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On the Effects of Income Volatility on Income Distribution: Asymmetric Evidence from State Level Data in the U.S.

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ABSTRACT
A previous study that tried to assess the impact of income volatility on income inequality in the U.S. used state level data and a balanced panel model to conclude that increased volatility worsens income distribution in the U.S., which implies that decreased volatility should reduce inequality. We use the same data set that is extended by nine years and revisit the issue using linear and nonlinear ARDL time-series models to show that the above conclusion does not hold in every state. While we discover short-run asymmetric effects of income volatility on a measure of inequality in most states, they translate to long-run asymmetric effects only in 16 states. Both increased volatility and decreased volatility are found to have unequalizing effects on income distribution in these states.

Key words: Income distribution, Income Volatility, Asymmetry, State Level Data, United State.

JEL Classification: O16

*.Valuable comments of two anonymous reviewers are greatly appreciated. Remaining errors, however, are our own.

I. Introduction

The inverted-U hypothesis, introduced by Kuznets (1955), basically identifies the level of economic activity as the main determinant of income inequality. More precisely, it asserts that at the early stages of economic growth, income inequality worsens and it only improves at the later stages. Empirical support for the hypothesis is rather mixed, mostly rejecting the hypothesis.[1] Another strand of the literature, however, argues that income or output volatility as a measure of uncertainty can worsen income inequality.

Hausmann and Gavin (1997) is perhaps the first study that alludes us to the adverse effects of income volatility on income distribution by arguing that poorer members of society are not well equipped to absorb economic shocks or uncertainties relative to richer members. Using cross-sectional data from 56 countries in Latin America and industrial economies, they found that while neither GDP growth nor inflation had any significant effects on income inequality, the volatility of real GDP had significantly adverse effects on income inequality. The same is supported by Caroli and Garcia-Penalosa (2001), who looked at the effects of volatility of wages on wage differentials between low skilled and high skilled workers. Similar arguments are extended to the distribution of human capital rather than distribution of income by Checchi and Garcia-Penalosa (2004) who develop a theoretical model, showing that aggregate production risk determines the average level of education and its distribution. The higher the production risk, the higher the educational inequality. Other cross-sectional studies that support the adverse impact of

[1] Examples of studies that fail to support the hypothesis include Papanek and Kyn (1986), Ram (1991), Anand and Kanbur (1993), Deininger and Squire (1996), Chen and Ravallion (1997), Jacobsen and Giles (1995), Li et al (1998), Barro (2000), Dollar and Kraay (2002), and Frank (2009). Studies that support the hypothesis are: .Paukert (1973), Cline (1975), Ahluwalia (1976), Campano and Salvatore (1988), Deininger and Squire (1998), Bahmani-Oskooee et al. (2008), Bahmani-Oskooee and Gelan (2012)

output volatility on income distribution are Breen and Garcia-Penalosa (2005) and Laursen and Mahajan (2005).

While the above studies have used cross-sectional data from different countries, two studies have used panel data across countries and over time. Calderon and Yeyati (2009) uses data from 75 countries over the 1970-2005 (5-year period observations) to show that even in a panel model, output volatility has adverse effects on income inequality measured by GINI coefficient. Their findings do not seem to be sensitive to different measures of volatility, nor to different measures of income inequality. They also assess asymmetric effects of output fluctuations by assigning dummy variables to output drops and output jumps to show that output volatility has asymmetric effects on income distribution.

Finally, Huang et al. (2015) criticize all of the above studies for not using recent advances in error-correction modelling techniques and employ a panel error-correction approach instead of the conventional method of using cross-sectional data. Their panel data is different than that of Calderon and Yeyati (2009) in that they use annual data from the 48 states of the continental U.S. from 1945 to 2004 which forms a balanced panel set with N = 48 and T = 60.[2] Their findings are no different than any of the previous studies, in that they also find that volatility of income has an adverse effect on income distribution in the U.S. and this conclusion is not sensitive to different measures of income inequality, nor to different measures of volatility.

The panel studies reviewed above do suffer from aggregation bias in that what is true in one cross-sectional unit, may not necessarily be true in another cross-sectional unit. To resolve the issue, we adhere to time-series modelling only and reconsider the relation between income volatility and income inequality in each state of the U.S. This is now possible, since Frank (2009) has extended his data set through 2013, providing 68 annual observations for each state.

[2] The data set comes from Frank (2009).

Since the two variables could be stationary or non-stationary, the appropriate approach will be the linear ARDL approach of Pesaran et al. (2001). Within time-series framework, we will take an additional step and assess the asymmetric effects of volatility on income distribution by using the nonlinear ARDL approach of Shin et al. (2014) which also allows us to detect asymmetric causality. This is a plausible inquiry since the rate at which income inequality responds to an increase in income volatility could be different than the rate at which it responds to a decline. Indeed, if poorer members of the society cannot absorb economic shocks or uncertainties as easily as richer members, both group will react differently to increased uncertainty compared to decreased uncertainty, hence asymmetric response. The rest of the paper is organized in the following manner. We outline our models and methods in Section II and present our empirical results in Section III. Section IV provides a summary and an Appendix reveals definition of variables and sources of the data.

II. The Models and Methods

Let GINI denote the measure of income inequality in each state and VOL, the measure of income volatility in the same state. We begin with the following bivariate model:

$$\ln GINI_t = \alpha + \beta \ln VOL_t + \varepsilon_t \qquad (1)$$

By way of construction, since an increase in GINI reflects increased income inequality, if an increase in income volatility is to increase inequality we would expect an estimate of β to be positive. However, the estimate of β which reflects the long-run effects of income volatility on GINI will be valid only if the two variables are cointegrated. According to Engle and Granger (1987) if the two variables are integrated of the same order d but ε_t in (1) is integrated of any order less than d, the two variables are cointegrated. If ε_t is not integrated of an order less than d, Banerjee et al. (1998) propose an alternative test for cointegration which is based on an error-correction model as follows:

$$\Delta \ln GINI_t = \alpha \ + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j \Delta \ln VOL_{t-j} + \lambda \varepsilon_{t-1} + \nu_t \qquad (2)$$

The alternative test is based on the estimate of λ and its significance. If $\hat{\lambda}$ is significantly negative, that will support cointegration. However, the t-test that is used to establish the significance of $\hat{\lambda}$ has a new distribution, for which Banerjee et al. (1998) tabulate new critical values.[3]

Once (2) is estimated and cointegration is established, Granger (1988, p. 203) argues for two possible sources of causality that runs from income volatility to GINI within this bivariate framework. One is through the first-differenced variables where VOL granger causes GINI if $\sum \hat{\pi}_j \neq 0$ and the other one is through ε_{t-1} if an estimate of λ is negative and significant. In the literature, the first causality is referred to as short-run causality and the second one as the long-run causality (Jones and Joulfaian, 1991, p. 151). Whereas, the t-test with new critical value is used to test the significance of $\hat{\lambda}$, the Wald test is used to establish $\sum \hat{\pi}_i \neq 0$. Note that all of the statistical properties associated with (2) will be valid only if both variables, i.e., GINI and VOL are integrated of the same order, say, I(1). In case one is I(1) and the other one is I(0), or both are I(1) or I(0), Pesaran et al (2001) offer an alternative approach. They suggest solving (1) for ε_t, lagging the solution by one period, and replacing ε_{t-1} in (2) by that solution to arrive at:

$$\Delta \ln GINI_t = \alpha \ + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j \Delta \ln VOL_{t-j} + \lambda \ln GINI_{t-1} + \gamma \ln VOL_{t-1} + \omega_t \qquad (3)$$

[3] See Banerjee et al. (1998, Table 1, p. 276).

Once (3) is estimated using a lag selection criterion, several hypothesis could be tested. First, short-run effects of income volatility on GINI is judged by the estimates of $\hat{\pi}_j$'s. Again, if the Wald test confirms $\sum \hat{\pi}_j \neq 0$, short-run causality will be established. Second, long-run effects of volatility on GINI will be derived from the estimate of γ normalized on λ.[4] However, for the normalized effects to be meaningful, cointegration must be established. Pesaran et al. (2001) propose applying the F test. However, in this set up they show that the F test has a new distribution. They then tabulate the new critical values that account for integrating properties of variables. Indeed, as mentioned above, variables could be combination of I(1) and I(0), which are properties of almost all macro variables.[5] Third, the alternative test proposed by Banerjee et al (1998) is equally applicable here. It amounts to testing for the significance of λ in (3) again. Like the F- test, Pesaran et al. (2001, p. 303) tabulate an upper and a lower bound critical value for this so called the t-test.[6] If an estimate of λ is negative and significant, that will not only support cointegration but also long-run causal relation from income volatility to GINI. Note that an alternative method of applying the t-test is to use normalized long-run estimate of $\hat{\beta} = -\hat{\gamma}/\hat{\lambda}$ from (3) and equation (1) to generate the error term, called ECM. Then replace the linear combination of lagged level variables in (3) by ECM_{t-1} to arrive at:

$$\Delta \ln GINI_t = \alpha + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j \Delta \ln VOL_{t-j} + \lambda ECM_{t-1} + \omega_t \qquad (4)$$

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[4] Note that in (3) $\gamma = \lambda\beta$, which implies that $\hat{\beta} = -\hat{\gamma}/\hat{\lambda}$.

[5] Indeed, we had to make sure that there is no I(2) variable by applying the ADF test to second-differenced data and by showing that the second-differenced data are stationary.

[6] At the asymptotic level Banerjee *et al*.'s critical values are almost the same as upper bound critical values of Pesaran *et al*.

A significantly negative estimate of λ using the t-test with new critical values will support cointegration.[7]

As mentioned in the previous section Calderon and Yeyati (2009) assigned dummy variables to output drops and output jumps to show that output volatility can have asymmetric effects on income distribution. Within time-series framework such as ours, there are a few ways to engage in asymmetry analysis. One way is to investigate the possibility of asymmetric nonlinear adjustment toward equilibrium following Sollis (2009) who basically relies on an error-correction model like (3) but includes a linear combination of ECM_{t-1} raised to different powers as follows:

$$\Delta \ln GINI_t = \alpha + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j \Delta \ln VOL_{t-j} + \lambda_3 ECM_{t-1}^{3} + \lambda_4 ECM_{t-1}^{4} + \omega_t \quad (5)$$

If the F test rejects the null of $\hat{\lambda}_3 = \hat{\lambda}_4 = 0$, nonlinear adjustment process will be supported. We will report the result of this test as "Sollis". We can also include ECM^2_{t-1} and follow Pascalau (2007) and estimate the following specification:

$$\Delta \ln GINI_t = \alpha + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j \Delta \ln VOL_{t-j} + \lambda_2 ECM_{t-1}^{2} + \lambda_3 ECM_{t-1}^{3} + \lambda_4 ECM_{t-1}^{4} + \omega_t \quad (6)$$

In (6) if the F test rejects the null of $\hat{\lambda}_2 = \hat{\lambda}_3 = \hat{\lambda}_4 = 0$, again that will support asymmetric nonlinear adjustment. This test will be reported as "Pascalau".[8]

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[7] Bahmani-Oskooee (2018) has demonstrated that estimating both (3) and (4) yield the same estimate for λ.

[8] For some other application of these tests see Arize *et al*. (2017).

While the above two tests provide some preliminary about nonlinear adjustment process toward long-run equilibrium, none of them can shed lights on the asymmetric effects of income volatility on GINI. To assess the asymmetric effects of income volatility on GINI, we follow Shin et al. (2014) and modify model (3). The modification amounts to forming ΔlnVOL, which includes positive values reflecting increased volatility and negative values, reflecting decline in volatility. Then two new time-series variables are generated using the partial sum concept as follows:

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

$$NEG_t = \sum_{j=1}^{t} \Delta \ln VOL_j^- = \sum_{j=1}^{t} \min(\Delta \ln VOL_j, 0) \qquad (7)$$

where POS_t is the partial sum of positive changes in volatility and reflects only increased volatility. Similarly, the NEG_t variable that is the partial sum of the negative changes in volatility reflects only decreased volatility. Shin et al. (2014) then propose moving back to (3) and replacing lnVOL with POS and NEG variables to arrive at:

$$\Delta \ln GINI_t = \alpha + \sum_{j=1}^{n1} \varphi_j \Delta \ln GINI_{t-j} + \sum_{j=0}^{n2} \pi_j^+ \Delta POS_{t-j} + \sum_{j=0}^{n3} \pi_j^- \Delta NEG_{t-1} +$$

$$\rho_0 \ln GINI_{t-1} + \rho^+ POS_{t-1} + \rho^- NEG_{t-1} + \mu_t \qquad (8)$$

Since constructing the two partial sum variables introduce nonlinear adjustment of income volatility, Shin et al (2014) refer to models like (4) as nonlinear ARDL models whereas, Pesaran et al. (2001) specification (3) is referred to as the linear ARDL model. Again, once (4) is estimated, a few assumptions concerning asymmetry causality and asymmetry cointegration could be tested. First, by applying the Wald test if we establish $\sum \pi_j^+ \neq 0$, then increased volatility is said to cause GINI in the short run. Second, if $\sum \pi_j^- \neq 0$, then decrease in volatility is said to cause GINI in the short run. Third, if $n2 \neq n3$, that will be an indication of adjustment asymmetry. Fourth, if the Wald test supports $\sum \pi_j^+ \neq \sum \pi_j^-$, then changes in income volatility is said to have short-run cumulative or impact asymmetric effects on income inequality. Fifth, asymmetry cointegration will be established by applying the F test again. Due to dependency between the two partial sum variables, Shin et al. (2014, p. 292) propose treating the two variables as a single variable so that the critical values of the F test stay the same when we move from the linear to nonlinear model. Again, the alternative test for cointegration, i.e., the t-test could be applied to establish the fact that the estimate of ρ_0 is negative and significant. Finally, by applying the Wald test if we establish that the normalized long-run coefficient estimate attached to the POS variable is different than the one attached to the NEG variable, i.e., if $(-\rho^+/\rho_0) \neq (-\rho^-/\rho_0)$, long-run asymmetric effects of income volatility on GINI will be established.[9]

II. The Results

We are now in a position to estimate both the linear and the nonlinear error-correction models (3) and (4) using aggregate level data for the U.S. as a whole and then state level data for each state of the U.S. Since data are annual, a maximum of four lags are imposed on each first-differenced variable and Akaike's Information Criterion (AIC) is used to select an optimum model. Since there are different critical values for different estimates, we have collected them in

[9] For some other applications of these concepts see Apergis and Miller (2006), Delatte and Lopez-Villavicencio (2012), Verheyen (2013), and Bahmani-Oskooee and Fariditavana (2016).

the notes to Table 1 and used them to denote a significant estimate at the 10% level by * and at the 5% level by **.

From the results that belong to the linear models (identified by L-ARDL) we gather that the measure of income volatility carries at least one significant short-run coefficient in Panel A in the results for Alaska, Arizona, Georgia, Maryland, Mississippi, Missouri, New Hampshire, North Dakota, Oklahoma, Pennsylvania, South Carolina, South Dakota, Texas, Washington, and West Virginia. Thus, in these 15 states, income volatility has short-run effects on income distribution. However, when we consider the results from the estimates of the nonlinear models (headed by NL-ARDL), we gather that either ΔPOS or ΔNEG carries at least one significant coefficient in 36 states. Clearly, introducing the nonlinear adjustment of income volatility yields more support for the short-run effects of volatility in GINI. From the short-run estimates of the nonlinear models we also gather that the short-run effects are mostly asymmetric since the estimates attached to the ΔPOS variable differ from those attached to the ΔNEG variable in size or sign in most states. However, sums of these coefficients are significantly different from each other only in 39 states, since the Wald test reported as Wald-S is significant in 39 states. The significance of the Wald-S reported in Panel C rejects the null of $\sum \pi_j^+ = \sum \pi_j^-$. Thus, there is overwhelming support for the short-run cumulative or impact asymmetric effects of income volatility on income distribution. From the Wald tests we also gather that the null of either $\sum \pi_j^+ = 0$ or $\sum \pi_j^- = 0$ is rejected in many more states (31 in total) than the null of $\sum \pi_j = 0$ (nine in total) in the linear models, supporting short-run asymmetric causality compared to symmetric causality.

In any state in which there is only one short-run coefficient estimate, it is easy to judge the direction of the short-run effects. For example, in Alaska or Arizona and the L-ARDL model, the coefficient is significantly positive, implying that an increase in volatility increases GINI, or worsens inequality. However, when there is more than one coefficient, the task is somewhat difficult and long-run estimates become useful. From the long-run estimates (Panel B), we gather that in the linear models, LnVOL carries a significantly negative coefficient that is supported by a significant F or t test for cointegration in none of the states. If we are to rely upon only the estimates of the linear model, we would have stopped here and conclude that income volatility has no significant long-run effects on income distribution in the U.S.[10] However, when we consider the estimates from nonlinear models, either the POS or the NEG variable carry a significant coefficient that is also supported by one of the cointegration tests in 15 states. The list includes Florida, Idaho, Indiana, Kansas, Louisiana, Michigan, Mississippi, Missouri, Montana, Nebraska, Nevada, Rhode Island, South Dakota, West Virginia, and Wyoming. Again, the increased number of states in which volatility has long-run effects on income distribution must be attributed to nonlinear adjustment of income volatility.

Clearly, the long-run results are state specific. For example, in Florida, increased volatility worsens inequality but decreased volatility has no long-run effects, a clear sign of long-run asymmetry that is also supported by the Wald test reported as Wald-L in panel C. The opposite is true in Idaho where decreased volatility worsens income inequality but increased volatility has no effect. Only in South Dakota increased volatility worsens inequality and decreased volatility improves it, since both the POS and NEG variables carry positive coefficients. All in all, it appears that in nine states, i.e., Florida, Indiana, Kansas, Louisiana, Michigan, Montana, Nebraska, South Dakota, and Wyoming increased income volatility worsens income inequality. In another 10 states, i.e., Idaho, Indiana, Michigan, Mississippi,

[10] Even the alternative test for cointegration, i.e. ECM_{t-1}, is not helpful since it carries an insignificant coefficient in most models. In some cases, the estimate attached to ECM_{t-1} is positive, though insignificant. If it was positive and significant (like in Hawaii), that would be a reflection of an unstable model.

Missouri, Nevada, New Hampshire, Rhode Island, West Virginia, and Wyoming decreased volatility worsens inequality. These asymmetric effects are supported by the Wald-L test. While asymmetric impact of income volatility is supported in a total of 19 states, nonlinear adjustment toward long-run is supported in another eight states of Arizona, Delaware, Idaho, Maine, Minnesota, New York, Texas, and Vermont. In these states either the "Sollis" or the Pascalau" F test in Panel C is significant.

Reported in Panel C are some other diagnostic statistics. To test for serial correlation, we report the Lagrange Multiplier (LM) statistic which is distributed as χ^2 with one degree of freedom. It appears to be insignificant in almost all models, supporting autocorrelation free residuals. Ramsey's RESET test for misspecification is also reported. This is also insignificant in most optimum models, implying that almost all models are correctly specified. We have also applied the CUSUM and CUSUMSQ tests to the residuals of all models to make sure that our estimates are stable. These two tests are identified by QS and QS^2 in panel C, where stable estimates are denoted by "S" and unstable ones by "US". Clearly, most estimates are stable. Finally, to judge the goodness of fit, we have reported the size of adjusted R^2.

Finally, in order to determine whether our findings are sensitive to a different measure of income inequality and omitted variables from the bivariate model, we used the Thiel measure of inequality (see Appendix) and added the Kuznets's effect measured by real income in each state as well as the population in each state as other determinants of income inequality in addition to income volatility. The results were somewhat different as follows. In the three states of Alaska, Hawaii, and Idaho, increased volatility made income distribution worse in the long run and decreased volatility improved it. In eight state of Florida, Indiana, Louisiana, Michigan, Nebraska, Ohio, W. Virginia, and Wisconsin increased volatility made income distribution worse but decreased volatility has no long-run impact, again a sign of asymmetry effects. The opposite was true in Washington where decreased volatility improved inequality but an increase in volatility had no effects. Finally, in Oklahoma and Wyoming both an increase and a decrease in volatility made income distribution worse.[11]

IV. Summary and Conclusion

In 1955 Kuznets (1955) identified the level of income or economic activity as the main determinant of income inequality. He asserted that at the early stages of development, income inequality gets worse and once labor migrates from rural to urban areas, it gets better. Since the pattern of movement of inequality over time resembles an inverted-U shape, it is known as the inverted-U hypothesis. Unfortunately, it has been a challenge for many researchers to verify the hypothesis empirically. Instead, what has been easy to verify in the literature is the unequalizing effect volatility of income or output. It has been argued that since income volatility introduces uncertainty into the economy, it redistributes income from workers to owners of capital or from poor to rich.

Previous research has tested and mostly verified unequalizing effects of income volatility on income distribution by using either cross-sectional data or panel that that is pooled from many countries over certain time period. One panel study has used a balanced panel data from 48 states of the continental U.S. from 1945 t0 2004 and concluded that in the U.S. income volatility worsens income inequality. The data in this study which comes from Frank (2009) has now been extended till 2013, yielding 69 time-series observations for each state. This allows us to introduce the first time-series study on the impact of income volatility on income distribution. Furthermore, our time-series approach removes the so called aggregation bias from the

[11] These results that are tabulated in 12 pages are available from the authors upon request.

mentioned panel study. In other word, the conclusion that in the U.S. income volatility has worsened income inequality may hold in some states but not in all states.

Therefore, in this paper, we use Farnk's (2009) extended data set at the state level to assess the impact of income volatility on a measure of income inequality (GINI) in each of the 50 states plus the District of Columbia. We employ Pesaran et al.'s (2001) linear ARDL approach to error-correction modeling and cointegration to investigate the short-run and long-run effects of volatility on GINI to show that in the short-run income volatility cause income distribution in nine states (i.e., in Alaska, Arizona, Georgia, Maryland, Massachusetts, Missouri, New Hampshire, Pennsylvania, and South Dakota). Judging by the sum of short-run estimates, the cumulative effects of volatility on GINI was unequalizing in Alaska, Arizona, and South Dakota, but equalizing in the remaining six states. However, in none of the states do we see short-run effects lasting into long-run significant effects.

Suspecting that the adjustment of income volatility could be nonlinear, we also considered the nonlinear ARDL approach of Shin et al. (2014) which allows us to assess the possibility of asymmetric effects of income volatility. Once the increase in volatility is separated from declines, we find that, indeed, the effects of volatility on GINI are asymmetric in nature. More precisely, we discover short-run cumulative asymmetric effects in 39 states but short-run asymmetric causality in 31 states, a significant improvement compared to the results from linear models. However, short-run effects translated to the long-run significant, meaningful, and asymmetric effects in 16 states. More precisely we found that in the nine states of Florida, Indiana, Kansas, Louisiana, Michigan, Montana, Nebraska, South Dakota, and Wyoming increased income volatility worsens income inequality and in 10 states, i.e., Idaho, Indiana, Michigan, Mississippi, Missouri, Nevada, New Hampshire, Rhode Island, West Virginia, and

Table1 continued.								
	West Virginia		Wisconsin		Wyoming		District of Washington	
	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL	L-ARDL	NL-ARDL
Panel A: Short-Run Estimates								
4 > v ' / E /$_t$								
4 > v ' / E /$_{t-1}$		.040(2.81)**			-.36(2.79)**		-.39(3.20)**	-.28(2.30)**
4 > v ' / E /$_{t-2}$		.24(1.69)*			-.32(2.60)**			
4 > v ' / E /$_{t-3}$		.25(1.70)*			-.25(2.05)**			
4 > v ' / E /$_{t-4}$								
4 > VOL$_t$	.01(.27)		.01(.29)		.01(.96)		-.01(.30)	
4 > VOL$_{t-1}$	-.02(2.18)**							
4 > VOL$_{t-2}$								
4 > VOL$_{t-3}$								
4 > VOL$_{t-4}$								
4 W K ^$_t$		.24(1.44)		-.44(1.83)*		.22(2.08)**		-.10(.22)
4 W K ^$_{t-1}$								1.07(2.10)**
4 W K ^$_{t-2}$								
4 W K ^$_{t-3}$								
4 W K ^$_{t-4}$								
4 E '$_t$		-.45(1.86)*		.21(.76)		-.30(2.05)**		-.36(1.34)
4 E '$_{t-1}$				-.52(1.66)*				
4 E '$_{t-2}$								
4 E '$_{t-3}$								
4 E '$_{t-4}$								
Panel B: Long-Run Estimates								
Constant	.87(.48)	.93(51.8)**	-.07(.06)	-.86(28.1)**	2.00(.32)	-.86(46.6)**	-.54(.98)	-.83(13.18)**
LnVOL$_t$	.42(.84)		.07(.28)		.44(.40)		-.04(.28)	
POS$_t$		.48(1.40)		.68(.88)		.50(2.13)**		-.24(.21)
NEG$_t$		-.91(2.70)**		-.80(1.01)		-.68(2.66)**		-1.44(1.29)
Panel C: Diagnostic Statistics								
F	2.33	4.49*	.31	2.69	.77	5.63**	.76	2.40
ECM$_{t-1}$	-.03(1.07)	-.50(3.49)*	-.01(.92)	-.20(2.45)	-.01(.42)	-.44(4.19)**	-.04(1.15)	-.25(2.57)
LM	1.02	1.32	.01	.05	4.91**	1.41	2.50	.39
RESET	.39	1.54	.15	3.18*	1.11	4.95**	.33	.23
QS(QS^2)	S(S)	S(S)	S(S)	S(S)	US(US)	S(S)	S(S)	S(S)
Adjusted R^2	.95	.95	.98	.98	.96	.96	.93	.93
Sollis	1.29		.32		.22		.41	
PASCALAU	.85		.21		.15		1.52	
Wald Tests								
T ‹$_j$ = 0	1.89		.08		.93		.09	
T ‹$_j^+$ = 0		2.08		3.34*		4.31**		2.06
T ‹$_j^-$ = 0		3.45*		.72		4.21**		1.79
Wald-S		10.60**		.09		15.37**		2.90*
Wald-L		245.89**		142.41**		237.68**		35.65**

Notes:

a. Numbers inside parentheses are t-ratios. **, * denote significance at the 5, 10% levels, respectively.

b. At the 10% (5%) significance level when there is one exogenous variable (k=1) and 65 observations, the upper bound critical value of the F test is 4.93 (5.98). These come from Narayan (2005, p. 1988).

c. Number inside the parenthesis next to ECM$_{t-1}$ is the absolute value of the t-ratio. Its upper bound critical value at the 10% (5%) significance level is -2.93 (-3.28) when k=1 and these come from Banerjee et al (1989, p. 276). In the nonlinear model where k=2, these critical values change to -3.20 (-3.57).

d. 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.

e. RESET is Ramsey's test for misspecification. It is distributed as χ^2 with one degree of freedom.