The Impacts of US state-level economic policy uncertainty on US state-level income distribution: Asymmetric Approach

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Abstract

This study aims to expand Bahmani-Oskooee and Hasanzade's (2022) research examining the impact of economic policy uncertainty (EPU) on income inequality in the US states. Our study differs from theirs as we use a newly calculated US state-level EPU index, whereas they used the US country-level EPU index in their previous work. While the linear ARDL model finds that the EPU has short-run effects on GINI in 15 US states, the nonlinear model finds it in 22. Similarly, while the nonlinear model finds that EPU has a long-run impact on GINI in 5 US states, the linear model finds it only in 1 US state. However, when the CSD is allowed, the linear model finds that EPU impacts GINI in 5 US states in the long run. While our study finds that decreased uncertainty worsens income inequalities in Texas and Washington, Bahmani-Oskooee & Hasanzade (2022) find uncertainty does not have long-run effects in these US states. Similarly, while we find that increased uncertainty improves inequality in Virginia, they also find worsening effects in this US state. Empirical findings reveal that state-level analysis discovers some hidden impacts of the EPU on GINI that we could not find in country-level analysis.

KEYWORDS
Income Inequality, GINI index, the US State-level Analysis, US State-level EPU Index.

JEL CLASSIFICATION
D31, D33, Q15

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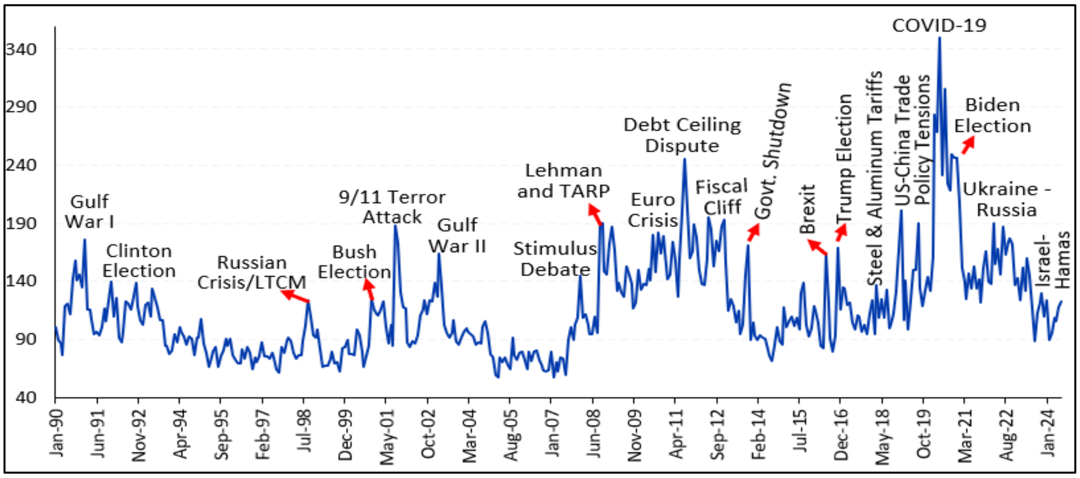
1 INTRODUCTION

Following Friedman (1984), many scholars have added the concept of 'uncertainty' in various forms as independent variables in their model within the framework of certain macroeconomic variables such as inflation (Klein, 1977; Arize, 2005), exchange rate uncertainty (Choi & Oh, 2003; Bahmani-Oskooee & Hegerty, 2007; bond rates uncertainty (Longstaff &Schwartz, (1993), interest rate uncertainty (Choudhry, (1999), monetary uncertainties (Choi & Oh, 2003; Ho & Iyke, 2017, output uncertainty (Aworinde, 2018), home prices (Ongan and Gocer, 2017), and stock exchange (Adrangi et al., 2023). All these uncertainty forms (independent variables) are conducted based on volatilities and are therefore scaled-measured in this way by each scholar individually. In fact, these defined forms of uncertainty may arise mainly due to the uncertain macroeconomic policies implemented by the governments. Therefore, this may be the reason for the widespread use of the economic policy uncertainty (henceforth the EPU) index recently developed by Baker et al. (2016) in literature.

The EPU index[1], as a policy-related economic uncertainty index, was constructed from three components: (1) Leading newspapers' coverages associated with economic uncertainty, (2) Reports by the Congressional Budget Office (CBO) about changing tax codes and (3) Forecasts by the Federal Reserve Bank of Philadelphia's Survey about current and future consumer prices relating to economic uncertainty. In other words, this index includes and quantifies (scans) some specific terms, such as "uncertainty," "uncertain," "deficit," and "the Federal Reserve (the FED)" related to the fiscal and monetary policies of the countries. Figure 1 below shows fluctuations in the US EPU index depending on several developments inside and outside the US during the study's sample period 1990-2024.

[1] For technical construction of the US country-level-EPU index, refer to https://www.policyuncertainty.com/methodology.html

FIGURE 1 The fluctuation of the US EPU index (1990-2024).



Source**:** Baker et al.'s. (2016) figure was extended to 2024.

According to Figure 1, many developments, such as the Gulf War in 1990-1991, the 2001 Terrorist attack, the US-China trade tension in 2018-2019, COVID-19 in 2020, and the recent Ukraine-Russia war in 2022, significantly affected the US EPU index.

Ever since the introduction of this index (measure), many scholars have used and examined the relationship between this measure and different micro-macroeconomic variables such as inflation (Jones & Olson, 2013; Balcilar et .al, 2017), stock markets (Brogaard & Detzel, 2013; Yongan et al., 2021), oil prices (You et al., 2017; Dutta et al., 2021), exchange rate (Krol, 2014; Bartsch, 2019), economic growth (Adedoyin et al., 2022; Songping, Z, & Gaofeng, 2022), food prices (Wen et al., 2021) and tourism demand (Ongan & Gozgor, 2018; Isik et al., 2020), commodity trade (Bahmani-Oskooee & Xu, 2022; Bahmani-Oskooee et al..2023).

However, although uncertainty shocks can determine income inequality as they affect asset prices and the real economy, the empirical literature examining the dynamic relationship between uncertainty and income inequality is relatively sparse, and the distributional effects of uncertainty shocks have been largely omitted (Theophilopoulou, 2018; Angeliki, 2021).

Before the EPU index was created, the following studies examined the impact of income or output volatility as a measure of uncertainty on GINI as a measure of income inequality and found that rises in income volatility worsened income distribution (Hausmann & Gavin, 1996; Caroli & Garcia-Penalosa, 2001; Checchi & Garcia-Penalosa, 2004; Breen & Garcia-Penalosa, 2005; Laursen & Mahajan, 2005; Calderon & Yeyati, 2009; Huang et al., 2015). Bahmani-Oskooee &

Ardakani (2020) found that both rises and falls in volatility improve the income distribution for different countries.

With the creation of the EPU index, a few studies examined the impacts of the EPU index on income inequality (GINI coefficient). In one of these few studies, Giacumo & Luca (2017) found significant effects of the changes in the EPU index on income inequality at the top end of the consumption distribution for the US. Fischer et al. (2021) also find strong relationships between the EPU index and income inequality in four US regions: Midwest, Northeast, South, and West. Finally, Bahmani-Oskooee & Hasanzade (2022) found the long-run asymmetric effects of the EPU index on income inequality for 25 US states.

Therefore, our main aim is to examine the asymmetric effects of changes in the EPU index on income inequalities defined by the GINI[2] coefficient at the US state level. However, this study differs from Bahmani-Oskooee & Hasanzade's (2022) US state-level study, which used the US country-level EPU index because state-level EPU indexes were not developed when the authors conducted this study. The newly developed US state-level index[3] by Baker et al. (2022) may provide more detailed and accurate information than this country-level index. This is because US states may differ in their economic size, population, tax rates, budgets, and laws; these differences may play a determining role in US states' economic policy uncertainty levels (EPU indices). Hence, all these differences may require using state-level data instead of country-level data in US state-level analyses, as we did in our study. This study's contribution is to expand, update, and contribute to the Bahmani-Oskooee & Hasanzade (2022) study, which utilizes the US country-level EPU index.

1.1. US country-level EPU index vs. US state-level EPU index

The US state-level EPU index, newly developed by Baker et al. (2022), differs and shares similarities with the US country-level EPU index previously developed by Baker et al. (2016). First, both indices scan and count the frequencies of some specific words from the newspapers. While the country-level index scans some words such as uncertain, uncertainty, uncertainty, and

[2] The GINI coefficient takes values between 0 (perfect equality) and 1 (perfect inequality). For technical construction, refer to OECD (2022) via https://data.oecd.org/inequality/income-inequality.htm#:~:text=The%20Gini%20coefficient%20is%20based,the%20case%20of%20perfect%20inequality.

[3] For technical construction of the US state-EPU index, refer https://doi.org/10.1016/j.jmoneco.2022.08.004

economy, the state-level index, in addition to these words, also scans other words such as local government bodies, state-specific legislation, and local policy initiatives. However, the country-level index covers 10 prominent newspapers such as USA Today, the Miami Herald, and WSJ. The state-level index covers 3,500 local newspapers across all US states, excluding national papers like the New York Times or Wall Street Journal. In other words, while the state-level index provides a more localized and customized perspective that reflects the direct effects of state policies on the economy, the country-level index provides the overall economic uncertainty. It measures the broad impacts of economic and policy decisions at the national level. Regarding the difference in index construction, the country-level index works on a single index that measures policy uncertainty across the country. US State-level index works on three indices for each US state: state sources (EPU_{State}), national sources ($EPU_{National}$), and a combination of these ($EPU_{Composite}$). (Baker et al., 2022).

2 THE MODEL AND METHODOLOGY

We use the following model to examine the effects of changes in the EPU index on income inequality:

$$lGINI_t^S = a + blY_t^S + clEPU_t^S + \varepsilon_t \tag{1}$$

where $lGINI$ and lY are the US state-level GINI coefficients and the US state-level per capita real income, respectively. The $lEPU$ is US state-level EPU index. If the sign of b to be negative, this will mean that an increase in per capita income will improve (decrease in GINI) income inequality in the long run. If this sign is positive, this will mean that an increase in per capita income will worsen (increase in GINI) income inequality. Finally, if the sign of c to be positive, this will mean that an increase in the EPU index will worsen income inequality. Adding the short-run effects of income on the GINI coefficient to the model above will also provide judging the Kuznets' Hypothesis by Kuznets (1955). Kuznets (1955) proposed that economic growth initially increases (worsens) income inequality in the short run and eventually decreases (improves) it after a certain level of income in the long run. Hence, by estimating the error correction model, we form the following model of Pesaran et al.'s (2001) autoregressive distributed lag (ARDL) model for both short- and long-run effects.

$$\Delta lGINI_t^S = \alpha + \sum_{j=1}^{n1} \beta_j \Delta lGINI_{t-j}^S + \sum_{j=0}^{n2} \delta_j \Delta lY_{t-j}^S + \sum_{j=0}^{n3} \theta_j \Delta lEPU_{t-j}^S + \lambda_0 lGINI_{t-1}^S + \lambda_1 lY_{t-1}^S + \lambda_2 lEPU_{t-1}^S + \mu_t \quad (2)$$

In the model in Eqn. 2, while short-run effects are reflected by the coefficient estimates of first-differenced variables, long-run effects are reflected by λ_1 and λ_2 divided by $-\lambda_0$. To confirm the cointegration of normalized estimates, Pesaran et al. (2001) proposes two tests. The first is the *F*-test to establish the joint significance of the lagged-level variables. The second is the *t*-test to establish the significance of λ_0, which must have a negative sign. To test the asymmetric effects of the EPU index on the US states' income inequalities, we decompose the EPU index into positive and negative changes. To this aim, we use the following partial sum concept and produce two new independent variables:

$$POS_t^S = \sum_{j=1}^{t} \max\left(\Delta lEPU_j^S, 0\right) \quad (3)$$

$$NEG_t^S = \sum_{j=1}^{t} \min\left(\Delta lEPU_j^S, 0\right) \quad (4)$$

where POS_t is the partial sum of positive changes denoting increased EPU index, NEG_t is the partial sum of negative changes denoting decreased EPU index. Finally, we add these two new independent variables to Eqn. 2 and obtain the following Shin et al.'s (2014) nonlinear ARDL model (N-ARDL). We will get the linear ARDL (L-ARDL) model estimates from Eqn. 2 and thus move the linear model to the nonlinear model.

$$\Delta lGINI_t^S = \alpha + \sum_{j=1}^{n1} \phi_j \Delta lGINI_{t-j}^S + \sum_{j=0}^{n2} \theta_j \Delta lY_{t-j}^S + \sum_{j=0}^{n3} \pi^+{}_j \Delta POS_{t-j}^S + \sum_{j=0}^{n4} \pi^-{}_j \Delta NEG_{t-j}^S + \rho_0\, lGINI_{t-1}^S + \rho_1 lY_{t-1}^S + \rho^+ POS_{t-1}^S + \rho^- NEG_{t-1}^S + \xi_t \qquad (5)$$

Following the estimate of the linear model by Pesaran et al.'s (2001) the ARDL model in Eqn. 2, in Eqn. 5, we can estimate a few asymmetry assumptions. In the first assumption, short-run asymmetric effects of the EPU on the $GINI$ will be confirmed, if at any given j, an estimate of $\pi^+{}_j$ is different than the estimate of $\pi^-{}_j$. However, the stronger short-run asymmetric effects (impact or cumulative effects) will be confirmed if the Wald test can reject the null hypothesis of $\sum\pi^+{}_j = \sum\pi^-{}_j$. In second assumption, short-run asymmetry will be confirmed, if ΔPOS takes a different lag order than ΔNEG (if $n3 \neq n4$). Lastly, in the third assumption, the long-run asymmetric effects of EPU on GINI if the Wald test rejects the null hypothesis of ($-\rho^+ / \rho_0$) = ($-\rho^- / \rho_0$).

3 EMPIRICAL FINDINGS

In this US state-level study using newly calculated-published state-level EPU indexes of the USA, the sample period covering the largest number of states was determined between 1990 and 2018. It should be noted that 2018 is the last year for the US state-level GINI coefficients to be published. Therefore, these conditions allow us to estimate 29 annual observations for each US state. However, Panopoulou & Pittis (2004) concluded that the ARDL approach performs better than other cointegration methods for small samples like ours. Therefore, we use critical values by Narayan (2005) for the *F-test*, which performs better in small samples than Pesaran et al.'s (2001) critical values. Additionally, we use Banerjee et al. (1998) for the t-*test*. First, we present the descriptive statistics for EPU for the US and 27 US states in Table 1. We report only 27 US states because only these states have regular US state-level EPU index series.

TABLE 1 Descriptive statistics for the EPU index.

US States	Mean	Minimum	Maximum	Std. Dev	Skewness	Kurtosis
California	96.73	52.45	172.25	33.91	0.58	2.17
Colorado	58.45	31.88	101.67	19.44	0.56	2.34
Washington D.C.	18.18	6.65	41.24	8.3	0.67	3.19
Florida	59.58	26.59	110.23	24	0.65	2.55
Georgia	62.72	30.78	136.62	28.31	1.17	3.63
Illinois	60.07	24.65	124.33	27.26	0.43	2.19
Kansas	64.83	21.23	119.61	26.21	0.31	2.43
Kentucky	63.73	33.63	125.78	23.82	1.03	3.7
Louisiana	69.03	28.25	152.94	28.76	1.19	3.98
Massachusetts	77.98	33.74	146.17	32.81	0.48	1.96
Minnesota	79.89	40.4	136.97	26.38	0.46	2.15
Missouri	61.52	27.62	97.16	19.41	-0.03	2.19
Nebraska	79.23	36.69	187.64	33.73	1.32	4.88
New Jersey	72.14	26.75	168.26	35.59	1.15	4.25
New York	66.2	36.31	161.45	27.05	1.68	6.43
North Carolina	67.32	30.12	139.58	26.54	0.69	2.94
Ohio	53.75	32.36	96.35	15.79	0.77	3.01
Oklahoma	56.09	27.31	87.35	13.83	0	2.76
Pennsylvania	46.23	18.32	76.95	12.73	0.1	2.92
Rhode Island	104.81	53.91	238.28	33.5	2.16	9.86
South Carolina	56.39	22.84	118.93	24.54	0.88	3.04
Tennessee	49.51	25.9	99.51	18.72	1.02	3.4
Texas	61.96	25.11	110.56	20.76	0.21	2.67
Utah	32.56	12.41	176.39	31.37	3.57	16.57
Virginia	71.78	36.36	123.69	25.94	0.38	2.08
Washington	65.25	34.65	95.94	19.9	0.09	1.54
Wisconsin	63.94	20.79	137.48	30.82	0.51	2.47
USA	**107.25**	**71.33**	**172.25**	**27.56**	**0.74**	**2.99**

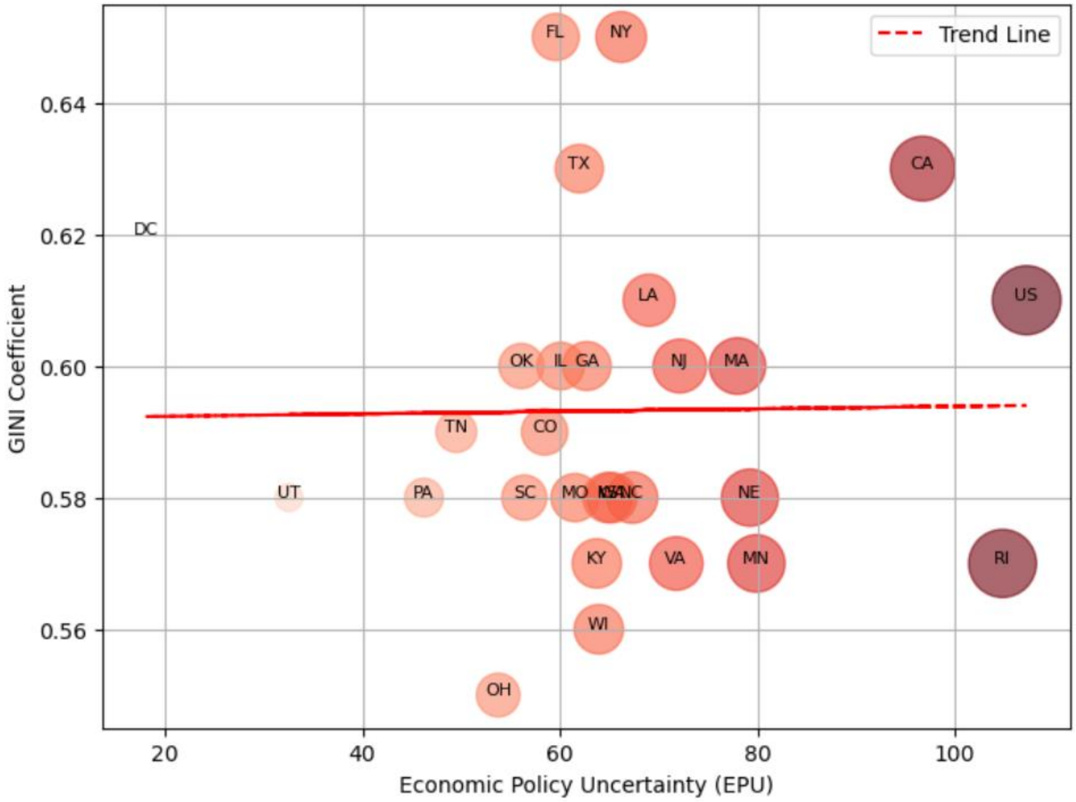
Regarding the descriptive statistics, Table 1 shows that the US states with the two highest mean values for EPU are RI (104.81) and CA (96.73), respectively, whereas the states with the two lowest mean values are Washington DC (18.18) and UT (32.56). The US states with the two highest standard deviation values for EPU, as a measure of volatility (Errais & Bahri, 2016), are NJ (35.59) and CA (33.91). In contrast, the states with the two lowest (i.e., more stable) are DC (8.3) and PA (12.73). On the other hand, the US's country-level mean value is 107. 25. This result shows that evaluating and analyzing the USA solely on a country level may be misleading. The descriptive statistics for GINI are reported in Table 2.

TABLE 2 Descriptive statistics for the GINI.

US States	Mean	Minimum	Maximum	Std. Dev	Skewness	Kurtosis
California	0.63	0.6	0.69	0.03	0.36	1.63
Colorado	0.59	0.56	0.63	0.02	0.36	1.79
Washington D.C.	0.62	0.56	0.66	0.02	-0.09	2.47
Florida	0.65	0.6	0.72	0.04	0.13	1.47
Georgia	0.6	0.56	0.65	0.03	0	1.35
Illinois	0.6	0.57	0.64	0.02	0.01	1.68
Kansas	0.58	0.55	0.61	0.02	-0.04	1.36
Kentucky	0.57	0.54	0.63	0.03	1.06	3.33
Louisiana	0.61	0.57	0.68	0.03	0.48	2.12
Massachusetts	0.6	0.56	0.65	0.03	0.19	1.61
Minnesota	0.57	0.54	0.6	0.02	0.24	1.69
Missouri	0.58	0.55	0.62	0.02	0.14	1.53
Nebraska	0.58	0.55	0.61	0.01	-0.09	2.19
New Jersey	0.6	0.56	0.65	0.03	0.25	1.67
New York	0.65	0.59	0.71	0.04	0.01	1.88
North Carolina	0.58	0.54	0.62	0.03	0.01	1.49
Ohio	0.55	0.53	0.59	0.02	0.12	1.55
Oklahoma	0.6	0.56	0.65	0.03	0.45	2.19
Pennsylvania	0.58	0.55	0.61	0.02	-0.28	1.64
Rhode Island	0.57	0.54	0.6	0.02	-0.17	1.62
South Carolina	0.58	0.54	0.64	0.03	0.51	2.21
Tennessee	0.59	0.56	0.65	0.03	0.47	2.18
Texas	0.63	0.59	0.67	0.02	0.12	2.07
Utah	0.58	0.55	0.62	0.02	0.2	1.76
Virginia	0.57	0.54	0.61	0.02	0.3	1.71
Washington	0.58	0.54	0.62	0.03	0.11	1.66
Wisconsin	0.56	0.53	0.59	0.02	0.02	1.27
USA	**0.61**	**0.57**	**0.64**	**0.02**	**-0.08**	**1.51**

Table 2 shows that the US states with the two highest mean values for GINI (denotes the worst income distribution) are Florida (0.65) and New York (0.65). Moreover, the standard deviation values of the GINI are lower than the standard deviation values of EPU. It may be interpreted that while it may take time for income distribution to worsen or improve, uncertainty can increase or decrease very quickly with economic changes and policy decisions. Figure 2 we created shows the relationship between the US state-level EPU index and US state-level GINI.

FIGURE 2 US state-level EPU index and US state-level GINI.



Source: This figure was generated using Python's Pandas, Seaborn, and Matplotlib libraries. Note: The size and color darkness of the circles are proportional to the size of the EPU index.

Figure 2 shows a slightly positive relationship between EPU and GINI (straight line). This means that when EPU increases, the US states' income distribution worsens (GINI increases). Bahmani-Oskooee and Ardakani (2018) explain this potential result as low-income groups being unable to absorb economic shocks or uncertainties as easily as high-income groups. According to Figure 2, the EPU index, which is over 100 for the USA, has even dropped below 40 in some US states, which reveals the need to examine the EPU index on a state level. The same figure shows that the US states with the two highest mean values for GINI (denotes the worst income distribution) are Florida and New York. On the other hand, Ohio is the US state with the best income distribution with the lowest GINI mean value.

Table 3 reports the US states' estimated coefficients following descriptive statistics. The first two columns show the estimates for each US state. The L-ARDL and N-ARDL represent the linear and nonlinear models, respectively. Panel A reports short-term estimates, Panel B reports long-term estimates, and Panel C reports diagnostic statistics.

Table 3:

According to the estimates of the linear ARDL (L-ARDL) model in Panel A, we found that economic policy uncertainty (EPU) carries at least one significant lagged coefficient, implying the EPU has short-run effects ($\Delta lEPU$) on GINI in 15 US states, namely, California (CA), Colorado (CO), Washington D.C. (DC).[4], Georgia (GA), Illinois (IL), Kansas (KS), Nebraska (NE), New Jersey (NJ), New York (NY), Ohio (OH), Oklahoma (OK), Pennsylvania (PA), Utah (UT), Virginia (VA), and Washington (WA). These results affirm the study of Bahmani-Oskooee & Hasanzade (2022) for CA, DC, GA, KS, NE, NJ, OH, PA, and UT.

The estimates of Panel B for the linear ARDL model (L-ARDL) found that EPU carries significant and meaningful coefficients, implying that economic policy uncertainty has long-run effects ($lEPU$) on GINI only in 1 US state, namely, Washington (WA).

According to short-run estimates of the nonlinear ARDL (N-ARDL) model in Panel A, we found either ΔPOS (increased EPU) or ΔNEG (decreased EPU) carries significant and meaningful lagged coefficient in 22 US states, namely, California (CA), Colorado (CO), Washington D.C. (DC), Georgia (GA), Illinois (IL), Kansas (KS), Kentucky (KY), Massachusetts (MA), Minnesota (MN), Missouri (MO), North Carolina (NC), Nebraska (NE), New Jersey (NJ), Ohio (OH), Oklahoma (OK), Pennsylvania (PA), South Carolina (SC), Tennessee (TN), Utah (UT), Virginia (VA), Washington (WA), and Wisconsin (WI). This should be considered a nonlinear adjustment in the short run from the linear model with 15 US states to the nonlinear model with 22 US states. Our study affirms the Bahmani-Oskooee & Hasanzade's (2022) study for 19 US states, namely, Colorado (CO), Washington D.C. (DC), Georgia (GA), Illinois (IL), Kansas (KS), Kentucky (KY), Massachusetts (MA), Minnesota (MN), Missouri (MO), North Carolina (NC), Nebraska (NE), New Jersey (NJ), Ohio (OH), Pennsylvania (PA), South Carolina (SC), Utah (UT), Virginia (VA), Washington (WA), and Wisconsin (WI). The results of our study confirm the following 19 out of 41 US states found in Bahmani-Oskooee & Hasanzade's (2022) study.

[4] Washington D.C is not a US state. It is a federal District of Columbia.

From the long-run estimates of the nonlinear (N-ARDL) model in panel B, we found either the POS or the NEG variable carry a significant and meaningful coefficient only in Washington DC (DC), Massachusetts (MA), Texas (TX), Virginia (VA), and Washington (WA) since their F-tests are significant in Panel C. These results affirm Bahmani-Oskooee & Hasanzade's (2022) study only for MA and VA. However, it should be noted that our study uses the US state-level EPU index, and most of this index started in 1990. and some US states do have data for this index.

The NEG variables have negative signs in Texas and Washington, implying that decreased uncertainty (NEG) worsens income inequality (GINI) in these two states in the long run. It can be interpreted that decreased uncertainty supported wealthy people to invest more, accumulating more wealth. However, the NEG and POS have positive signs in Washington DC. (DC), and Massachusetts (MA), implying that while decreased uncertainty (NEG) improves income inequality, increased uncertainty (POS) worsens income inequality in these two US states. The negative sign of POS in Virginia (VA) implies increased uncertainty improves income inequality in this US state. This can be interpreted as more people from low-income groups investing in more risky businesses and enhancing their quality of life or income. Regarding the Kuznets' hypothesis, only the N-ARDL model verifies the validity of the Kuznets' hypothesis only in Washington (WA) since an increase in economic growth worsens inequality in the short-run but improves it in the long run (significant negative sign)[5].

While short run Wald test (Wald-S) supports the short-run asymmetric effects in California (CA), Colorado (CO), Washington D.C. (DC), Georgia (GA), Illinois (IL), Massachusetts (MA), Missouri (MO), North Carolina (NC), Ohio (OH), Oklahoma (OK), Pennsylvania (PA), Tennessee (TN), Texas (TX), Utah (UT), Virginia (VA), and Washington (WA), the long-run Wald test (Wald-L) supports the long run asymmetric effects only in Illinois (IL), Massachusetts (MA), Utah (UT), Virginia (VA), Washington (WA), and Wisconsin (WI).

Regarding the USA at a country level, the L-ARDL and N-ARDL models didn't find any effect of EPU on GINI in either the short or long run. This means the whole picture changes when we examine the USA at the state level. It may also be interpreted that state-level analysis discovers some hidden effects of the EPU on GINI that we could not find in country-level analysis.

[5] The negative sign indicates a long-run income distribution improvement (a decrease in GINI).

4 ROBUSTNESS CHECK

Changes (shocks) in any state may affect state-level policy uncertainty, GINI, and GDP data of other states in the USA. For instance, policy uncertainty in California will no doubt affect Washington State. For this reason, we need to allow for cross-sectional dependence in these measures. For this purpose, this part of the study carried out panel data analyses considering cross-sectional dependence.

The existence of cross-sectional dependence among states was examined with the Pesaran et al. (2008) Bias-adjusted Cross-section Dependence (CD) test. CD tests are based on the Lagrange Multiplier (LM) test developed by Breusch and Pagan (1980). They started following the panel data model:

$$y_{it} = \beta_i' X_{it} + e_{it}, \qquad for\ \ i = 1, 2, \dots, N;\ t = 1, 2, \dots, T \tag{6}$$

After Eqn.6, the following equation was used to calculate the LM statistic:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(\hat{\rho}_{ij}^2\right) \sim \chi^2_{\frac{N(N-1)}{2}} \tag{7}$$

where T is time dimension, N is the cross-section dimension of the panel, $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals.

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}} \tag{8}$$

However, this test gives biased results when the group mean is zero and the individual mean is different from zero. Pesaran et al. (2008) corrected this bias by adding the variance and mean to the test statistics. Therefore, the name of the test is expressed as the bias-adjusted LM test (LM_{adj}):

$$LM_{adj} = \left(\frac{2}{N(N-1)}\right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left[\hat{\rho}_{ij}^{2} \left(\frac{(T-K-1)\hat{\rho}_{ij} - \hat{\mu}_{Tij}}{\vartheta_{Tij}}\right)\right] \sim N(0,1) \qquad (9)$$

where $\hat{\mu}_{Tij}$ is mean and ϑ_{Tij} is variance. The test statistic obtained here asymptotically shows a standard normal distribution. The null hypothesis of this is:

$$H_0 : Cov(e_{it}, e_{jt}) = 0, for\ all\ t\ and\ i \neq j \qquad (10)$$

It means no cross-sectional dependency. In this study, the existence of cross-sectional dependence in the variables and cointegration equation (Eq. 1) was checked with the Bias-adjusted CD test (LM_{adj}) test, and the results in Table 4 were obtained.

TABLE 4 Bias-adjusted CD test results.

	Stat	**Prob**
$\boldsymbol{lGINI^S}$	49.517	0.000
$\boldsymbol{lY^S}$	51.467	0.000
$\boldsymbol{lEPU^S}$	9.604	0.000
Cointegration Equation	66.911	0.000

The results in Table 4 require rejecting the null hypothesis. Therefore, cross-sectional dependence between the states should be considered in the analysis.

The series stationarity was examined using the Cross-sectional Augmented Dickey-Fuller (CADF) test developed by Pesaran (2007). In the CADF test, the error term (u_{it}) is assumed to consist of two parts: common factors (f_t) and individual effects (ε_{it}).

$$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + u_{it}, i = 1, \ldots, N\ ; t = 1, \ldots, T \qquad (11)$$

$$u_{it} = \lambda_i f_t + \varepsilon_{it} \qquad (12)$$

Here, f_t represents the unobservable common elements and is always assumed to be stationary. In this model, cross-sectional dependence is assumed to arise from unobservable common elements. ε_{it} is the unique element of the series and is independently and identically distributed. When Eq. 12 is transformed into a difference equation and written in place of u_{it}, Eq. 13 is obtained:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \lambda_i f_t + \varepsilon_{it} \quad (13)$$

where $\alpha_i = (1-\phi_i)\mu_i$, $\beta_i = -(1-\phi_i)$ and $\Delta y_{it} = y_{it} - \Delta y_{i,t-1}$. The unit root hypothesis of interest, $\phi_i = 1$, can now be expressed as:

$H_0: \beta_i = 0 \;\; for\ all\ i$

$H_1: \beta_i < 0, i = 1, 2, \dots, N_1, \;\; \beta_i = 0, \;\; i = N_1 + 1, N_1 + 2, \dots, N$

Pesaran (2007) averaged individual CADF test statistics to obtain the entire panel (CIPS) test statistic.

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \quad (14)$$

Following Eqn. 14, the CADF unit root test results are shown in Table 5.

TABLE 5 CADF unit root test CIPS results.

	Level	**1st Difference**
$\boldsymbol{lGINI^S}$	-2.313	-4.161***
$\boldsymbol{lY^S}$	-2.875	-3.620***
$\boldsymbol{lEPU^S}$	-4.083***	-

Note: The critical values for CIPS in Pesaran (2007, p. 281) are -2.81, -2.66, and -2.58 at 1%, 5%, and 10% significance levels, respectively. *** shows stationarity at 1%.

According to the results in Table 5, $lGINI^S$ and lY^S series are $I(1)$, $lEPU^S$ series is $I(0)$. Since the series are stationary at different levels, we used the Durbin-H method Westerlund (2008) developed in the cointegration analysis. We can rewrite Westerlund's (2008) Fisher equation by generalizing:

$$y_{it} = \alpha_i + \beta_i X_{it} + z_{it} \quad (15)$$

$$z_{it} = \lambda_i' F_t + e_{it} \quad (16)$$

$$F_{jt} = \rho_i F_{j,t-1} + u_{jt} \quad (17)$$

$$e_{it} = \phi_i e_{i,t-1} + v_{it} \tag{18}$$

where F_t is a k −dimensional vector of common factors, F_{jt} with $j = 1, \dots, k$, and λ_i is a conformable vector of factor loadings. From here, Westerlund (2008) developed two separate Durbin–Hausman (DH) test statistics for the group (DH_g) and the panel (DH_p).

$$DH_g = \sum_{i=1}^{n} \hat{S}_i \left(\tilde{\phi}_i - \hat{\phi}_i\right)^2 \sum_{t=2}^{T} \hat{e}_{i,t-1}^2 \tag{19}$$

$$DH_p = \hat{S}_n \left(\tilde{\phi} - \hat{\phi}\right)^2 \sum_{i=1}^{n} \sum_{t=2}^{T} \hat{e}_{i,t-1}^2 \tag{20}$$

For the panel test, the null and alternative hypotheses are formulated as $H_0: \phi_i = 1\ for\ all\ i = 1, \dots, n$ versus $H_1^p: \phi_i = \phi\ \ and\ \phi < 1\ for\ all\ i$ and $H_1^g: \phi_i < 1\ \ for\ at\ least\ some\ i.$

Westerlund (2008) Durbin-H panel cointegration test results are shown in Table 6.

TABLE 6 Westerlund (2008) Durbin-H panel cointegration test results.

	Stat	**Prob**
DH_g	26.765***	0.000
DH_p	2.356***	0.009

According to the results in Table 6, the null hypotheses were firmly rejected, and it was decided that there was cointegration in the states and the panel. The cointegration test developed by Banerjee and Carrioni-Sivestre (2017) was used to see the individual cointegration results presented in Table 7.

TABLE 7 Banerjee and Carrion-i-Sivestre (2017) cointegration test results.

State	**Test Statistics**
CA	-4.348***
CO	-5.889***
DC	-4.982***
FL	-2.910
GA	-2.132
IL	-2.414
KS	-3.116*

KY	-4.649***	
LA	-4.949***	
MA	-2.423	
MN	-3.292*	
MO	-3.483**	
NE	-3.044*	
NJ	-4.374***	
NY	-3.733**	
NC	-3.696**	
OH	-1.794	
OK	-2.899	
PA	-3.538**	
RI	-3.138*	
SC	-2.064	
TN	-1.399	
TX	-3.096*	
UT	-3.134*	
VA	-3.608**	
WA	-3.632	
WI	-2.482	
Critical Values for Individual Cointegration Test		
1%	5%	10%
-4.12	-3.34	-2.97
Panel	-3.34***	
Critical values for panel cointegration Test		
1%	5%	10%
-2.30	-2.15	-2.07

Note: ***, **, * show cointegration at 1%, 5% and 10% significancy, respectively.

Table 7 shows cointegration at CA, CO, DC, KS, KY, LA, MN, MO, NE, NJ, NY, NC, PA, RI, TX, UT, and VA. The cointegration result obtained for the panel with this method confirms the outcome of the Westerlund (2008) Durbin-H panel cointegration test.

Long-term cointegration coefficients estimated Augmented Mean Group (AMG) estimator of Eberhardt and Bond (2009). Eberhardt and Bond (2009) used weighting to overcome this shortcoming of Pesaran's (2006) Common Correlated Effects (CCE) estimators, which calculate the panel outcome by averaging individual outcomes. Eberhardt (2012) suggested using the "*xtmg*" library to perform AMG analysis with Stata. In this study, long-run cointegration coefficients were estimated using the AMG method using the "*xtmg*" library in Stata, following Eberhardt (2012), and the results are presented in Table 8

TABLE 8 Lon-Run cointegration coefficients.

	lY^S	$lEPU^S$
CA	0.0169 (0.545)	0.006 (0.632)
CO	-0.010 (0.626)	0.011 (0.368)
DC	0.003 (0.910)	0.031* (0.066)
FL	0.006 (0.689)	0.017*** (0.007)
GA	-0.0008 (0.955)	0.016** (0.016)
IL	0.019 (0.120)	0.004 (0.349)
KS	-0.004 (0.625)	0.010*** (0.001)
KY	-0.058 (0.102)	-0.015 (0.356)
LA	-0.072* (0.065)	0.014 (0.382)
MA	0.067** (0.038)	-0.0006 (0.965)
MN	-0.015 (0.283)	0.015** (0.037)
MO	-0.021 (0.171)	-0.006 (0.384)
NE	-0.026* (0.051)	-0.004 (0.417)
NJ	0.078** (0.019)	0.007 (0.535)
NY	0.104*** (0.000)	-0.004 (0.645)
NC	0.002 (0.892)	-0.006 (0.448)
OH	-0.033** (0.020)	0.008 (0.313)
OK	-0.051* (0.094)	-0.008 (0.675)
PA	0.005 (0.384)	-0.011*** (0.005)
RI	-0.001 (0.871)	0.001 (0.756)
SC	-0.026 (0.490)	-0.010 (0.561)
TN	-0.425 (0.109)	0.004 (0.738)
TX	-0.040*** (0.002)	0.011 (0.138)
UT	-0.016 (0.128)	0.012*** (0.003)
VA	0.012 (0.572)	0.010 (0.296)
WA	0.042 (0.151)	-0.013 (0.431)
WI	-0.021*** (0.003)	0.007*** (0.007)
Panel	-0.008 (0.232)	0.003* (0.089)
Wald chi2(2):		4.32** (0.01)
Root Mean Squared Error (sigma):		0.0189

Note*:* *, **, ***; 10%, 5%, 1%. Probe values for the z-test are given in parentheses.

After allowing for cross-sectional dependence, EPU significantly affects GINI only in DC, KS, MN, PA, UT, and the entire USA panel.

5 SUMMARY AND CONCLUSION

This study aims to expand, update, and contribute to Bahmani-Oskooee & Hasanzade's (2022) study. Their study examined the effects of economic policy uncertainty on income inequalities in the US states. For this reason, they used the GINI coefficient to measure income inequality at the US state level. However, the economic policy uncertainty (EPU) index was used to measure US country-level uncertainty. Therefore, although the authors do not make such a claim, this study assumes that the country-level EPU index represents all US states within the model. This was not their choice but a necessity. During Bahmani-Oskooee & Hasanzade's (2022) study, US state-level EPU index series were unavailable. This country-level index could represent the entire USA, just as a single EPU index was created for other countries. However, as it is known, US states differ significantly from each other in terms of economics, demographics, budgeting, and tax rates. These factors may change each state's economic policy uncertainty, that is, the EPU index value. Therefore, the variables used in US state-based studies should be state-level if the data is available.

Therefore, our study aims to close this gap and support the study of Bahmani-Oskooee & Hasanzade (2022). However, it should be noted that to cover the largest number of US states, we selected the most extended sample period, 1990-2018, because some US states do not have regular data. Hence, this absence of data allowed us to examine only 27 US states and Washington DC out of 50 US states. Therefore, both studies should be evaluated and compared within this framework.

The most common point of both studies is that the N-ARDL model allows the examination of more US states than the L-ARDL model. This result can be interpreted to mean that, with increasing uncertainties in the world, economic actors have more nonlinear-asymmetric behaviors, and therefore, nonlinear models may be more successful in explaining the variables in economic models to some extent. Bahmani-Oskooee & Ardekani (2018) also found more US states in the nonlinear model than in the linear model in their study.

In addition, both studies have similar and different findings in the state-level analyses of the USA. For example, we found that decreased uncertainty (NEG) worsens income inequalities in Texas and Washington in the long run; Bahmani-Oskooee & Hasanzade (2022) found that economic policy uncertainty does not have long-run effects in these US states. Similarly, while we found increased uncertainty (POS) improves inequality in Virginia, they found worsening effects in this

US state. In another example, we found that decreased uncertainty (NEG) improves income inequality in Massachusetts (MA), and they found the worsening effects in this US state.

Based on the results, this study draws attention to the importance of using state-level economic policy uncertainty indexes in future US state-level studies if data permits. This approach will help US state policymakers understand the causes of economic policy uncertainties in their states and accordingly produce customized policies at the state level to improve income distribution. In parallel with this, sharing information and practices with US states that face similar problems that cause uncertainty in economic policy will make the struggle to reduce inequality in income distribution between US states more effective and sustainable.

CONFLICT OF INTEREST STATEMENT
The author declares no conflict of interest

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Data Set:

To cover the largest number of US states in the study, the most extended observation sample period available is between 1990 and 2018. 2018 is the latest year in which the GINI coefficient was measured for US states. The US state-level GINI coefficient (SGINI) and the per capita real income (SY) data were obtained by Frank, M. W. 2014 and Frank et al. (2015), respectively, reported on https://www.shsu.edu/eco_mwf/inequality.html. The data of the SEPU index were obtained by Baker et al. (2016) and reported on https://www.policyuncertainty.com/. Finally, the population data was obtained by the US Census Bureau (CB, 2022).

TABLE 3 Estimates of both linear (L-ARDL) and nonlinear ARDL (N-ARDL) models.

	CA		**CO**		**DC**		**FL**		**GA**		**IL**	
	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	NA-RDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL
Panel A: Short–Run Estimates												
$\Delta lGINI_{t-1}^{S}$	0.54(2.92)**	0.57(2.2)*	-0.34(1.38)	0.04(0.21)	-0.35(1.74)*	2.05(2.66)**	-0.33(1.7)	-0.38(1.54)	0.19(0.92)	-0.45(1.11)	0.02(0.08)	0.08(0.47)
$\Delta lGINI_{t-2}^{S}$		0.16(0.75)		-0.09(0.53)		-1.47(3.42)**			0.06(0.25)	-0.50(1.42)	0.21(0.86)	
$\Delta lGINI_{t-3}^{S}$				-0.85(3.29)**		-1.90(3.5)**			0.47(1.91)*		0.39(1.67)	
ΔlY_{t}^{S}	0.24(2.44)**	-0.10(0.68)	0.03(0.34)	-0.07(1.1)	-0.10(0.74)	-0.19(0.94)	0.26(3.08)**	0.29(2.87)**	-0.005(0.005)	0.04 (0.42)	0.12(1.3)	0.23(2.85)**
ΔlY_{t-1}^{S}	-0.37(3.44)**	-0.36(2.11)*	-0.38(3.71)**	-0.59(5.76)**		-0.27(1.5)					-0.13(1.28)	
ΔlY_{t-2}^{S}		-0.36(1.62)	-0.33(2.64)**	-0.28(2.93)**		-0.57(2.28)*					-0.17(1.81)*	
ΔlY_{t-3}^{S}			-0.37(3.38)**	-0.17 (1.62)							-0.19(2.19)**	
$\Delta lEPU_{t}^{S}$	-0.003(0.2)		-0.05(2.67)**		0.04 (1.91) *		0.02(1.03)		-0.01(1.02)		-0.02(1.11)	
$\Delta lEPU_{t-1}^{S}$	0.0005(0.04)		0.09(3.16)**						-0.02(1.91)*		0.03(2.44)**	
$\Delta lEPU_{t-2}^{S}$	-0.04(2.4)**		0.04(2.2) **									
$\Delta lEPU_{t-3}^{S}$	-0.02(1.47)		0.01(1.1)									
ΔPOS_{t}^{S}		-0.11(3.13)**		-0.11(4.58)**		-0.12(2.88)**		0.005(0.02)		0.003(0.16)		0.01(1.01)
ΔPOS_{t-1}^{S}		-0.17(2.75)**		0.005 (0.01)		0.07(1.53)				0.03(1.06)		0.03(2.64)**
ΔPOS_{t-2}^{S}		-0.17(2.78)**		-0.06 (1.61)		0.14(2.41)*				0.041.09)		
ΔPOS_{t-3}^{S}		-0.12(2.61)**		-0.04(2.46)*		-0.17(2.53)*				0.05 (2)*		
ΔNEG_{t}^{S}		0.11(3.02)**		-0.005(0.22)		0.58(3.45)**		0.04(1.05)		-0.03(0.81)		-0.01(0.84)
ΔNEG_{t-1}^{S}		0.16(2.79)**		0.02(0.71)		0.07(0.59)				-0.07(2.41)**		
ΔNEG_{t-2}^{S}		0.10(1.6)		0.05(2.75)*		0.50(4.02) **				-0.05(2.37)**		
ΔNEG_{t-3}^{S}		0.12(2.42)*		0.07(4.06)**		0.43(3.23) **				-0.04(2.14)*		
Panel B: Long-Run Estimates												
lnY^{S}	0.05(1.37)	0.14(3.17)**	3.28(0.08)	2.43(0.58)	0.02(0.68)	-0.04(0.77)	0.11(3.92)**	0.26(0.87)	0.13(5.51)**	0.84(0.27)	0.13(2.05) *	-0.04(0.55)
$lEPU^{S}$	0.04(0.41)		-17.81(0.08)		0.03(0.56)		0.06(1.47)		0.02(0.67)		-0.14(0.96)	
NEG^{S}		0.04(1.58)		-1.59(0.5)		0.12(2.46)*		0.13(0.82)		-0.27(0.34)		-0.05(1.52)
POS^{S}		0.02(1.16)		-2.27(0.53)		0.11(4.36)**		0.05(1.12)		-0.41(0.29)		-0.001(0.06)
Constant	-1.06(2.49)**	-1.66(4.31)**	43.69(0.08)	-21.46(0.6)	-0.79(2.81) **	0.02(0.05)	-1.76(7.46)**	-2.85(1.07)	-1.81(6.69)**	-8.99(0.29)	-1.19(5.71) **	-0.31(0.51)
Panel C: Diagnostic Statistics												
F	1.69	4.13	5.92**	8.64**	1.43	5.44**	1.7	1.3	2.04	1.39	2.56	1.47
$\hat{\rho}_0$ (t-test)	-0.25 (2.22)	-0.62 (2.21)	-0.26 (1.65)	-0.33 (1.52)	-0.56 (2.16)	-0.74 (1.39)	-0.41(1.99)	-0.42(1.92)	-0.38(2.42)	-0.31(1.1)	-0.43(2.07)	-0.29(1.65)
LM	0.41	1.02	2.44	12.56**	0.72	6.26**	0.24	0.02	14.66**	9.43**	0.21	0.04
RESET	3.85*	0.003	2.79	7.54*	0.63	0.53	4.74**	4.45*	0.16	0.05	1.1	1.55
Adjusted R^2	0.49	0.7	0.46	0.82	0.48	0.78	0.42	0.37	0.11	0.26	0.37	0.53
CS (CS^2)	S (U)	S (U)	S (S)	S (U)	S (S)	S (S)	S (S)	S (S)	S (S)	S (S)	S (S)	S (S)
Wald-S		11.77**		8.97**		14.52**		0.42		6.91**		4.41*
Wald-L		0.99		0.32		0.29		0.26		0.04		3.44 *

TABLE 3 (Continued).

	KS		KY		LA		MA		MN		MO	
	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL
Panel A: Short–Run Estimates												
$\Delta lGINI^S_{t-1}$	-0.69(1.53)	-0.37(1.44)	0.27(1.29)	0.40(1.39)	0.08(0.38)	0.13(0.56)	0.38(2.02)*	-0.86(2.29)*	0.10(0.44)	0.19(0.61)	-0.03(0.14)	-0.60(2.07)*
$\Delta lGINI^S_{t-2}$	-0.95(2.1)*	-0.70(3.04)**		0.72(2.12)*	0.29(1.35)	0.24(0.81)	0.36(1.9)*	-0.46(1.54)	0.03(0.16)	-0.10(0.3)	0.31(1.35)	-0.28(1.18)
$\Delta lGINI^S_{t-3}$	-0.57(1.43)			1.21(2.62)**	0.37(1.67)	0.45(1.63)		-0.71(2.41)*		0.38(1.44)	0.38(1.78)*	
ΔlY^S_t	0.19(2.17)*	0.36(3.35)**	0.13(1.35)	-0.02(0.11)	0.07(0.51)	0.10(0.55)	0.24(2.1)*	0.24(2.06)*	0.15(2.18)**	0.12(0.93)	0.08(0.79)	0.37(2.36)**
ΔlY^S_{t-1}	0.12(1.16)	-0.16(1.7)		0.41(1.86)	-0.22(1.89)*	-0.35(2.25)*	-0.21(1.47)	-0.08(0.47)		-0.13(0.96)	-0.02(0.19)	0.39(2.29)**
ΔlY^S_{t-2}	0.15(2.06)*	0.14(1.41)		0.37(1.25)	0.13(1.01)	0.25(1.22)		-0.91(2.84)**		0.20(1.38)	-0.07(0.68)	
ΔlY^S_{t-3}	-0.14(2.14)*	-0.22(2.76)**		-0.35(1.8)	-0.46(3.16)**	-0.58(2.58)**		-0.46(2.04)*		-0.18(1.64)	-0.24(2.67)**	
$\Delta lEPU^S_t$	-0.008(0.78)		-0.01(1.11)		-0.006(0.32)		-0.02(1)		-0.01(0.94)		-0.02(1.31)	
$\Delta lEPU^S_{t-1}$	0.03(1.86)*						0.01(1.08)		0.02(1.4)			
$\Delta lEPU^S_{t-2}$	0.03(1.85)*						0.01(1.41)					
$\Delta lEPU^S_{t-3}$	0.02(2.2)*											
ΔPOS^S_t		-0.03(1.67)		0.0002(0.01)		0.03(0.72)		0.04(1.72)		-0.004(0.15)		0.02(0.71)
ΔPOS^S_{t-1}		0.04(2.41)**		-0.12(1.37)		-0.04(0.88)		0.36(3.99)**		0.05(1.71)		0.09(2.67)**
ΔPOS^S_{t-2}		0.01(1)		0.02(0.37)		0.03(0.78)		0.22(3.83)**		0.02(0.63)		0.04(1.64)
ΔPOS^S_{t-3}		0.02(1.62)		0.04(1.18)				0.03(1)		0.06(2.24)*		
ΔNEG^S_t		0.03(2.29)*		0.05(1.15)		0.01(0.22)		-0.09(2.42)*		-0.02(0.74)		-0.07(2.84)**
ΔNEG^S_{t-1}				0.20(2.32)*		-0.004(0.1)		0.12(2.89)**				
ΔNEG^S_{t-2}				0.05(0.96)		-0.09(1.82)		0.02(1.43)				
Panel B: Long-Run Estimates												
lnY^S	-0.08(0.18)	0.53(1.25)	0.05(1.08)	-0.57 (0.71)	0.06 (0.63)	0.27(1.11)	0.10(2.65)**	0.38(2.38)*	0.08(2.77)**	-0.33(1.05)	0.07(2.97)**	-0.38(1.39)
$lEPU^S$	0.23(0.39)		-0.10(1.04)		-0.16 (0.52)		-0.08(0.68)		-0.03(0.58)		-0.06(1.46)	
NEG^S		0.06(1.26)		-0.006 (0.06)		0.12(0.69)		0.58(3.05)**		-0.25(0.8)		-0.32(1.75)
POS^S		-0.08(0.85)		0.22 (0.9)		0.04(0.25)		0.46(3.34)**		-0.08(0.37)		-0.13(1.58)
Constant	-0.64(0.31)	-5.43(1.41)	-0.62(0.89)	4.37 (0.63)	-0.22 (0.12)	-2.81(1.38)	-1.17(2.99)**	-3.68(2.74)**	-1.23(4.41)**	2.24(0.82)	-0.93(3.04) **	2.55(1.11)
Panel C: Diagnostic Statistics												
F	2.77	1.57	1.79	3.8	1.3	1.44	2.79	5.71**	1.76	2.32	2.21	3.54
$\hat{\rho}_0$ (t-test)	-0.50(1.58)	-0.19(0.68)	-0.23(2.08)	-0.78(3.55)	-0.28(1.56)	-0.54(2.31)	-0.33(2.86)	-0.38(1.37)	-0.31(1.84)	-0.41(1.81)	-0.44(2.46)	-0.43(2.01)
LM	1.52	0.03	0.11	9.13**	1.86	12.12**	0.81	11.80**	1.29	15.25	2.94*	4.08**
RESET	0.18	2.32	0.28	2.44	1.43	0.04	3.60*	0.89	3.34*	2.62	0.07	0.38
Adjusted R^2	0.35	0.48	0.3	0.42	0.4	0.32	0.46	0.74	0.22	0.36	0.43	0.48
CS (CS^2)	S (S)	S (S)	S (U)	S (U)	S (S)	S (S)	S (S)	S (S)	S (S)	S (S)	S (U)	S (S)
Wald-S		0.27		2.17		0.73		15.09 **		3.28		8.10 **
Wald-L		1.09		0.65		0.81		4.20*		1.76		2.9

TABLE 3 (Continued).

	NC		**NE**		**NJ**		**NY**		**OH**		**OK**	
	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL
Panel A: Short–Run Estimates												
$\Delta lGINI_{t-1}^{S}$	0.15(0.72)	-0.60(2.34)**	-0.46(2.41)**	-0.94(2.77)**	0.71(2.96)**	0.80(3.14)**	0.40(1.35)	1.92(2.23)*	0.29(1.3)	-0.16(0.7)	-0.007(0.03)	0.17(1.27)
$\Delta lGINI_{t-2}^{S}$		-0.54(2.28)**		-0.52(1.73)	0.39(1.5)	0.15(0.52)	0.25(1.15)	1.72(2.17)*	0.23(1.07)	0.18(0.95)		0.23(1.82)
$\Delta lGINI_{t-3}^{S}$					0.45(1.97)*	0.47(1.59)		0.67(1.07)	0.42(1.97)*	0.25(1.26)		0.45(2.84)**
ΔlY_{t}^{S}	0.10(1.02)	0.13(1.35)	0.18(2.49)**	-0.003(0.03)	0.05(0.31)	0.02(0.16)	0.15(1.98) *	-0.08(0.41)	0.13(1.26)	-0.10(0.98)	0.04(0.38)	-0.40(5.27)**
ΔlY_{t-1}^{S}		0.29(2.31)**	-0.05(0.62)	0.08(0.57)	-0.40(2.72)**	-0.40(1.75)	-0.20(1.84) *	-0.70(2.42)*		-0.06(0.58)		-0.42(3.16)**
ΔlY_{t-2}^{S}			0.09(1.31)	0.28(2.08)*	-0.14(1.03)	0.007(0.06)		-0.77(1.88)		-0.11(1.27)		-0.59(4.05)**
ΔlY_{t-3}^{S}			-0.17(2.46)**	-0.18(1.65)	-0.20(1.64)	-0.25(1.71)		-0.31(1.25)		-0.41(4) **		-0.41(5.16)**
$\Delta lEPU_{t}^{S}$	-0.01(0.87)		-0.008(0.83)		-0.01(0.73)		0.002(0.11)		0.02(1.13)		-0.005(0.27)	
$\Delta lEPU_{t-1}^{S}$			0.01(1.8)*		-0.01(1.03)		-0.003(0.25)		-0.03(1.88)*		-0.06(2.07)*	
$\Delta lEPU_{t-2}^{S}$					-0.02(1.85)*		-0.03(2.34)**		-0.03(2.14)*		-0.03(1.6)	
$\Delta lEPU_{t-3}^{S}$					-0.03(2.33)**		-0.01 (1.37)					
ΔPOS_{t}^{S}		0.01(0.7)		-0.009(0.38)		-0.001(0.07)		-0.05(1.16)		-0.12(3.12)**		-0.06(1.69)
ΔPOS_{t-1}^{S}								0.02(0.48)				-0.31(5.67)**
ΔPOS_{t-2}^{S}								-0.05(1.75)				-0.05 (1.11)
ΔPOS_{t-3}^{S}								-0.08(1.83)				-0.16(3.48)**
ΔNEG_{t}^{S}		-0.05(2.25)**		-0.05(1.61)		-0.04(1.2)		0.03(0.6)		0.04(1.81)*		-0.03(1.08)
ΔNEG_{t-1}^{S}		-0.05(2.48)**		0.10(2.58)**		-0.07(1.05)		0.18(1.73)		0.04(1.57)		-0.03(1.14)
ΔNEG_{t-2}^{S}		-0.08(3.38)**		0.05(1.9)*		-0.05(1.38)		0.12(1.63)				-0.19(6.33)**
ΔNEG_{t-3}^{S}		-0.05(2.08)*				-0.05(2.08)*		0.05(1.28)				
Panel B: Long-Run Estimates												
lnY^{S}	0.11(3.94)**	-0.20(0.31)	0.03 (0.79)	-1.03(1.04)	0.06(3.78)**	0.07(0.12)	0.10(3.92)**	0.10(2.84)**	0.06(3.81)**	0.77(0.7)	0.07(1.65)	1.66(1.28)
$lEPU^{S}$	-0.03(0.75)		-0.09 (0.99)		-0.07(1.3)		0.03(0.46)		0.10(2.39)**		0.21(0.74)	
NEG^{S}		-0.33(0.73)		-0.54(1.05)		-0.04(0.21)		-0.05(2.82)**		-0.16(0.52)		0.69(1.09)
POS^{S}		-0.17(0.73)		-0.17(0.88)		-0.04(0.58)		-0.04 (2.2) *		-0.46(0.63)		0.12(0.5)
Constant	-1.51(4.73)**	1.55(0.25)	-0.39(0.59)	8.34(0.97)	-0.80(2.23)**	-1.27(0.23)	-1.51 (7.92) *	-1.36 (4.3)**	-1.61(8.56)**	-7.19(0.76)	-2.09(1.54)	-14.40(1.33)
Panel C: Diagnostic Statistics												
F	1.2	2	1.89	2.34	4.25	3.02	2.22	2.23	3.13	2.56	2.01	16.31**
$\hat{\rho}_0$ **(t-test)**	-0.28(1.89)	-0.12(0.64)	-0.30(1.42)	-0.32(1.38)	-0.37(3.3)	-0.39(3.83)*	-0.51(2.54)	-1.29(2.35)	-0.37(1.84)	-0.34(2.26)	-0.30(1.96)	-0.41(1.87)
LM	0.4	12.25**	1.71	0.22	1.03	9.37**	0.49	6.36**	7.10**	1.55	0.07	11.25**
RESET	0.54	0.005	0.64	0.52	3.02	0.33	0.53	0.01	0.05	0.008	0.15	1.01
Adjusted R^2	0.22	0.52	0.58	0.59	0.51	0.55	0.33	0.3	0.26	0.55	0.2	0.87
CS (CS^2**)**	S (S)	U (S)	S (S)	U (U)	S (S)	S (S)	S (U)	S (U)	S (U)	S (U)	S (S)	S (U)
Wald-S		14.43**		2.74		2.85		3.59		10.11**		4.78*
Wald-L		0.35		1.22		0.00003		0.33		0.4		1.63

TABLE 3 (Continued)

	PA		**RI**		**SC**		**TN**		**TX**		**UT**	
	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL
Panel A: Short–Run Estimates												
$\Delta lGINI_{t-1}^{S}$	-0.20(0.82)	-0.15(0.48)	0.27(1.23)	0.12(0.4)	0.21(0.86)	-0.92(2.8)**	0.55(2.37) **	0.27(1.04)	-0.35(1.52)	-0.49(1.35)	-0.89(2.57)**	1.03(2.44)**
$\Delta lGINI_{t-2}^{S}$	-0.30(1.38)	-1.12(3.54)**			0.48(1.94)*		0.10(0.43)	-0.30(1.46)	-0.09(0.4)	-0.27(0.77)	-0.93(2.88)**	0.38(1.36)
$\Delta lGINI_{t-3}^{S}$		-0.42(1.76)					0.72(2.83)**	0.50(2.13)*	-0.39(1.6)	-0.65(1.84)*	-0.62(2.17)*	
ΔlY_{t}^{S}	0.19(2.6)**	0.73(3.99)**	0.14(1.76)*	0.15(1.83)*	0.08(0.52)	0.34(1.93)	-0.06(0.33)	0.02(0.14)	0.19(3.26)**	0.23(1.89)*	0.20(3.15)**	0.25(2.82)**
ΔlY_{t-1}^{S}	-0.02(0.28)	0.44(2.97)**		0.13(1.39)	0.008(0.05)	-0.28(1.93)	0.03(0.22)	-0.11(0.75)		0.40(1.83)*	-0.09(1.28)	-0.08(0.94)
ΔlY_{t-2}^{S}	0.05(0.6)	0.72(3.23)**		0.17(2.02)*	-0.30(1.89)*	-0.53(3.32) **	0.12(0.9)	0.31(3.06)**		0.18(1.97)*	0.05(0.69)	
ΔlY_{t-3}^{S}	-0.21(2.72)**	0.39(2.09)			-0.26(1.53)	-0.28(1.77)	-0.29(2.44) **	-0.19(1.23)			-0.27(3.27)**	
$\Delta lEPU_{t}^{S}$	-0.01(1.19)		0.005(0.41)		0.01(0.49)		0.006(0.3)		-0.008(0.62)		-0.02(1.46)	
$\Delta lEPU_{t-1}^{S}$	0.02(2.02) *				0.02(0.78)		-0.04(1.76)				0.04(1.93)*	
$\Delta lEPU_{t-2}^{S}$					-0.02(1)						0.02(1.33)	
$\Delta lEPU_{t-3}^{S}$												
ΔPOS_{t}^{S}		0.11(2.83)**		0.02(0.82)		-0.01(0.25)		0.05(1.96)*		0.02(0.67)		-0.02(1.68)
ΔPOS_{t-1}^{S}		0.009(0.46)				-0.12(2.89)**				0.04(1.49)		0.02(1.19)
ΔPOS_{t-2}^{S}		0.03(1.52)				-0.19(3.9)**				0.09(1.66)		-0.01(1.04)
ΔPOS_{t-3}^{S}		0.08(2.82)**				-0.12(3.22)**						-0.06(2.29)*
ΔNEG_{t}^{S}		0.08(2.21)*		-0.006(0.25)		0.03(1.16)		-0.11(2.69)**		-0.04(1.47)		0.05(1.73)
ΔNEG_{t-1}^{S}		-0.14(2.53)*				-0.002(0.04)		-0.19(3.44)**				0.13(2.29)*
ΔNEG_{t-2}^{S}		-0.12(2.94)**				-0.02(0.57)		-0.08(1.27)				0.12(2.57)**
ΔNEG_{t-3}^{S}		-0.16(3.09)**				-0.05(1.54)		-0.07(1.71)				0.10(2.9)**
Panel B: Long-Run Estimates												
lnY^{S}	0.04(0.91)	0.25(1.63)	0.07(5.52)**	-0.02(0.26)	-0.04(0.3)	-1.38(0.79)	0.07(2.15)*	0.22(1.88)	0.08(6.35)**	0.03(0.76)	2.06(0.08)	0.009(0.56)
$lEPU^{S}$	-0.19(0.89)		-0.007(0.25)		-0.10(0.6)		0.05(0.73)		-0.04(1.46)		-2.07(0.08)	
NEG^{S}		0.24 (1.4)		0.006 (0.12)		-0.46 (0.71)		0.05 (0.93)		-0.04(2.31) **		-0.08(4.36)**
POS^{S}		0.19 (1.6)		0.05 (1.09)		0.003 (0.02)		0.007 (0.2)		-0.02(0.69)		-0.02(2.14)*
Constant	-0.19(0.15)	-3.03(2.08)	-1.19(5.78)**	-0.51(0.75)	0.36(0.18)	11.31(0.74)	-1.37(2.35)**	-2.64(2.44)**	-1.07(6.58)**	-0.84(2.41)**	-13.15(0.09)	-0.67(4.64)**
Panel C: Diagnostic Statistics												
F	2.55	2.49	1.49	1.48	1.81	7.94**	3.14	4.57*	4.96*	4.81*	2.6	3.6
$\hat{\rho}_0$ **(t-test)**	-0.42(1.63)	-0.25(0.68)	-0.47(2.16)	-0.37(1.6)	-0.27(1.87)	-0.29(0.76)	-0.42(2.91)	-0.73(4.18)**	-0.53(1.88)	-0.94(2.39)	-0.33(1.16)	-0.42(1.05)
LM	1.31	0.86	0.37	0.99	1.31	9.97**	10.16**	0.07	1.06	0.17	1.58	3.41*
RESET	2.66	0.04	0.89	0.96	0.39	0.51	0.32	0.63	7.09**	2.01	5.21**	2.45
Adjusted R^2	0.55	0.75	0.35	0.36	0.29	0.72	0.42	0.72	0.53	0.53	0.57	0.57
CS (CS^2)	(S)	U (S)	S (S)	S (S)	S (U)	S (U)	S (U)	S (S)	S (S)	S (S)	S (S)	S (S)
Wald-S		12.65**		0.46		2.93		9.97**		3.57*		12.14**
Wald-L		0.83		1.36		0.78		1.27		2.43		32.76**

	VA		WA		WI		USA	
	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL	L-ARDL	N-ARDL
Panel A: Short–Run Estimates								
$\Delta \boldsymbol{lGINI}^S_{t-1}$	0.22(1.05)	-0.13(0.85)	0.46(2.57)**	-0.24(1.72)	0.11(0.53)	-2.61(2.34)*	-0.1(0.41)	-0.79 (1.44)
$\Delta \boldsymbol{lGINI}^S_{t-2}$	0.73(2.79)**	-0.02(0.07)	0.15(0.77)			-1.39(1.5)	-0.27(1.41)	-0.7(1.47)
$\Delta \boldsymbol{lGINI}^S_{t-3}$	0.60(2.05)*	0.36(2.45)**	0.41(2.03)*			-1.07(1.52)		-0.22 (0.72)
$\Delta \boldsymbol{lY}^S_{t}$	0.06(0.69)	-0.11(1.51)	0.14(1.49)	-0.04(0.65)	0.12(1.93)*	0.21(1.3)	-0.11(0.42)	-0.47 (1.33)
$\Delta \boldsymbol{lY}^S_{t-1}$	-0.30(3.1)**	-0.36(3.6)**	-0.36(3.57)**	-0.21(3.04)**		-0.17(1.5)	-0.04(0.17)	-0.02 (0.08)
$\Delta \boldsymbol{lY}^S_{t-2}$	-0.16(1.47)		0.004(0.04)	-0.10(1.39)		-0.23(1.88)	-0.01(0.05)	0.07 (0.2)
$\Delta \boldsymbol{lY}^S_{t-3}$	-0.18(1.84)*		-0.29(2.73)**	-0.08(1.16)		-0.20(1.56)	-0.86(3.43)**	-1.33 (4.34)*
$\Delta \boldsymbol{lEPU}^S_{t}$	-0.03(2.34)**		-0.03(1.55)		0.003(0.37)		-0.04 1.57)	
$\Delta \boldsymbol{lEPU}^S_{t-1}$			0.03(1.91)*				0.01(0.26)	
$\Delta \boldsymbol{lEPU}^S_{t-2}$							0.36(1.74)	
$\Delta \boldsymbol{lEPU}^S_{t-3}$								
$\Delta \boldsymbol{POS}^S_{t}$		-0.05(4.19)**		-0.09(5.16)**		-0.04(2.02)*		0.08(1.79)
$\Delta \boldsymbol{POS}^S_{t-1}$		-0.07(4.16)**		-0.12(5.07)**		-0.05(2.26)*		-0.02(0.57)
$\Delta \boldsymbol{POS}^S_{t-2}$		-0.05(2.85)**		-0.11(6.15)**		-0.06(2.56)*		0.06(1.13)
$\Delta \boldsymbol{POS}^S_{t-3}$				-0.08(4.51)**		-0.04(2.62)**		0.004(0.09)
$\Delta \boldsymbol{NEG}^S_{t}$		0.05(2.5)**		0.04(2.07)*		0.09(2.37)*		-0.07(1.36)
$\Delta \boldsymbol{NEG}^S_{t-1}$		0.07(3.83)**		0.15(5.42)**		-0.17(2.11)*		0.04(1.02)
$\Delta \boldsymbol{NEG}^S_{t-2}$		0.06(2.88)**		0.02(0.75)		-0.10(2.3) *		0.02(0.9)
$\Delta \boldsymbol{NEG}^S_{t-3}$				-0.02(1.23)				0.01(0.3)
Panel B: Long-Run Estimates								
$\boldsymbol{lnY}^S$	0.08(5.48)**	0.19(5.63)**	0.05 (2.97)**	-0.18(2.99)**	0.07(2.36)**	-0.18(9.52)**	0.27(11.72)**	0.12(1.52)
$\boldsymbol{lEPU}^S$	-0.11(2.63)**		-0.14 (2.01)*		0.02 (0.65)		0.02(1.48)	
$\boldsymbol{NEG}^S$		0.01(0.66)		-0.13(3.8) **		-0.12 (9.93) **		-0.02(0.82)
$\boldsymbol{POS}^S$		-0.02(2.12) *		-0.02(0.58)		-0.005 (0.93)		0.02(1.14)
Constant	-0.85 (5.01)**	-2.32(7.55)**	-0.41(1.04)	1.15(2.13)*	-1.32(6.01)**	0.91(5.65)**	-3.5(17. 4)**	-1.81(2. 19)*
Panel C: Diagnostic Statistics								
F	3.96	9.39**	4.72*	13.46**	1.3	3.35	3.79	4.24*
$\boldsymbol{\hat{\rho}_0}$ **(t-test)**	-0.34(1.87)	-0.66(2.89)	-0.48(2.79)	-0.33 (2.02)	-0.26 (1.82)	-0.53 (1.36)	-0.11 (0.46)	0.56(0.94)
LM	16.84	8.35**	0.32	2.67	1.04	5.99**	1.48	19.31**
RESET	1.56	0.06	3.22	0.84	4.81**	0.06	3.34**	0.15
Adjusted R^2	0.35	0.72	0.49	0.89	0.1	0.26	0.32	0.49
CS (CS^2)	S (U)	S (S)	S (U)	S (S)	S (S)	S (U)	S (S)	S (U)
Wald-S		22.72**		44.57**		0.02		0.99
Wald-L		11.01**		12.80**		146.56**		0.07

Notes: **, * show the significance at the 5% and 10% respectively. Numbers inside parentheses are absolute values of the t-ratios. The F test due to Narayan (2005) is denoted by Narayan. In the case of L-ARDL at the 5% and 10% significance level when there are two exogenous variables (k=2) and n=30, its critical value is 5.473 and 4.47. This comes from Narayan (2005, Table CI-Case III, page 1988). For N-ARDL models its critical values are 5.018 and 4.15 with k=3. Number inside the parenthesis next to Banerjee is the absolute value of the t-ratio, denoted by BDM in the text. In the case of N-ARDL its critical value of -4.05 and -3.64 at 5% and 10% level of significance when k=4 and T=50 comes from Banerjee et al. (1998, Table I, page 276). For L-ARDL models its critical values are -3.82 and -3.45 correspondingly. LM is Lagrange Multiplier test of residual serial correlation. It is distributed as $\chi 2$ with one degree of freedom (first order). Its critical value at 5% and 10% level is 3.84 and 2.71. RESET is Ramsey's test for misspecification. It is distributed as $\chi 2$ with one degree of freedom and its critical value at 5% and 10% level is 3.84 and 2.71.CS and CS^2 are CUSUM and CUSUMQ respectively to test stability of all coefficients..