Journal of Management and Sustainability; Vol. 6, No. 1; 2016
ISSN 1925-4725 E-ISSN 1925-4733
Published by Canadian Center of Science and Education

Modeling the Clustering Volatility of India's Wholesale Price Index and the Factors Affecting It

Mohammad Naim Azimi[1]

[1] Department of Industrial Economics and Business Administration, Rana University, Kabul, Afghanistan

Corresponding: Mohammad Naim Azimi, Department of Industrial Economics and Business Administration, Rana University, Kabul 5225, Afghanistan. E-mail: vc@ru.edu.af

Received: November 29, 2015 Accepted: December 11, 2015 Online Published: February 25, 2016

doi:10.5539/jms.v6n1p141 URL: http://dx.doi.org/10.5539/jms.v6n1p141

Abstract

This paper proposes to examine the clustering volatility of India's Wholesale Price Index throughout the period 1960 to 2014 by applying the ARCH (1) and GARCH (1) model. The pre-conditional requirement for the computation of ARCH (1, 1) required us to perform several other tests i.e. Dickey Fuller, Ordinary Least Squared Regression and post OLS tests for investigating the ARCH effect in the first difference of WPI. The statistical analysis reveals a *p-value* of 0.569 for the GARCH mean model which is not significant at ∂ 0.05 to explain that the previous period's volatility can influence the WPI. The coefficient of WPI at first difference exhibits a value of less than 1 which is nice in magnitude with a *p*-value of 0.005 for ARCH at ∂ 0.05 which is significant to explain the volatility of the WPI. The diagnostic test of autocorrelation in the residuals reveals that the residuals are white noise by exhibiting a corresponding probability value of 0.3757. Since, the overarching objective of this paper is to examine the clustering volatility of the aforementioned variable with regards to the internal shocks, there might have been other factors of external shocks on WPI that have deliberately been overlooked in this paper.

Keywords: clustering volatility, ARCH model, GARCH model, WPI, Gaussian distribution

1. Introduction

Wholesale Price Index (WPI) as a macroeconomic variable has always been the central theme of many research papers studying to investigate the reason of movement in the values overtime, given rise to critics in which clustering volatility is a significant economic phenomenon to be debated. The economic variables exhibited significant fluctuations in the last few decades and it is only recently that the researcher became interested in the economic consequences of their volatility for developing countries (Plosser, 2009). Gaunersdorfer & Hommes (2007) state that changes in price appear to be unpredictable, whereas the magnitude of such changes measured by the absolute or squared variables, appear to be predictable in the sense that the high volatility tends to follow the high volatility of either signs and low volatility tends to follow the low volatility in a time series process. Mandelbort (1967) was the first researcher who observed this economic phenomenon in the price of commodity and later pioneered by Engle (1982) and Bollerslev (1986). The most common econometrics models that have so far been applied to examine the clustering volatility or stylized facts of the macroeconomic variables are the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) by a vast number of researchers (Bera et al., 1992; Chung & Wu, 2005; Bonomo & Martins, 2003; Daal et al., 2007; Cont, 2007; Gonzalez & Gimeno, 2012; Chit et al., 2010). It is assumed that the computation of ARCH and GARCH model is only a decade ago, but its initiation goes far as back as to Bachelier (1900) who had initially observed and tested for the price speculation. WPI is one of the most changing and volatile variable and is widely used in the Indian cases to measure the economic performance of the country overtime as it has a large coverage of commodities and its computation is as important as the other economic variables (Bhaskara & Singh, 2006). The extensive literature on economic and financial time series analysis suggest that such volatile and gradually changing variables computation is based on ARCH and GARCH models (Guo, 2006; Nelson, 1991; Zakoian, 1994; Higgins et al., 1992; Ding et al., 1993; Engle, 1982). This paper will test the clustering volatility of the wholesale price index of India by applying ARCH (1, 1) model that a concise discussion of which follows this para.

1.1 ARCH (1, 1) and Clustering Volatility

According to Miles (2008) ARCH is an effective econometric testing model which is applied on those specific variables that exhibit ARCH effect. Given rise to most of the economic variables with due to their fluctuations overtime, both ARCH effect and clustering volatility can be observedthat tends to move overtime. Chang & McAleer (2015) argue that using volatility measures based on the assumption of constant volatility over period of time when the resulting series moves through time is statistically and logically victimized by autocorrelation. Tickling the serial correlation associated with the ARCH model requires diagnostic tests to ensure that the model is nicely fitted and the anticipated research finding is of value to a maximum extent (see, section 2.2.4) which all such issues are taken into account in this paper. The remainder of this paper is organized as follow: Section 2, illustrates the data and testing procedures plus the pre-conditional requirements for the application of ARCH and GARCH model, Section 3, presents the data analysis and research findings, Section 4, concludes the paper and is followed by acknowledgement of the author and the list of references.

2. Data and Method

2.1 Basic Data

The data used in this study is retrieved from WDI (World Development Indicator) on Wholesale Price Index of India. The observation is for the period 1960 to 2014 and is arranged on annual basis. The initial research plan on data collection was the monthly observation, but the concerned source of data used herein, does not provide monthly data on Indian WPI (see, Table 1 for descriptive statistics).

2.2 The Model

Following the model of ARCH (1) and GARCH (1) developed by Engle (1982) and pioneered by Bollerslev (1986) the data collected for this study is tested against the clustering volatility of the previous periods volatility on the Wholesale Price Index of India. In our approach to use the ARCH and GARCH model, there are two fundamental conditions to fulfill e.g., 1) the existence of Clustering Volatilityin the residuals that tends to determine the period of high volatility being followed by high volatility and that the period of low volatility is being followed respectively and 2) there is an ARCH effect in the residuals. Therefore, to ensure that our data fulfills the requirements, we apply the following sequential econometric test models to obtain an accurate result:

2.2.1 Dickey Fuller Test

As an initial point to start, a Dickey Fuller test is applied to check the stationarity for the series of the model that includes 1 to *k* lags at first difference with at 5% critical value (Dickey & Fuller, 1979). The equation used to fit the model is:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta_t + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + \dots + \zeta_k \Delta y_{t-k} + \varepsilon_t \tag{1}$$

Here we test the null hypothesis of D.WPI being non-stationary and has unit root against the alternative being stationary with no unit root at 5% critical value. Since, the first attempt to test the null is with drift, there are two other alternative tests that we perform to check the stationarity of the data at its first difference:

- DF with time trend and;
- Stationarity with non-zero but with no linear time trend.

The rejection of null under DF test will allow us to go further and apply our next test model. The approach to conclude the test is designed on DF with drift at 5% critical value (see, Table 1).

2.2.2 OLS Regression Test

To compute the ARCH/GARCH mean model (1, 1), we regress the OLS (Ordinary Least Square) with constant-only to facilitate the determination of ARCH effect in the residuals and to test the null being no ARCH effect vs. there is ARCH effect in the residuals (see, Table 2).

2.2.3 Lagrange Multiplier test for ARCH effects

For testing the null, we borrow from the work of Engle (1982) to test for ARCH (*p*) effects that can fit on Ordinary Least Square (simply OLS) regression of $\hat{u}_t^2$ on $\hat{u}_{t-1}^2, \dots, \hat{u}_{t-p}^2$:

$$\hat{u}_t^2 = \gamma_0 + \gamma_1 \hat{u}_{t-1}^2 + \dots + \gamma_p \hat{u}_{t-p}^2 + \varepsilon \tag{2}$$

Where the t statistics is nR^2 and is asymptotically distributed $X^2(p)$ (Baum, 2001). Before computing the LM test for ARCH effects, we test the residuals collected from the OLS regression (refers to as "D.Ln_WPI") to see the periods of tranquility and periods of high volatility in the residuals (see, Figure 1 D.Ln_WPI). This ensures that the model is a good candidate for ARCH / GARCH computation.

2.2.4 ARCH/ GARCH Mean Model

The ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models have been primarily developed to deal with issues of clustering volatility in the financial time series (Nelson, 1991). We use the models for examining whether the previous periods of volatility affect the Indian Wholesale Price Index for the purpose of which, we perform all pre-conditional requirement discussed in sections 2.2.1, 2.2.2 and 2.2.3. The prime ARCH model which has been designed and introduced by Engle (1982) was modeled that the variance of the regression disturbance is a linear function of the lagged values of the squared regression disturbance (Glosten et al., 1993). For the mean model of ARCH (m), we can fit the following equation:

Conditional Mean
$$y_t = X_t\beta + \varepsilon_t \tag{3}$$

Conditional Variance
$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \gamma_2\varepsilon_{t-2}^2 + \ldots + \gamma_m\varepsilon_{t-m}^2 \tag{4}$$

The ε_t^2 is the squared residual and the γ_i represents the ARCH parameter. ARCH model accounts both for mean and conditional variance. The variance itself is a function of the size for the prior unexpected innovations. The GARCH (*m, k*) model which was developed by Bollerslev (1986) and is applied in this paper can be expressed as of the following equation:

$$y_t = X_t\beta + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \gamma_2\varepsilon_{t-2}^2 + \ldots + \gamma_m\varepsilon_{t-m}^2 + \delta_1\sigma_{t-1}^2 + \delta_2\sigma_{t-2}^2 + \ldots + \delta_k\sigma_{t-k}^2 \tag{4}$$

In the GARCH model equation above, γ_i are the ARCH parameters and δ_i are accounting for GARCH parameters. The serial correlation associated with the model is tested by Bartlett White Noise method for the randomness and normality of the residuals. The null is that serial correlation is white noise and randomly distributed against the alternative being the serial correlation is not white noise and is not randomly distributed (see, Table 7 and Figure 3).

3. Data Analysis

$STATA_{14}$ statistical software is used to analysis the data and to apply the sated models for testing the clustering volatility of the variables throughout the period 1960 to 2014. In this section, we shall present all the statistical analysis and findings of the research in a sequential order and as discussed in section 2.2.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
OBS	55	1987	16.02082	1960	2014
WPI	55	37.72777	35.96942	3.09674	129.9643
Ln_WPI	55	3.072632	1.158971	1.13035	4.86726

Observation represents the time period from 1960 to 2014 annualized data on Wholesale Price Index of India. Ln_WPI is the log differences of the Wholesale Price Index calculated by use of excel function for the concerned period of time under study.

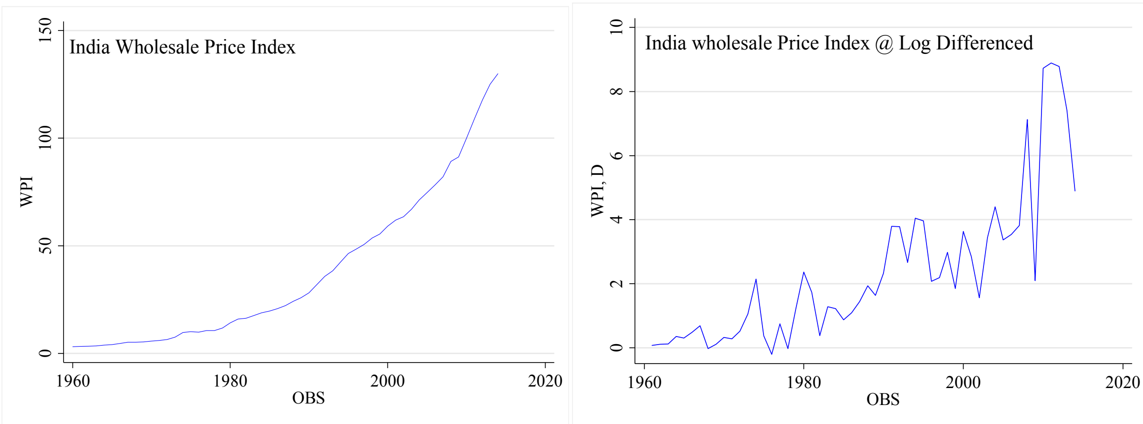

Figure 1. Line plot

The line-plot for original variable (WPI) shows a moving trend by an upward slop which means that the variable is non-stationary. Since the application of ARCH (autoregressive conditional heteroskedasticity) and GARCH (generalized autoregressive conditional heteroskedasticity) model in determining the volatility of the residuals in the stated variable requires stationarity (low periods of volatility following the low periods of volatility and higher volatility tends to follow the higher volatility for prolong period) to reflect the clustering volatility, the WPI is plotted at its first difference which is exactly the same as we plot it on its residual which shows the D.WPI tends to follow a clustering volatility.

Table 2. Dickey fuller test

				Number of obs = 54	
				----------- Z(t) has t-distribution -----------	
	Test Statistics		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	11.756		-2.400	-1.675	-1.298
p-value for Z(t) = 1.0000					
D.WPI	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]
WPI					
L1.	.0584619	.0049731	11.76	0.000	484826 .0684411
_cons	.2436217	.2451871	0.99	0.325	.2483822 .7356256

The Dickey Fuller test result shows that the value of *t* statistics (the absolute value) is more than the critical value at 0.05 (5%) (We ignore the negative sign of the critical value here) which means that we can reject the null hypothesis in the favor of the alternative hypothesis. Hence, the variable is stationary at first difference (Note 1) and this is what we require to facilitate the application of ARCH / GARCH (1, 1) model. The autocorrelation associated with this model is also tested that the result of which, documents that the autocorrelation is white noise with a *p-value* > 0.05 (say, 0.3757, see, Figure 3) and randomly distributed which is desirable for our statistical analysis. To begin with, we regress the WPI (the variable) at first difference and continue our analysis (see, Table 3).

Table 3. Linear regression at first difference of WPI

Source	SS	Df	MS	Number of obs	=	54
Model	0	0	.	F(0, 53)	=	0.00
Residual	287.875097	53	5.4316056	Prob > F	=	.
				R-squared	=	0.0000
Total	287.875097	53	5.4316056	Adj R-squared	=	0.0000
				Root MSE	=	2.3306
D.WPI	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
_cons	2.349399	.3171518	7.41	0.000	1.713273	2.985525

The clustering volatility of the D.WPI (WPI in first difference) is documented by plotting it (see, Figure 1 India Wholesale Price Index at first difference) and the white noise distribution of residuals (see, Figure 3 *p-value* 0.3757 > 0.0500) in the regression and the ADF test also proves to be desirable in our study on the basis of which, we continue to test the existence of ARCH effect or the clustering volatility of the mean model (1, 1) by testing the following hypothesis:

H_0: Mean Model has no ARCH effect

H_A: Mean Model has ARCH effect

Table 4. LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	Df	Prob > chi2
1	52.724	1	0.0000

The LM test for autoregressive conditional heteroskedasticity presents a *p*-value of 0.0000 which is < 0.05 (we normally test at α .05/95% confidence level) and therefore, the null hypothesis can be rejected against the alternative and we know that the mean model (1, 1) has an ARCH effect. In other words, on the basis of the *p*-value being less than 0.05, the mean model (1, 1) has clustering volatility (see, Engle, 1982).

Table 5. ARCH family regression

Sample:	1961 – 2014				Number of obs =	54
Distribution:	Gaussian				Wald chi2 (.) =	.
Log likelihood =	101.388				Prob > chi2 =	.
D.Ln_WPI		OPG				
	Coef.	Std. Err.	Z	P>|z|	[95% Conf. Interval]	
Ln_WPI		OPG				
_cons	.0555279	.0037517	14.80	0.000	.0481746	.0628812
ARCH						
Arch						
L1.	1.204121	.425251	2.83	0.005	.3706443	2.037598
Garch						
L1.	.0741623	.1302192	0.57	0.569	-.1810626	.3293873
_cons	.0002523	.000217	1.16	0.245	-.0001731	.0006777

Table 5 shows the estimation of ARCH (1) parameter with a value of 1.204 and consequently the GARCH (1) parameter reflects a value of 0.741, that our fitted GARCH (1, 1) model can be expressed as follow:

$$y_t = 0.555 + \varepsilon_t$$
$$\sigma_t^2 = 1.204\,\varepsilon_{t-1}^2 + 0.741\,\sigma_{t-1}^2$$
$$y_t = Ln(WPI_t) - Ln(WPI_{t-1})$$

The corresponding probability value of *z* statistics for ARCH is 0.005 which is < 0.05 meaning that the ARCH *p*-value is significant to explain the volatility of WPI. On the other hand, the corresponding value of the *z* statistics for GARCH is 0.569 being > 0.05 which means that this value for GARCH is not significant to explain the volatility of the WPI. Hence, the previous years' volatility of the Indian Wholesale Price Index (simply, WPI) cannot influence the WPI. Keeping the account for the serial correlation, we further test the following hypothesis:

H_0: There is no serial correlation

H_A: There is serial correlation in this model.

Since, the ARCH / GARCH (1, 1) model is computed on Gaussian based approach, we create another residual (say, GR) to execute the autocorrelation and partial correlation functions on 10 lags as below:

Table 6. AC and PAC

LAG	AC	PAC	Q	Prob>Q
1	0.2582	0.2602	3.8039	0.0511
2	-0.1821	-0.2670	5.7327	0.0569
3	-0.1244	0.0036	6.6504	0.0839
4	-0.3027	-0.3718	12.194	0.0160
5	-0.2401	-0.0880	15.751	0.0076
6	0.1383	0.0977	16.955	0.0094
7	0.4360	0.3673	29.184	0.0001
8	0.1138	-0.1748	30.036	0.0002
9	-0.0582	0.0446	30.264	0.0004
10	0.0126	0.0534	30.274	0.0008

The table above in AC and PAC (see, Figure 2 for the AC and PAC graphs as well) shows very smaller values both with positive and negative signs that are closer to zero that represent stationarity of the variable GR.

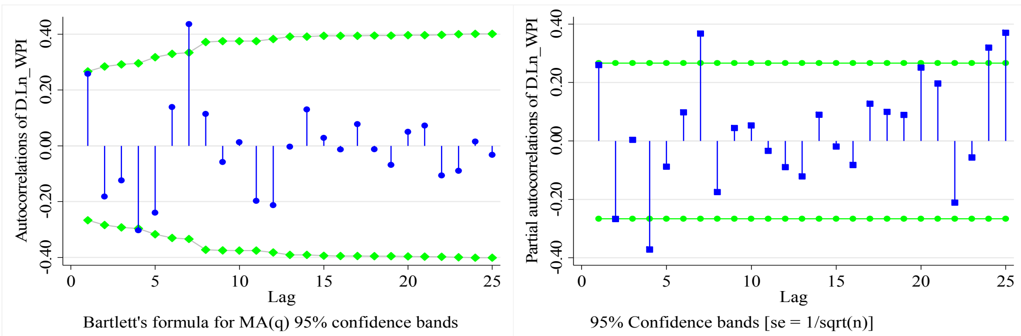

Figure 2. AC and PAC

On the other hand, the corresponding probability value of the Q statistics is higher in some lags and lesser than 5% in the following lags which almost shows a serial correlation in the residuals. Hence, we have to develop and test the following hypothesis for its normal and random distribution:

H_0: The residuals are random and normally distributed

H_A: The residuals are not random and not normally distributed

Table 7. Cumulative periodogram white-noise test

Bartlett's (B) Statistics	=	0.9125
Prob > B	=	0.3757

For testing the above hypothesis and to check for randomness of the residual (GR) distribution, the white noise test developed by Bartlett (1995) is used and is shown in Table 7. The corresponding probability value of 0.3757 in the test is > 0.05 on the basis of which, we cannot reject the null hypothesis, rather we accept it and further submit that the residual distribution is white noise and within the band (see also, Figure 3).

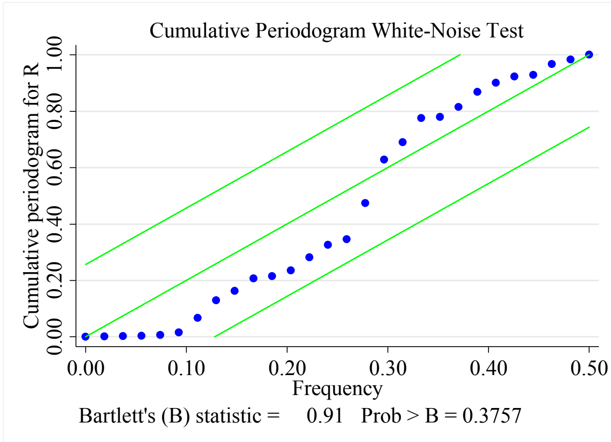

Figure 3. White noise test

The values represented by blue squares are seen to be always within the confidence bands directed by the limelines in the graph. The corresponding p-value of the Bartlett test is 0.3757 which is > 0.05, meaning that the residuals are normally distributed and are white noise. In other word, we can conclude that the variable in process is not different from white noise and never crossed the bands.

4. Conclusion

For investigating the clustering volatility of the Indian Wholesale Price Index (WPI), ARCH and GARCH mean model is applied. The data for a wide range of time series over 55 years on WPI has been carefully tested that the result of which reveals that the GARCH L1 corresponding probability value of 0.569 being > 5% is not significant to explain WPI and therefore, we can conclude that the volatility of the previous periods of the WPI is not significant to influence the WPI. In addition to this, the ARCH L1 corresponding probability value of 0.005 being < 5% is significant to explain volatility of the WPI under the Gaussian model. Since, the model has almost suffered from autocorrelation but the residuals under the Gaussian model are white noise by 0.3757 which shows that the residuals are random and normally distributed.

Acknowledgements

With profound words, I acknowledge the presence of the academic and research members of Rana University and their effective comments with regards to this paper. The author acknowledges the constructive and valuable comments of the anonymous editor and reviewer in relation to this study.

References

Bachelier, L. (1900). Théorie de la spéculation. *Annales Scientifiques de l'École Normale Supérieure, 3*, 21-86.

Bartlett, M. S. (1995). *An Introduction to Stockhastic with Special Reference to Methods and Applications*. Cambridge: Cambridge University Press.

Baum, C. F. (2001). Stata: The language of choice for time series analysis? *Stata Journal*, *1*(1), 1-16.

Bhaskara Rao, B., & Singh, R. (2006). Demand for money in India: 1953-2003. *Applied Economics*, *38*(11), 1319-1326. http://doi.org/10.1080/00036840500396228

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(1), 307-327. http://doi.org/10.1109/TNN.2007.902962

Bonomo, M., Martins, B., & Pinto, R. (2003). Debt composition and exchange rate balance sheet effect in Brazil: A firm level analysis. *Emerging Markets Review*. http://doi.org/10.1016/S1566-0141(03)00061-X

Chang, C. L., & McAleer, M. (2015). Econometric analysis of financial derivatives: An overview. *Journal of Econometrics*, *187*(2), 403-407. http://doi.org/10.1016/j.jeconom.2015.02.026

Chen, S. L., & Wu, J.-L. (2005). Long-run money demand revisited: evidence from a non-linear approach. *Journal of International Money and Finance*, *24*(1), 19-37. http://doi.org/10.1016/j.jimonfin.2004.10.004

Chit, M. M., Rizov, M., & Willenbockel, D. (2010). Exchange Rate Volatility and Exports: New Empirical

Evidence from the Emerging East Asian Economies. *The World Economy*, *33*(2), 239-263. http://doi.org/10.1111/j.1467-9701.2009.01230.x

Cont, R. (2007). Volatility clustering in financial markets: Empirical facts and agent-based models. *Long Memory in Economics* (pp. 289-309). http://doi.org/10.1007/978-3-540-34625-8_10

Daal, E., Naka, A., & Yu, J. S. (2007). Volatility clustering, leverage effects, and jump dynamics in the US and emerging Asian equity markets. *Journal of Banking and Finance*, *31*(9), 2751-2769. http://doi.org/10.1016/j.jbankfin.2006.12.012

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of Th American Statistical Association*, *74*(366a), 427-431. http://dx.doi.org/10.1080/01621459.1979.10482531

Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*. http://doi.org/10.1016/0927-5398(93)90006-D

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987-1007. http://doi.org/10.2307/1912773

Gaunersdorfer, A., & Hommes, C. H. (2007). A Nonlinear Structural Model for Volatility Clustering. *Long Memory in Economics* (pp. 265-288). http://doi.org/10.2139/ssrn.241349

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, *48*(5), 1779-1801. http://doi.org/10.2307/2329067

Gonzalez, C., & Gimeno, R. (2012). Financial Analysts Impact on Stock Volatility. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2175491

Guo, H. (2006). Time-varying risk premia and the cross section of stock returns. *Journal of Banking and Finance*, *30*(7), 2087-2107. http://doi.org/10.1016/j.jbankfin.2005.05.022

Higgins, M. L., Bera, A. K., & others. (1992). A class of nonlinear ARCH models. *International Economic Review*, *33*(1), 137-158. http://doi.org/10.2307/2526988

Mandelbrot, B. (1967). The Variation of Some Other Speculative Prices. *The Journal of Business*. http://doi.org/10.1086/295006

Miles, W. (2008). Volatility clustering in US home prices. *Journal of Real Estate Research*, *30*(1), 73-90. Retrieved from http://ares.metapress.com/index/2N3V544976H11635.pdf

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*(2), 347-370. http://doi.org/10.2307/2938260

Plosser, C. I. (2009). Financial econometrics, financial innovation, and financial stability. *Journal of Financial Econometrics*, *7*(1), 3-11. http://doi.org/10.1093/jjfinec/nbn014

Schwart, G. (1989). Test for Unit Root: A Monte Carlo Investigation. *Journal of Business and Economics Statistics*, *7*, 147-160.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, *18*(5), 931-955. http://doi.org/10.1016/0165-1889(94)90039-6

Note

Note 1. The DF test was also applied with trend and $p_{\max}$ an experiment suggested by Schwart (1989) to ensure the ultimate result on which we can base our analytical opinion that is not either biased or is suffered by lag length p, both ways resulted in rejecting the null hypothesis and accept the alternative.

Copyrights