(3.12)	-.23(3.65)*	-.23(3.61)*	-.27(4.27)**	-.29(3.93)**	-.36(4.07)**
LM	.00	.00	1.92	2.82*	.87	.30	.27	.22
RESET	6.20**	7.24**	1.06	.01	.06	1.31	1.02	.69
QS(QS ²)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)	S(S)
Adjusted R ²	.32	.36	.19	.22	.23	.27	.49	.31
Wald-S		2.91*		.12		.84		.89
Wald-L		.59		11.44**		5.38**		9.87**

Note:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables (k=2), the upper bound critical value of the F test is 4.47 (5.47). These come from Narayan (2005, p. 1988) for our sample size.
3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when k=2 and these come from Banerjee et al (1989, p. 276). In the nonlinear model where k=3, these critical values change to -3.46 (-3.91).

4. LM is Lagrange Multiplier test of residual serial correlation. It is distributed as χ^2 with one degree of freedom (first order). Its critical value at 10% (5%) significance level is 2.70 (3.84). These critical values are also used for Wald tests since they also have a χ^2 distribution with one degree of freedom.
5. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom.

4.4 Conclusion

Studies that have assessed the impact of monetary policy on income inequality have provided mixed outcome and almost all of them assume that the effects are symmetric. This study focuses on the links between monetary policy and income inequality on the United States and its 50 states as well as District of Columbia over a long period of time (1918- 2015). It goes beyond the literature and argue that the effects could be asymmetric. First, I assume that distributional effect of monetary policy is symmetric based on Pesaran et al.'s (2001) linear ARDL approach; and then, I consider the asymmetric effects based nonlinear ARDL approach of Shin et al. (2014).

linear model outcomes imply that monetary policy has no significant impact on U.S income inequality in both short run and long run. However, with assuming asymmetric effects in the nonlinear model, it is found that a contractionary monetary policy (decline in monetary base to GDP ratio) has equalizing effect in the U.S. in the long run. Then, both linear and nonlinear model estimated for each state of the U.S. The linear model predicted short run effects of monetary policy on GINI in 21 states of Alabama, Arizona, Kentucky, North Dakota, New Mexico, South Carolina, Tennessee, Vermont, West Virginia, Connecticut, Delaware, Indiana, Louisiana, Minnesota, New York, Texas, Massachusetts, Maine, Ohio, Washington, and District of Columbia. These short run effects translate into the long run significant effects (Cointegrated) only in four states Iowa, Minnesota, Montana, and Wyoming. An expansionary monetary policy reduces income inequality in of Iowa, Minnesota, and Montana, and increase it in Wyoming in the long run.

However, with estimate of nonlinear model, the number of states with significant effects increased from 21 to 24 in the short run, and from 4 to 34 states in the long run. The increase in the number of states must be attributed by asymmetric effects of monetary policy.

Indeed, the nonlinear model predicted short run asymmetric effects of monetary policy on income inequality in 24 states of Alaska, Arkansas, Colorado, Connecticut, Delaware, Georgia, Kentucky, Louisiana, Massachusetts, Maine, North Carolina, New Hampshire, New Mexico, New York, Ohio, Oregon, Rhode Island, South Carolina, Tennessee, Texas, Vermont, Washington, West Virginia, and District of Columbia. These short run effects lasted into long run effects in 34 states of Alaska, Alabama, Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, Montana, North Carolina, North Dakota, New Hampshire, New Jersey, New York, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Dakota, Tennessee, Vermont, Wisconsin, and District of Columbia.

5. Summary and Conclusion

Empirical studies pertaining to the effects of macroeconomics -such as tariff rate, policy uncertainty and monetary policy- on income inequality are rather mixed. Here in this thesis, I studied the distributional effects of average tariff and two other macroeconomic variables -policy uncertainty and monetary policy- in the U.S.

Kuznets' (1955) inverted-U hypothesis implies that economic growth worsens income inequality in the short run and improves it in the long run after a threshold.

I studied the distributional effects of average tariff rates on income inequality in the U.S. within the traditional Kuznets model over the period 1929–2015. The empirical results indicates that there is no significant link between income inequality and the average tariff rate in the U.S. However, I found that these results may suffer from aggregation bias. Means that, different states may react differently to a tariff cut. Therefore, using state-level data, I explore the distributional effect of tariff rate on income inequality in each state as well. Moreover, this study goes beyond the literature and argue that effects of a tariff on income inequality could be asymmetric.

First, assuming symmetric effects, I study the effects of tariff on GINI are symmetric based on Pesaran et al.'s (2001) linear ARDL approach. The linear model predicted short-run effects of tariff on GINI in 6 states of Alaska, Connecticut, Delaware, North Carolina, Nevada, and Washington. However, short-run significant or insignificant effects lasted into the long run only 3 states of Alaska, Iowa, and Utah. In all three states tariff cuts reduced inequality in the long run.

Next, we assume the effects are asymmetric and rely upon the nonlinear ARDL approach of Shin et al. (2014). The nonlinear model predicted short-run asymmetric effects of the U.S. average tariff rate on income inequality in 22 states of Alaska, Arizona, Arkansas, Connecticut,

Delaware, District of Columbia, Hawaii, Iowa, Kentucky, Louisiana, Maine, Missouri, North Carolina, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Dakota, Virginia, Washington, and West Virginia. Short-run effects lasted into long run effects in 12 states of Alaska, Arizona, Connecticut, District of Columbia, Iowa, Idaho, Illinois, Indiana, New Hampshire, New Jersey, Pennsylvania, and Utah.

This increase in the number of states from 6 to 22 states in the short run and from 3 to 22 states in the long run from linear to non-linear model, must be attributed to the asymmetric effect of tariff rate. Since the nonlinear model separates the effect of an increased in tariff rate from a decreased in tariff rate. And the size and the sign of the effects are different in different states. The significant findings from both linear and non-linear models are summarized respectively in Panel A and Panel B of Table 5.

The other macroeconomic variable that was studied in this thesis is U.S. policy uncertainty. Unlike the previous studies that used volatility of income as a measure of policy uncertainty, this study used a more comprehensive policy uncertainty index and assessed its asymmetric impact on a GINI coefficient as a measure of income inequality.

Linear model results show that policy uncertainty affects income inequality in the short run only in Arkansas and this effect will not translate into long run. From the nonlinear model, however, I find short-run asymmetric effects of policy uncertainty in 41 states, and long-run asymmetric effects in 25 states. These results show that in 20 states decreased policy uncertainty worsened income inequality and in 14 states increased policy uncertainty improved it (Table 6).

Next, I aimed to identify the possible nonlinear effects of monetary policy on income inequality for the United States as a whole and for each of the 50 states and the District of Columbia.

Results from linear model on annual data from 1918 to 2015 indicate that monetary policy has significant effect on state income inequality in the 21 states of Alabama, Arizona, Kentucky, North Dakota, New Mexico, South Carolina, Tennessee, Vermont, West Virginia, Connecticut, Delaware, Indiana, Louisiana, Minnesota, New York, Texas, Massachusetts, Maine, Ohio, Washington, and District of Columbia. These short-run effects translate into the long-run significant effects (Cointegrated) in four states of Iowa, Minnesota, Montana, and Wyoming.

Then, I assume that the effects are asymmetric and short-run outcomes from nonlinear model show significant effects in 24 states including Alaska, Arkansas, Colorado, Connecticut, Delaware, District of Columbia, Georgia, Kentucky, Louisiana, Massachusetts, Maine, North Carolina, New Hampshire, New Mexico, New York, Ohio, Oregon, Rhode Island, South Carolina, Tennessee, Texas, Vermont, Washington, and West Virginia.

The significant and sometimes insignificant short-run effects last into the long-run significant effects (cointegrated) in 34 states including Alaska, Alabama, Arkansas, California, Colorado, Connecticut, Delaware, Discrete of Columbia, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Massachusetts, Maryland, Maine, Michigan, Minnesota, Missouri, Montana, North Carolina, North Dakota, New Hampshire, New Jersey, New York, Ohio, Oklahoma, Pennsylvania, Rhode island, South Dakota, Tennessee, Vermont, and Wisconsin.

The increase in number of the states in the short run from 21 in linear model to 24 in nonlinear model, and the increase in the number of states with long-run effects from 4 (in the linear model), to 34 states (in the non-linear model) must be attributed by the nonlinear adjustment of monetary base (Table 7).

In addition, results from the linear model, which assumes the effects are symmetric, do not show any significant distributional effects in the United States as a whole for none of the three variables -tariff rate, policy uncertainty and monetary policy- neither short run nor long run.

However, when I assume asymmetric effects and use the nonlinear ARDL approach, I find decreased uncertainty worsens inequality in the United States in the long run, but increased uncertainty has no long-run effect. Also, my findings demonstrate that a contractionary monetary policy decreases U.S. income inequality in the long run while an expansionary monetary policy does not affect it. No significant asymmetric links found between tariff rate and U.S. income inequality.

Panel A						
Table 5: Summary Information Estimates of Linear ARDL Model (Average Tariff Rate)						
State	Short-Run					Long-Run
	ΔLnTR_t	ΔLnTR_{t-1}	ΔLnTR_{t-2}	ΔLnTR_{t-3}	ΔLnTR_{t-4}	LnTR_t
Alaska	-.017	-.08	.07	-.10*		.23**
Connecticut	.01	-.04*				.07
Delaware	-.03	-.06*				.06
Iowa	.02					.05**
North Carolina	-.02	.01	-.02	.05**		-.04
Nevada	.02	-.07**				.03
Utah	.01					.05*
Washington	-.02	-.03*				.01

Panel B													
Table 5: Summary Information Estimates of Nonlinear ARDL Model (Average Tariff Rate)													
State	Short-Run								Long-Run				
	APOS _t	APOS _{t-1}	APOS _{t-2}	APOS _{t-3}	APOS _{t-4}	ANEG _t	ANEG _{t-1}	ANEG _{t-2}	ANEG _{t-3}	ANEG _{t-4}	POS _t	NEG _t	
Alaska	-10	-06	-06	-.35**		.05	-.05	.15**			-.02	.21**	
Arizona	.00	-.09*	-.10**			.02					.08*	-.02	
Arkansas	-.11*					.07**					-.14	-.03	
Connecticut	-.04					.03	-.06*	-.05			.06	.10*	
Delaware	-.17**	-.15**				.02					-.08	.00	
District of Columbia	.03	-.09*	-.12**			.01					.12**	.02	
Hawaii	-.01					.06*					-.05	.02	
Iowa	-.06					.05*					.03	.05**	
Idaho	-.00					-.04					.07**	-.04**	
Illinois	.00					.04					-.03	.09*	
Indiana	-.00					.03					-.07	.06*	
Kentucky	-.10*					.00					-.07	.03	
Louisiana	-.04	-.02	-.10*	.13**		-.02					-.04	-.00	
Maine	-.20**					.03					-.11	.06	
Missouri	-.11**					.02					-.05	.02	
Mississippi	-.10					.07*					-.28	.03	
North Carolina	-.11**					.01					-.24	-.05	
New Hampshire	-.09					.03					-.06	.08**	
New Jersey	-.03					-.00					.01	.07*	
New Mexico	-.13*	-.08	-.14**			-.01					.07	-.04	
Nevada	-.04					.05	-.08**				.08	.02	
Ohio	-.05					.02					-.07	.08*	
Oklahoma	-.15**					.01					.02	-.03	
Oregon	-.01	-.10**				.03					-.00	.01	
Pennsylvania	-.09*					.05**					-.12	.08**	
Rhode Island	-.14**					.03					-.08	.05	
South Dakota	-.02					.01	.02	.05	-.07**		.03	.04	
Utah	-.06					.03					.02	.06*	
Virginia	-.04	.03	-.04	.09**		.00					.01	.01	
Washington	-.04	-.10**				-.03					.02	-.02	
West Virginia	-.14**					.04	.06**				-.25*	.03	

Notes:

1. Numbers inside parentheses are t-ratios; **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables (K=2), the upper bound critical value of the F test is 4.47 (5.47). These come from Narayan (2005, p. 1988) for our sample size.
3. Number inside the parenthesis next to $\hat{\beta}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when K=2 and these come from Banerjee et al (1989, p. 276). In the nonlinear model where K=3, these critical values change to -3.46 (-3.91).

Panel A						
Table 6: Summary Information Estimates of Linear ARDL Model (Policy Uncertainty)						
States	Short-Run					long-Run
	$\Delta \ln \text{PU}_t$	$\Delta \ln \text{PU}_{t-1}$	$\Delta \ln \text{PU}_{t-2}$	$\Delta \ln \text{PU}_{t-3}$	$\Delta \ln \text{PU}_{t-4}$	$\ln \text{PU}_t$
Alaska	-.45					-9.22
Alabama	-.01					-.04
Arkansas	.043	.01	-.08**	-.06**		.09
Arizona	-.03**					-.15*
California	-.05**	.04*	.10**			-3.12
Colorado	-.02					-.09
Connecticut	-.02	.07**	.06**			-4.23
Delaware	-.02					-.04
District of Columbia	.08**					.06**
Florida	-.02	-.03				-.04
Georgia	-.04**					-.51
Hawaii	-.00					-.02
Iowa	.01					.043
Idaho	-.03					-.06
Illinois	-.01					-.10
Indiana	-.03**					-.09*
Kansas	-.05**	.03*	.04*			-.23
Kentucky	-.01					-.02
Louisiana	-.02	-.04**	-.02	-.06**		
Massachusetts	-.05**	-.01	.05**			-.09
Maryland	-.03	.01	.05**	.02		-.46
Maine	-.06**	.14**	.06**	.03		-.14**
Michigan	-.02**	-.02	-.01	-.04**		-.04
Minnesota	-.02					.23
Missouri	-.04**					-.12**
Mississippi	.00					.11
Montana	-.02					-.05
North Carolina	-.04**	-.03**				-.07
North Dakota	-.01	-.03	-.05**			.11
Nebraska	-.03**	.02	.04**			-.15*
New Hampshire	-.02					-.08
New Jersey	-.04*	.04	.06**			.67
New Mexico	-.07*					-.18**
Nevada	-.05*					-.39
New York	-.00					.02
Ohio	-.04**					-.13**
Oklahoma	-.03					-.07
Oregon	-.02					-.04
Pennsylvania	-.02**					-.07**
Rhode Island	-.04**					-.08*
South Carolina	-.04*	-.05*	-.03	-.06**		-.02
South Dakota	-.04**					-.06**
Tennessee	-.05**	-.04*	-.06**	-.05**		-.07
Texas	-.03*					-.04
Utah	-.05**	.02	.04*			-.14
Virginia	-.02					-.14
Vermont	-.03**					-.07**
Washington	-.02	.02	.06			-.28
Wisconsin	-.03**					-.11*
West Virginia	-.05*					-.23*
Wyoming	-.03*					-.81

Panel B										
Table 6: Summary Information Estimates of Nonlinear ARDL Model (Policy Uncertainty)										
States	Short-Run								Long-Run	
	ΔPOS_t	ΔPOS_{t-1}	ΔPOS_{t-2}	ΔPOS_{t-3}	ΔNEG_t	ΔNEG_{t-1}	ΔNEG_{t-2}	ΔNEG_{t-3}	POS_t	NEG_t
Alaska	.03	-.02			-.01	-.11	-.08	-.08	.08**	.21**
Alabama	-.02				-.00				-.048	-.03
Arkansas	.05	-.05	-.13	-.11*					9.78	17.60
Arizona	-.03				-.02	.11**	.08*	.05	-.03	-.11**
California	.01	.05	.15**		-.12**				.01	-.15
Colorado	.04	-.05	.10**	.02	-.04	-.06*	-.10**	-.13**	.10**	.03**
Connecticut	.02	.10**	.17**	-.11	-.05	.19**	-.02	.14**	-.05	-.42
Delaware	-.01	-.03**	-.02	-.04**	-.04**	.12**	.06**	.02	-.02*	-.07**
District of Columbia	.05	-.06			.16**				.11**	.03
Florida	-.03	-.04	.03		-.05	.08	.04		-.04**	-.15**
Georgia	-.04	.05	.13**	.10	-.09**	.22**	.17*		-.07**	-.17**
Hawaii	-.08**	.06**	-.04**	.02	.04*	.16**	.21**	.16**	-.10**	-.13**
Iowa	-.01	.032	.05	.03	.01	.06	.02		-.05**	-.12**
Idaho	.01	.02	.04	-.08**	.00	-.04	-.21**	-.18**	.38	.63
Illinois	.03	.06*	.12**	.03	-.07*	.05			.01	-.11**
Indiana	-.07**	-.03			-.01	.10*	.07		-.07**	-.11**
Kansas	-.01	.05*	.06*		-.08*				-.07	-.18
Kentucky	.15**	.00	.11**		-.10**	-.20**	-.28**	-.18**	-.84	-.89
Louisiana	-.09**				-.03				.02	-.02
Massachusetts	.00	-.03	.09**		-.12**				.08**	-.10*
Maryland	.02	-.01	.06**		-.08*				.09**	-.12**
Maine	-.06	.10	.02	-.09	-.10	.23**	.09	.14**	-.16**	-.14**
Michigan	-.06**				-.00	.10	.10**		-.08**	-.17**
Minnesota	-.00	.01	.07**		-.04	.10**			-.02	-.18**
Missouri	-.07**				-.04	.14**	.09*		-.13**	-.18**
Mississippi	-.16**	-.01	-.08*	.07*	.18**				.07	.11
Montana	-.00	-.06	.18**	.06	-.13*	-.07	-.13	-.21**	-.05	-.29
North Carolina	.06*	-.10**	-.11**	-.08*	-.01				-.06	-.00
North Dakota	-.03	-.03	-.05**		.01				.04	-.04*
Nebraska	-.04**	.07**	.10**		-.08**	.14**	.10**	.13**	-.17**	-.24**
New Hampshire	-.06				.02	.06	.10*	.05	-.1	-.26*
New Jersey	-.03	.01	.08**		-.05	.08**			2.52	3.84
New Jersey	.00	-.13**	-.10	-.09	.00	-.18*	-.17	-.14*	26.83	53.76
Nevada	.02	.12*	.29**		-.10	.31**			-.11**	-.26**
New York	.03	-.03			-.01				.10**	-.02
Ohio	-.06**	-.04			-.04	.12*	.07	-.04	-.07**	-.14**
Oklahoma	-.03				-.04				-.00	-.27
Oregon	-.02				-.01				-.02*	-.05**
Pennsylvania	-.04**				-.02	.07**	.04		-.07**	-.12**
Rhode Island	.00	.04*	.08**		-.06**	.10**	.03	.06**	-.01	-.09**
South Carolina	-.03	-.08**			-.04	-.07	-.05	-.15**	-.02	-.03
South Dakota	-.06**				-.01				-.08*	-.02
Tennessee	-.05	-.06	-.08	-.06	-.07				-.01	.02
Texas	-.02				-.04				-.03	-.10**
Utah	-.02	.04	.08		-.08*	.08*	.06	.04	-.02	-.11**
Virginia	.06**	.01	.09**		-.08**	.06**			.07**	-.12**
Vermont	-.06**				-.01	.08**	.05		-.10**	-.09**
Washington	.03	.07	.13**		-.10				-3.31	-16.94
Wisconsin	-.05	.00	.01	.03	.00	.12**	.08		-.03**	-.16**
West Virginia	-.03				-.05	.08	-.14	-.10	-.07	-.08
Wyoming	.04	.09**	.09**		-.03	.28**	.09*		-.05**	-.16**

Notes:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables ($k=2$), the upper bound critical value of the F test is 4.47 (5.47). These come from Narayan (2005, p. 1988) for our sample size.
3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when $k=2$ and these come from Banerjee et al (1989, p. 276). In the nonlinear model where $k=3$, these critical values change to -3.46 (-3.91).

Panel A						
Table 7: Summary Information Estimates of Linear ARDL Model (Monetary Policy)						
States	Short-Run					Long-Run
	$\Delta \ln MB_t$	$\Delta \ln MB_{t-1}$	$\Delta \ln MB_{t-2}$	$\Delta \ln MB_{t-3}$	$\Delta \ln MB_{t-4}$	$\ln MB_t$
Alabama	-.09*					-.00
Arizona	.08	-.24**	-.13**			.04
Connecticut	-.07	.18**				-.14
Delaware	.17**	.06				-.00
District of Columbia	-.12**					-.04
Iowa	-.03					-.03**
Indiana	-.06	.01	.10**			-.04
Kentucky	-.11**					-.05
Louisiana	-.06	.08	-.03	.12**		-.03
Massachusetts	-.12**	.11*	.08			-.17
Maine	-.07	-.17**	.13*			-.02
Minnesota	-.03	.08*	.01	.11**		-.06*
Montana	-.07					-.05*
North Dakota	-.07*					-.04
New Mexico	-.05	-.09*				.00
Nevada	-.04					.03
New York	-.02	.14**				-2.20
Ohio	-.11**	.07	.09*			-.08
South Carolina	-.07*					-.02
Tennessee	-.09*					.01
Texas	-.07	.02	.01	.07*		-.03
Vermont	-.09*					.01
Washington	-.16**	.13**	.08			-.02
West Virginia	-.14**					-.03
Wyoming	-.04					.02**

Panel B												
Table 7: Summary Information Estimates of Nonlinear ARDL Model (Monetary Policy)												
States	Short-Run										Long-Run	
	ΔPOS_t	ΔPOS_{t-1}	ΔPOS_{t-2}	ΔPOS_{t-3}	ΔPOS_{t-4}	ΔNEG_t	ΔNEG_{t-1}	ΔNEG_{t-2}	ΔNEG_{t-3}	ΔNEG_{t-4}	POS_t	NEG_t
U.S.	-.03					.04					-.01	.18**
Alaska	-.06					1.41**	.78				-.13**	-.43
Alabama	-.06					-.04	.16	.15			-.02	.17**
Arkansas	-.01	-.14**				.20					.07*	.15**
California	-.01					-.01					-.02	.15**
Colorado	.04					.03	.30**	.16	.32**		.02	.14**
Connecticut	-.04					.16	.34**				-.02	.26**
Delaware	-.04					.37**	.32**	-.26*	-.30**		.02	.31**
District of Columbia	-.06					-.25*					-.09**	-.03
Florida	.00					.16	.15				.04	.29**
Georgia	.02					-.19	.10	.14	-.22**		.04	.14**
Idaho	.03					-.05					.03**	-.12**
Illinois	-.02					.01	.09	.13			-.01	.22**
Indiana	-.01					-.08					-.03	.12**
Kentucky	-.12*					-.09					-.05	.12**
Louisiana	-.01	-.03	-.13**	.13**		-.16	.32**				-.01	.10
Massachusetts	-.05					-.09	.34**				-.04	.19**
Maryland	-.05					-.10	.14				-.04	.16**
Maine	-.08					.13	-.19	.36**			-.04	.15**
Michigan	-.05					.19					-.05	.24**
Minnesota	-.01					.03					-.02(.73)	.11**
Missouri	.00					.07					.00	.15**
Montana	-.04					-.15					-.02	-.09**
North Carolina	.01					-.01	.20**				.00	.18**
North Dakota	-.05					-.01					-.00	-.13**
New Hampshire	-.02					-.01	.30**	.16			-.02	.12**
New Jersey	-.06					-.02					-.05	.21**
New Mexico	-.04	-.15**				-.04					.03	.00
New York	-.01					.01	.30**				.00	.32**
Ohio	-.04					-.12	.22**				-.03	.17**
Oklahoma	-.03					.02					-.04	.10**
Oregon	-.00					-.15	.19*				-.00	.04
Pennsylvania	-.06					.17					-.03	.23**
Rhode Island	-.09					.03	.22*				-.06*	.21**
South Carolina	-.03	-.16**				-.09	.02*	.02	-.22**		-.02	.49
South Dakota	-.02					-.01					-.02	-.14**
Tennessee	-.05					-.22*	.21*	.07	-.25**		.00	.10**
Texas	-.01					-.19*	.22**	.13			-.01	.04
Vermont	-.06	-.09				-.12	.33**				.02	.12**
Washington	-.09					-.23	.48**				.00	-.00
Wisconsin	-.06					-.01					-.03	.11**
West Virginia	-.10*	-.11*				-.05					.01	.14

Notes:

1. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.
2. At the 10% (5%) significance level when there are two exogenous variables ($k=2$), the upper bound critical value of the F test is 4.47 (5.47). These come from Narayan (2005, p. 1988) for our sample size.
3. Number inside the parenthesis next to $\hat{\rho}_0$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -3.24 (-3.64) when $k=2$ and these come from Banerjee et al (1989, p. 276). In the nonlinear model where $k=3$, these critical values change to -3.46 (-3.91).

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Appendix: Data Sources

Annual data over the period 1929–2015 are used to carry out the empirical exercise on the effect of tariff rate, for the monetary policy effects data are available from 1918 to 2015, except for Alaska and Hawaii for which data are restricted to their period of statehood (1959–2015). Data for policy uncertainty is available from 1985 to 2015.

In this study, I use Gini coefficient as a measure of income inequality that is constructed for the U.S. as well as for each state by Mark W. Frank and is publicly available on his web site⁷. He constructs Gini from tax data reported in Statistics of Income published by the Internal Revenue Service (IRS). The pre-tax adjusted gross income reported by the IRS includes wages and salaries, capital income (dividends, interest, rents, and royalties) as well as entrepreneurial income from small businesses and self-employment. For the construction method see Frank (2009, Appendix). Gini data are available from 1918 to 2015.

Total income including imputed income of non-filers in current thousand dollars is constructed by Mark W. Frank from individual tax filing data. Then, we have divided Frank's measure of total income by CPI (Base year 2015) and population of each state to get the real total per capita income (RGDP) for U.S and for each state. The population data come from the Bureau of Economic Analysis⁸. Following literature, we use U.S. annual monetary base (MB) -not seasonally adjusted- as a measure of monetary policy rate and it is available from 1918 to 2019 on Federal Reserve Bank of St. Louis website.⁹ News-based Policy Uncertainty for U.S comes from “Measuring Economic Policy Uncertainty” by Scott Baker, Nicholas Bloom and Steven J.

⁷ http://www.shsu.edu/eco_mwf/inequality.html

⁸ <https://www.bea.gov/regional/index.htm>

⁹ https://fred.stlouisfed.org/series/AMBNS?utm_source=series_page&utm_medium=related_content&utm_term=other_formats&utm_campaign=other_format#0

Davis¹⁰ and it is available from 2015. U.S. average tariff rate: Data come from the United States International Trade Commission, and it is available from 1891¹¹. Tariff rate in percentage is defined as duties collected in dollars divided by total imports in dollars. Total imports include value of duty-free imports for consumption and value of dutiable goods for consumption.

¹⁰ www.PolicyUncertainty.com

¹¹ https://www.usitc.gov/documents/dataweb/ave_table_1891_2016.pdf