EXCHANGE TRADED FUNDS AND THE VOLATILITY OF THE UNDERLYING ASSETS

ADAMU, Abdul
Department of Business Administration,
Nasarawa State University, Keffi
&
Aruwa, Suleiman A.S.
Department of Accounting,
Nasarawa State University, Keffi

Abstract
This study examines the effect of ETF on the volatility of its underlying asset in Nigeria. Newgold ETF that tracks daily prices of gold/g in rand was used in the study. We collected data on daily prices from January, 2014 to May, 2015 on the ETF and the gold and tested for volatility using ARCH and GARCH model. The result shows that ETF is not significant in influencing the underlying asset and that previous days return information of the gold price and its shock influences the volatility of the underlying stock. It was recommended that investors and fund managers should not only rely on current domestic news about the ETF but should take into considerations international news about the underlying asset as there are spillovers.

Introduction

Exchange Traded Funds (ETFs) are securities that provides the diversification of a mutual funds but trades on securities exchange like stocks. The Investment Company Institute (ICI) (2014) for instance, defines ETF as an investment company that offers investors a proportionate share in a portfolio of stocks, bonds or other securities. Like, individual equity securities, ETFs are traded on a stock exchange and can be bought and sold throughout the day through a broker – dealer.

ETFs are widely acknowledged to be one of the most useful innovations of the past few decades, especially for index traders. They are essentially exchange-traded assets that represent a basket of securities comprising a particular index. ETFs allow investors to take positions in a given market without selecting individual securities, and provide them with an opportunity to easily trade indices, in small amounts, and at very low costs (De Winne, Gresse & Platten, 2009). They are thus generally not considered as redundant assets, but rather as new financial instruments that complete markets in an economic sense. They are particularly well suited for passive investors and combine the advantages closed-end and open-end mutual funds with much lower expense fees. As close-end funds, ETFs can be traded throughout the day in the secondary market, and is considered open-end mutual funds, as the creation and redemption of ETF shares is allowed (De Winne et al, 2009).

As a result of these features, ETFs are now very popular investment vehicles. A BlackRock (2011) Report that there were 3,987 ETFs and ETPs with 8,027 listings, on 52 *exchanges, from 182 providers around the world. The ETF market has grown from $79* billion in 2000 to more than $1.4 trillion in 2010 and Investment in ETFs accounts for 40% of the total amount invested in index mutual funds in the U.S. (Aggarwal, 2012; and Blackrock, 2011). Therefore, understanding how and why ETFs contribute to the quality of stock markets is thus of great interest.

The ETF market in Africa is mostly dominated by South African products. According to BlackRock (2011) Report, there are about 28 ETFs listed on the Johannesburg Stock Exchange (JSE) as at June, 2011, with Asset Under Management (AuM) totalling about $3,085Mn. This attractive figures explain the significant role this product is playing in providing the necessary depth on JSE. This can also explained why Nigeria is trying to make the capital market deeper, broader and more institutionalized by introducing new products, of which ETF is prominent among them. Presently, there are four ETFs listed on the Nigerian Stock Exchange (NSE).

Despite the importance ETFs have gained, little is known about their volatility and how it affects that of the underlying asset especially in Africa and Nigeria. The academic literature focuses on their performance and their impact on associated instruments such as index constituents, index derivatives and competing index mutual funds. For instance, studies done by Agapova (2011), Elton, Gruber and Blake (1996) and Gastineau (2004) indicated that the existence of higher tracking errors. The negative relationship between costs and performance cause those tracking errors. The expense ratios (i.e. costs) are, to a great extent, a compensation for management services (Gastineau, 2004). Tang and Xiong (2012) found that ETFs are associated with an increase in cross-commodity market correlation because findings based on international markets are not evident in Chinese commodity markets, which are not available to foreign investment. Thus, this study examines the effects of ETF on the volatility of its underlying asset. It also examine other internal and external factors that affects the volatility of the underlying asset apart from the ETF.

Volatility of ETFs and its Underlying Assets

The theoretical channel for the effect of ETFs on limited arbitrage and clientele effects is such that if arbitrage is limited, liquidity shock can propagate from the ETF market to the underlying securities and add noise to prices. To illustrate this effect, consider the example of a large liquidity sell order of ETF shares by an institutional trader. As captured by the models of Greenwood (2005) and Gromb and Vayanos (2010), arbitrageurs buy the ETF and hedge this position by selling the underlying portfolio. Arbitrageurs with limited risk-bearing capacity require a compensation in terms of positive expected returns to take the other side of the liquidity trade. Hence, the selling activity leads to downward price pressure on the underlying portfolio.

Through this channel, the repeated arrival of liquidity shocks in the ETF market adds a new layer of non-fundamental volatility in the prices of the underlying securities. An additional assumption to obtain this result is that, in the absence of ETFs, liquidity trades would not hit the underlying security with the same intensity. Rather, it has to be the case that ETFs attract a new clientele of high-turnover investors that impound liquidity shocks at a higher rate (Goldman Sachs, 2013). This conjecture seems warranted in light of Amihud and Mendelson's (1987) model, which predicted that short-horizon investors self-select into more liquid assets, such as ETFs.

ETFs tend to hold stocks in the same proportion as in the index that they track. The identification comes from the fact that variation in ETF ownership, across stocks and over time, depends on factors that are exogenous with respect to volatility and turnover. Specifically, the same stock appears with different weights in different indexes. Furthermore, the fraction of ETF ownership in a firm depends also on the size of the ETF (its assets under management) relative to that of the company. As a result, while it is possible that flows into ETFs are correlated with fundamental information regarding the underlying stocks (e.g., sector-related news), it is unlikely that fundamental reasons produce an effect on volatility that is stronger for stocks with higher ETF ownership.

The increase in volatility is not necessarily a negative phenomenon if it results from enhanced price discovery which makes prices more reactive to fundamental information. This case corresponds to an improvement of price efficiency. To test whether this effect is behind the observed increase in volatility, the impact of ETFs on the mean-reverting component of stock prices is measured. Using intraday variance ratios as in O'Hara and Ye (2011), it showed that price efficiency deteriorates for stocks with higher ETF ownership at the fifteen second frequency, which captures the investment horizon of ETF arbitrageurs. At the daily frequency, ETF flows trigger price reversals suggesting a persistence of liquidity shocks at lower frequencies as well. In sum, ETFs appear to inflate the mean-reverting component of stock prices which suggests a deterioration in price efficiency, both intraday and at the daily frequency.

To bring further evidence on the driving channel for the volatility effect, Ben-David, Franzoni, and Moussawi (2014) documented that volatility increases at times when arbitrage is more likely to occur, that is, when the divergence between the ETF price and the net asset value (NAV) is large. Ben-David et al (2014) also found that ETF flows impact the volatility of the underlying stocks and this effect is stronger for stocks with high ETF ownership. Further supporting the arbitrage channel, they show that the volatility effect is more pronounced among stocks with lower limits of arbitrage, as captured by bid-ask spreads and share lending fees.

The hypothesis that ETFs attract a new clientele of high-turnover investor's yields the testable prediction that turnover should also increase with ETF ownership. The evidence suggests that this is the case. In particular, a one-standard deviation increase in ETF ownership is associated with an increase of 19% of a standard deviation in daily turnover. Also, the higher turnover is linked to the same arbitrage channels that are driving the volatility effect. This finding corroborates the view that the high turnover clientele of ETFs is inherited by the underlying stocks as a result of arbitrage.

Speculators facilitate the proper functioning of basket markets by enabling hedgers to transfer risk. Furthermore, basket trading imposes fewer costs than trading the underlying securities, making the basket market attractive to speculators. Therefore, speculators are critical of the volatility effect of basket trading. Friedman (1953) concluded that the activities of speculators result in gains, through buying when prices are low and selling when prices are high, and simultaneously stabilize the market. However, Kaldor (1960) pointed out that speculation may end up with a net loss, with some speculators gaining, and may destabilize the market.

One of the major volatility linked issues associated with ETFs is the rebalancing trades that occur at the end of the trading day. For ETFs to meet their investment mandates, it is necessary for them to rebalance their portfolio as market movements require. Many analysts have thought for some time that it is this rebalancing process that is causing or even abetting excess volatility (Carver, 2009; Gardner & Welsh, 2005; Humphries, 2010; Rompotis, 2008). Many market experts believe that ETF rebalancing due to the unwillingness and reticence to hold positions overnight is boosting late-day volume, with some estimates in the range of 20-30% of last hour trading being accredited to ETFs (Avellaneda & Zhang, 2009; Knain-Little, 2010). In 2010, a Morgan Stanley report estimated that ETFs accounted for about 30% of daily listed market volume, which is three times more than in 2005.

The Investment Company Institute in 2010 believed that more than $780 billion is invested in ETFs (Milonas & Rompotis, 2006). Leveraged ETFs have drawn their own concerns due to the amplified volumes purchased and sold that are associated with fund rebalancing. If one was to investigate broad funds like index trackers, the rebalancing process of one large ETF investment could be as large as a buy or sell on every selected stock on the ETF index in question. Hundreds of billions of United States dollars of ETF funds capital is now invested in contracts that were once dominated by commodity producers and consumers who sought to hedge specifically against commodity-market volatility for day-today company risk reduction.

Rompotis (2009) investigated the dynamics of various investment styles and found that active ETFs underperform their corresponding passive ETFs and the market indices. The results also indicate that the percentage correlation between the trading price of the ETF and the underlying index range between 0.2 per cent and 39.1 per cent. This finding is echoed by Gastineau (2004) and Lu and Wang (2009). A 'herd effect' has been identified by identified in associated ETF research (Miffre, 2007). This effect is found to have been amplified by global uncertainties, as investors are less willing to hold overnight positions due to the increased risk of off-market-hours price fluctuations.

Trainor (2010) investigated the link between leveraged ETFs and equity market volatility. Of the one hundred and fifty leveraged and inverse ETFs with assets of more than $30 billion in 2010, intra-day volatility since the year 2000 was not found to be associated with the rebalancing process of ETF fund managers. This result was also found to hold during periods of extreme intra-day volatility such as during the United States subprime crisis. Cheng and Madhaven (2009) found that leveraged ETFs have a large effect on market-on-close (MOC) volumes. Large moves in price could be further exacerbated by the rebalancing process of ETFs at the end of the day. Cherry (2004) found that ETFs are on average, 17% more volatile than their underlying components and 70% of this volatility can be explained by transaction and holding costs. Madura and Richie (2004) found substantial overreaction of ETFs during normal trading hours and after hours, presenting opportunities for feedback traders.

Methodology

The research design for this study is the descriptive design and the population covers all ETFs listed on the NSE and their underlying assets. In total, there are about four ETFs, 30 most capitalized stocks, halal stocks and gold price. One ETFs, NewGold which track the daily prices of gold in South African rand was selected as sample because it is the first ETF listed on the NSE and it started trading at the beginning of 2014. The data for the study is secondary in nature as daily prices of ETFs between 2nd January, 2014 and 29th may, 2015 were used.

The daily returns for the ETF and the underlying asset were computed, and tested whether it is stationary or not using *Augmented Dickey-Fuller (ADF) test. The data was* then tested for volatility clustering to determine whether it has volatility effect or not. After that the Auto Regressive Conditional Heteroscedasticity (ARCH) and the Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model were used to analyse how ETF affects the volatility of its underlying asset. This is because volatility of a process is measured via variance and ARCH or GARCH models are fitted when errors of a regression model, have variances which are not independent, or the variance of the current error term is related to the value of the previous periods' error terms, as well as past variances.

The mean and variance equation for GARCH (1, 1) is as follows;

Mean equation

$$GOLDPRICE = \beta_1 + \beta_2 * NEWGOLD + \square \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Variance equation

$$\sigma_t^2 = \beta_3 + \beta_4 *{}_{t-1}^{2} + \beta_5 * \sigma_{t-1}^2 + \beta_6 * NEWGOLD \ldots\ldots\ldots\ldots (2)$$

Where; GOLDPRICE is the daily returns on gold price which is the dependent variable

NEWGOLD is the ETF that track the daily gold price/g in South African rand.

$\sigma_t^2$is the current day's volatility/variance of gold price (it is the variance of the error term derived from the mean equation.

${}_{t-1}^{2}$is the previous day's return information about volatility (i.e. the ARCH term).

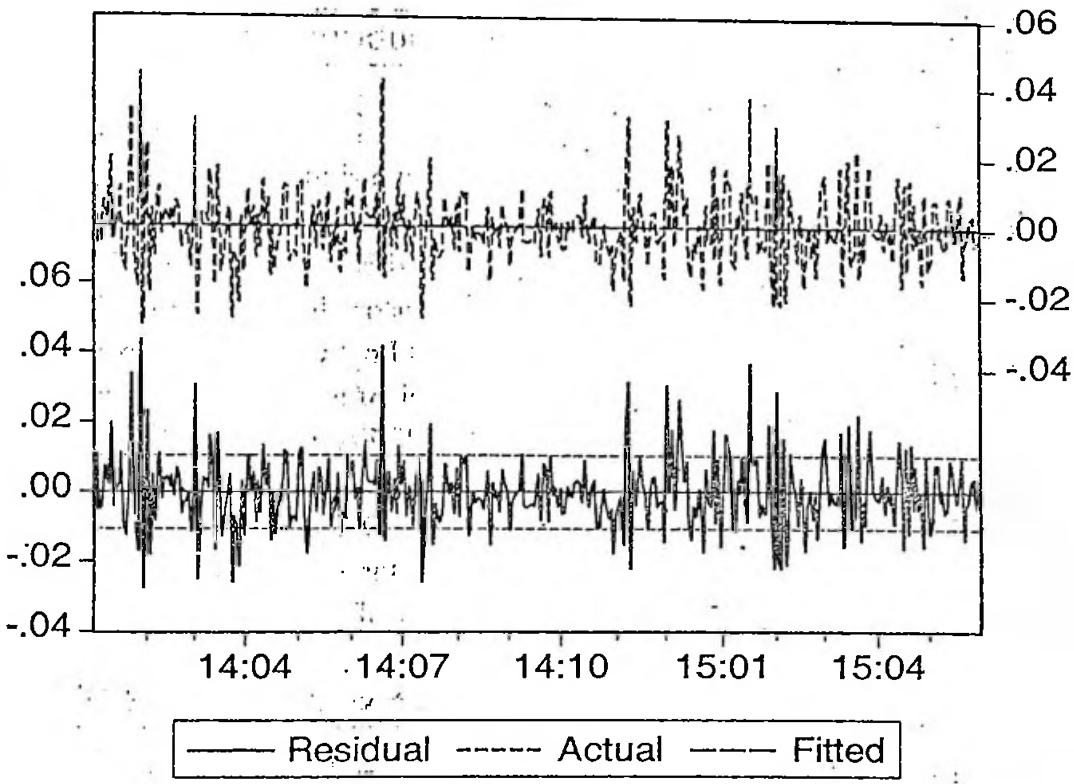
$\sigma_{t-1}^2$is the volatility of gold price (i.e. The GARCH term).

To test the validity of the model, it was tested for ARCH effect by running diagnostic test, we also checked for serial correlation and whether the residuals are normally distributed.

Results and discussions

The stationarity test shows that the data are stationary at level and there is volatility clustering which shows the presence of ARCH effect. Fig. 1 shows the volatility clustering of the residuals.

Fig 1. Volatility clustering of the underlying asset



Source; Eview output

The figure shows that there is a prolonged period of high volatility between January and February, 2014. This is followed by a prolonged period of low volatility from then till November 2014, then followed by a prolonged period of high shocks until May 2015. In other words, period of high volatility tends to be followed by periods of high volatility and periods of low volatility tend to be followed by periods of low volatility. This suggest that the residual or error term is conditionally heteroscedastic and as such it can be modelled with ARCH and GARCH model.

The result of the ARCH and GARCH model is shown in table 1. The underlying asset, GOLDPRICE is the dependent variable while NEWGOLD ETF is the independent variable as the study examine the effect of ETF on the volatility of the underlying asset.

Table 1. Volatility persistence for gold price returns

Coefficient	***GOLDPRICE***	***Probability***
C	0.0000353	0.0044
ARCH (α)	0.216978	0.0042
GARCH (β)	*0.482596*	*0.0009*
α + β	0.699574	
NEWGOLD	0.0000523	0.7604

Source; Eviews output

The result shows that ARCH term is significant at 5% which means that the previous day return of gold price information influences today's gold price return by about 22%. The implication of this finding is that previous day's return is a significant determinant of what price will look like during the days pricing of gold. Similarly, the coefficient of the GARCH term is also significant and it means that previous day shock in gold price (volatility) influences today's gold price volatility. Therefore, the volatility of the gold price is significantly influenced by its own ARCH and GARCH factors or its own shocks.

The degree of volatility persistence, measured by $\alpha + \beta$ is 0.699574. It did show significant persistency during the period under study, the volatility of the underlying stock is significant and affected by it internal shocks and these persistency will continue in the long-run as $\alpha + \beta$ is not close to 1. This conclusion is in agreement with literature which indicates that the sum of the ARCH and GARCH effects is a measure of volatility persistence. If that sum is closer to one, it means that effects of shocks fade away very slowly. The lower the values of GARCH & ARCH effects, the faster the effects fade away.

The ETFs is not significant in influencing the volatility of gold price. Since it is not significant, it means that NEWGOLD ETFs which is an outside shock cannot influence or transmit volatility to gold price. This finding is consistent with Trainor (2010) who found that ETF is not associated with market volatility but he looked at the market volatility generally while our study looked at the asset volatility specifically. The finding is not consistent with that of Ben-Davids et al. (2014) who found that ETF affect the volatility of the underlying asset.

Finally, to check whether the distribution is the best for this study, the test for ARCH effect reject the null hypothesis of no ARCH effect, that of serial correlation reject the null hypothesis of no serial correlation and that of normality test reject the null hypothesis of not normally distributed. Therefore, the estimators are consistent and so the model can be used for forecasting and measuring volatility in this study.

Conclusion and Recommendations

The findings of this study indicate that underlying asset of the ETF is volatile and persistently significant for a long period of time. We also found that the underlying assets' volatility is influenced by its own previous return information and also its previous days volatility. That shows that the gold price is influenced by its own internal shocks. We also do not found any evidence of external transmission of volatilities between ETF returns and the underlying assets return. We therefore conclude that such evidence could be related to the stage of development of the NSE, or the institutional structure supporting the market, or merely lack of timely information available to traders of those securities.

Collectively, practical implications of the findings include ability of investment and fund managers with access to news on the underlying asset to react to changes faster than those who do not have such access. Investors should not only rely on current domestic news on the ETF to guide their investment decisions, but also take into consideration international news on the asset for there are spillovers.

Given that volatilities can proxy for risk, there are implications for both individual and institutional investors in terms of further examining pricing securities, hedging and other trading strategies as well as framing regulatory policies.

In general, it is noted that the stock markets are indeed becoming more and more integrated. As such, it is important that information from both domestic and global markets be studied before investors (institutional and individual) make investment decisions since international spillovers for both returns and their volatilities are significant.

Second, since volatilities indicate risks, volatility transmissions open up a new area for financial products that are tailor-made to allow investors to benefit from (or hedge against) sudden changes in market volatility.

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Appendices

1. Stationarity (Unit root) test

ADF Test Statistic	-8.557103	1% Critical Value*	-3.4537
		5% Critical Value	-2.8712
		10% Critical Value	-2.5719

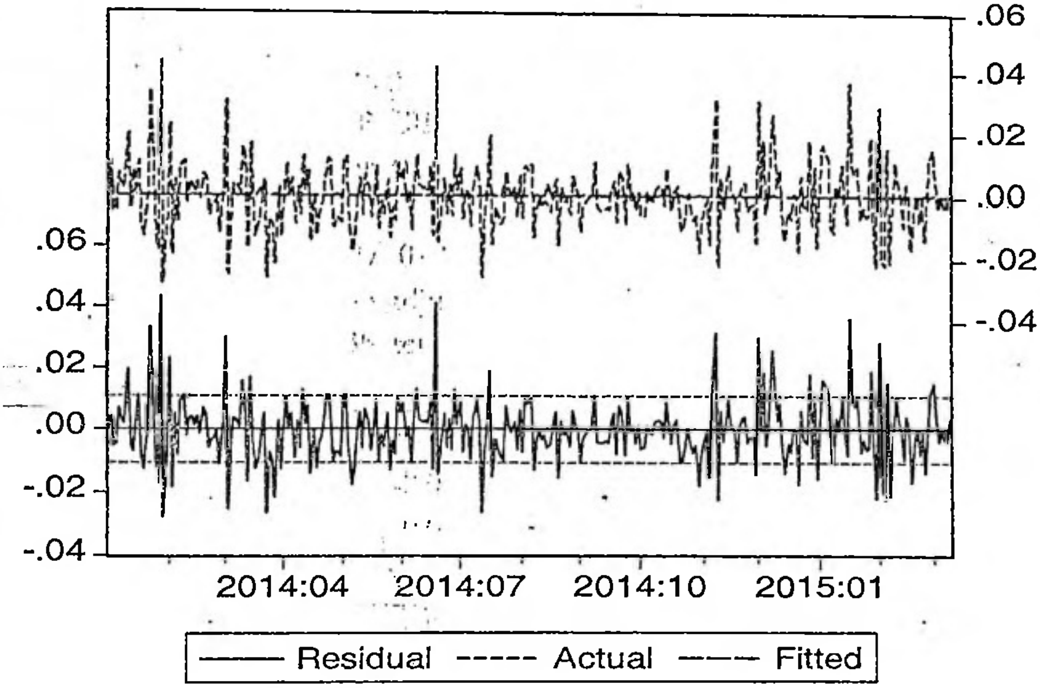
*MacKinnon critical values for rejection of hypothesis of a unit root.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEWGOLD)
Method: Least Squares
Date: 07/12/15 Time: 21:54
Sample(adjusted): 1/09/2014 3/10/2015
Included observations: 304 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NEWGOLD(-1)	-1.031433	0.120535	-8.557103	0.0000
D(NEWGOLD(-1))	0.036409	0.105135	0.346309	0.7294
D(NEWGOLD(-2))	0.035330	0.087458	0.403963	0.6865
D(NEWGOLD(-3))	0.019792	0.066016	0.299812	0.7645
D(NEWGOLD(-4))	0.007430	0.046822	0.158689	0.8740
C	-0.006513	0.004225	-1.541330	0.1243

R-squared	0.497616	Mean dependent var	3.95E-05
Adjusted R-squared	0.489187	S.D. dependent var	0.100753
S.E. of regression	0.072010	Akaike info criterion	-2.404494
Sum squared resid	1.545245	Schwarz criterion	-2.331132
Log likelihood	371.4832	F-statistic	59.03431
Durbin-Watson stat	2.000150	Prob(F-statistic)	0.000000

2. **Volatility clustering**



3. **ARCH and GARCH test**

Dependent Variable: GOLDPRICE
Method: ML - ARCH (Marquardt)
Date: 07/12/15 Time: 22:36
Sample(adjusted): 1/02/2014 3/10/2015
Included observations: 309 after adjusting endpoints
Convergence achieved after 135 iterations
Variance backcast: ON

	Coefficient	Std. Error	z-Statistic	Prob.
NEWGOLD	-0.007293	0.006031	-1.209174	0.2266
C	0.000559	0.000555	1.007200	0.3138
	Variance Equation			
C	3.53E-05	1.24E-05	2.844962	0.0044
ARCH(1)	0.216978	0.075841	2.860980	0.0042
GARCH(1)	0.482596	0.145306	3.321234	0.0009
NEWGOLD	5.23E-05	0.000172	0.304904	0.7604

R-squared	-0.003417	Mean dependent var	0.000312
Adjusted R-squared	-0.019975	S.D. dependent var	0.010596
S.E. of regression	0.010701	Akaike info criterion	-6.299182
Sum squared resid	0.034697	Schwarz criterion	-6.226690
Log likelihood	979.2236	Durbin-Watson stat	2.291642

4. **ARCH effect test**

ARCH Test:

F-statistic	0.035705	Probability	0.850252
Obs*R-squared	0.035934	Probability	0.849652

~~Test~~ Equation:

Dependent Variable: STD_RESID^2

Method: Least Squares

Date: 07/12/15 Time: 22:44

Sample(adjusted): 1/03/2014 3/10/2015

Included observations: 308 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.013478	0.127037	7.977844	0.0000
STD_RESID^2(-1)	-0.010800	0.057157	-0.188957	0.8503

R-squared	0.000117	Mean dependent var	1.002654
Adjusted R-squared	-0.003151	S.D. dependent var	1.986838
S.E. of regression	1.989966	Akaike info criterion	4.220585
Sum squared resid	1211.749	Schwarz criterion	4.244806
Log likelihood	-647.9700	F-statistic	0.035705
Durbin-Watson stat	1.999494	Prob(F-statistic)	0.850252

5. Serial correlation test

Date: 07/12/15 Time: 22:40

Sample: 1/02/2014 3/10/2015

Included observations: 309

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.011	-0.011	0.0363	0.849
.|. |	.|. |	2	-0.029	-0.029	0.3020	0.860
.|. |	.|. |	3	0.014	0.014	0.3653	0.947
.|. |	.|. |	4	0.033	0.032	0.7044	0.951
.|. |	.|. |	5	-0.029	-0.027	0.9678	0.965
.|. |	.|. |	6	-0.006	-0.005	0.9803	0.986
.|. |	.|. |	7	0.008	0.005	1.0011	0.995
.|* |	.|* |	8	0.068	0.067	2.4608	0.964
.|. |	.|. |	9	-0.034	-0.030	2.8274	0.971
.|. |	.|. |	10	0.021	0.023	2.9645	0.982
.|. |	.|. |	11	-0.049	-0.053	3.7307	0.977
.|. |	.|. |	12	-0.014	-0.016	3.7912	0.987
.|. |	.|. |	13	-0.024	-0.022	3.9804	0.991
.|. |	.|. |	14	-0.053	-0.056	4.8951	0.987
.|* |	.|* |	15	0.108	0.111	8.7338	0.891
.|. |	.|. |	16	-0.008	-0.015	8.7538	0.923
.|* |	.|* |	17	0.070	0.085	10.349	0.888
.|. |	.|. |	18	-0.010	-0.016	10.381	0.919
.|. |	.|. |	19	-0.010	-0.007	10.416	0.942
.|. |	.|. |	20	0.015	0.016	10.486	0.958
.|. |	.|. |	21	-0.003	-0.004	10.488	0.972
.|. |	.|. |	22	-0.010	0.001	10.519	0.981
.|* |	.|. |	23	0.072	0.053	12.271	0.966
.|. |	.|. |	24	0.001	0.009	12.271	0.977
.|. |	*|. |	25	-0.039	-0.058	12.775	0.979
.|. |	.|. |	26	-0.044	-0.030	13.427	0.980
.|. |	.|. |	27	0.052	0.041	14.334	0.978
.|. |	.|. |	28	0.013	0.025	14.395	0.984
.|. |	.|. |	29	0.033	0.059	14.774	0.987
.|. |	.|. |	30	-0.031	-0.045	15.102	0.989
.|. |	.|. |	31	0.059	0.062	16.307	0.986
.|. |	.|. |	32	-0.022	-0.043	16.478	0.989
.|. |	.|. |	33	-0.005	0.006	16.487	0.993
.|. |	.|. |	34	0.054	0.063	17.498	0.991
.|. |	.|. |	35	0.063	0.054	18.888	0.988
.|. |	.|. |	36	-0.046	-0.035	19.623	0.988

6. Normality test