# LONG MEMORY AND STRUCTURAL BREAKS IN MODELLING THE VOLATILITY DYNAMICS OF VIX-ETFS

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## ABSTRACT

*This paper investigates for the presence of structural breaks in Volatility Index (VIX) ETFs returns. Using daily data that spans from October 3, 2011 to December 31, 2013, the study examine the existence of structural changes in tested VIX-ETFs series variance via Iterated Cumulative Sums of Squares (ICSS). Then, the study continues to investigate the implication of structural breaks in VIX-ETFs volatility clustering estimation process. The study employs ARFIMA and FIGARCH models to measure the long memory in VIX-ETFs returns, and compares with and without the structural break. Imposing identified the breaks in the variance of returns series, the study models their relationship by incorporating those breaks in the volatility clustering procedure, like ICSS-ARFIMA-FIGARCH. The results of dual long memory in VIX-ETFs are relation with term structure of VIX-ETFs and are better estimation with imposing structure breaks model.*

## 1. Introduction

The Exchange Traded Funds (ETFs) has grown substantially worldwide. By 2013, they consisted of 8,200 funds with a combined market capitalization approximated to $11.5 trillion worldwide (World Federation of Exchanges, 2013)[1]. ETFs are hybrids of mutual funds and close-end funds. ETFs were launched in the United States in 1993, and the study of Guedj and Huang (2009) indicated the first ETFs listed in U.S. in order to replicate the Standard and Poor's (S&P) 500 indexes. On the whole, there are three groups of ETFs. First, normal ETFs are those whose goal return is equal to the return on the underlying asset or index. Second, inverse ETFs whose return are in the opposite direction of the underlying asset or index. Third, leveraged ETFs are those whose return is multiple times of the return on the underlying asset or index.

ETFs have received much attention in the last past decade, their research file focus on the international stock market indexes (Ackert and Tian, 2008), commodities (Lixia et al., 2010; Ivanov, 2013), bonds (Drenovak, 2012), and real estate market (Ivanov, 2012). In the equity market, the tradeoff between return and volatility is one of the most interesting issues in finance. Therefore, other stem of studies have considered the demand various issues, i.e., the efficiency and the pricing structure of index funds (Lin et al., 2006), ETF performance relative to traditional funds (Barnhart and Rosenstein, 2010), and risk exposure through international index ETFs (Hughen and Mathew, 2009; Krause and Tse, 2013).

A popular indicator of short-term market volatility, namely the VIX, which represents a market consentience speculation of future 30 days stock market volatility in U.S. stocks market (Fleming et al., 1995; Whaley, 2000). The VIX was published by the Chicago Board Options Exchange (CBOE) and has become the standard measure of volatility risk in the US stock market. The goal of the VIX index is to calculate the volatility of the Standard and Poor's 500 (S&P 500) over 30 days implied in stock index option prices. The VIX is modern as a major asset classification with investors for two reasons. First, the VIX provides diversification profits to investors because it's negative relationship with S&P 500. Second, there are some productions (e.g. ETF and Exchange Traded Note (ETN)) offering investors approach to evaluate asset classification for the first time. The VIX tracked the underlying of ETF as a matter of course, because it is relation with S&P 500 index.

If the forecasting models do not consider structural breaks, the results yielded unstable forecasts as compared to models with structural breaks (Bai and Perron, 2003; Pesaran and Timmermann, 2004). On the empirical front has proved that structural breaks impacted on the time series behaviors and estimation accuracy. Structural breaks possess of characteristic a flock of time series containing interest rates (Esteve et al., 2013), exchange rate (Cerrato et al., 2013), commodities price (Zainudin and Shaharudin, 2011), stock market (Badhani, 2008; Chunxia et al., 2012), treasury bond (Covarrubias et al., 2006), futures market (Ewing and Malik, 2013), and others (Abu-Qarn and Abu-Bader, 2008). Moreover, Jouini and Boutahar (2005) employed the U.S. time series to examine structural number, showing that the performance of model with multiple structural breaks is better than the model with single structural break.

The precious financial theory, the efficient market hypothesis (EMH) was proposed by Fama (1965). The purpose of the efficient market hypothesis is to prove that all information reflects in the stock market, and nobody can get excess returns from the efficient market. Specially, the efficient market had three forms i.e. weak, semi-strong, and strong form. The weak-form efficiency assumes that investors can not apply past price to predicate future price. In other words, somebody can depend on history price, volume, and

[1] Data Source: http://world-exchanges.org.

other information to get excess profit, implying that the random walk of stock market failed. A large volume of literature deals with long memory and financial return series dynamics: volatility index (Wiphatthananthakul and Sriboonchitta, 2010), commodity (Kyongwook and Shawkat, 2009; Arouri et al., 2012), stock market (Kang and Yoon, 2007; Caporale and Gil-Alana, 2008), and exchange rate (Choi et al., 2010). Indeed, Herzberg and Sibbertsen (2004) confirmed that the pricing of financial derivatives with well forecasting capability must be considered financial time series with long memory.

The study examines VIX-ETFs applying multiple structure breaks proposed by Inclan and Tiao (1994), which evaluated long memory models proposed by Granger and Joyeux (1980), Hosking (1981), and Baillie et al. (1996). To the best of our knowledge, no study has specifically investigated the structural break and long memory process of VIX-ETFs that aim to evidence the efficient market hypothesis. There are three contributes in this study. First, the work increases the existing literature on ETFs in the following distinct ways. Second, the study offers some suggestions for academic and market practitioners to decide whether to practice the efficient market hypothesis or not. Third, the work testes and verifies structural break date conforming to important economic shocks.

The rest of this paper is structured as follows. Section 2 presents a review of related literature. Section 3 describes the data and explains the methodology. Section 4 summarizes the empirical results. Section 5 provides the conclusions.

## 2. Related Literature

The exchange traded funds (ETFs) have become widespread investment instruments and have increased fast among financial products. According Investment Company Institute[2] (ICI), there is more than 1,200 ETFs trading on the U.S. exchanges. ETF assets under management in the U.S. have reached to nearly 1.3 trillion dollars. ETFs are provided with lower costs, trading flexibility, tax efficiency, and exposure to a variety of markets. There are a number of papers that studied the performance of ETFs tracking different country's equity indexes (Jares and Lavin, 2004; Ackert and Tian, 2008; Blitz and Swinkels 2012), others underlying instruments (Ivanov, 2012; Mukul et al., 2012; Padungsaksawasdi and Daigler, 2013; Daigler et al., 2014), and fix income/bonds (Drenovak et al., 2012; Houweling, 2012). For the U.S. equity indexes, the study of Ackert and Tian (2008) examined the pricing of the U.S. ETFs and country ETFs listed in the United States. The result provided that the U.S. funds are negative relation among fund premium and market liquidity. They also indicated that the mispricing of country funds derived from momentum, illiquidity, and size effects. In addition, Bum (2011) compared with the U.S. ETFs and Asia-Pacific ETFs across the U.S., Japan, South Korea, Hong Kong, Taiwan, Singapore, Australia, New Zealand and China to demonstrate the causality and spillover effects from 2004 to 2010. He exhibited that the U.S. equity market caused of Asia-Pacific equity market, but Asia-Pacific equity market cannot cause of the U.S. equity market. He also confirmed the Asia-Pacific region has a sensitive link with the U.S. economy. On the other hand, Blitz and Swinkels (2012) used ETFs and mutual funds were listed in Europe to evaluate their performance. Those instruments tracked the major equity market indexes for the U.S., Europe, Japan, and emerging markets. They corroborated that dividend taxes were important factor for the performance of index funds and ETFs.

A large volume of literature deals with commodity ETFs, the empirical study of Ivanov (2012) compared the profit effect between the Vanguard REIT-ETFs and iShares Dow Jones US REIT-ETFs during the financial crisis. The results revealed that the REIT-ETFs did not track the Dow Jones U.S. Real Estate Index before the financial crisis, but the REIT-ETFs were robust tracking their underlying indexes during and after the crisis. Padungsaksawasdi and Daigler (2013) employed commodity option VIXs for the euro, gold, and oil to evaluate the return-implied volatility. The analysis showed that the return of gold ETF presented significantly positive relation, and price change relation between the commodity ETFs and their option VIX changes. Recently, Daigler et al. (2014) applied the euro-currency ETFs (FXE) and the euro option VIX (EVZ) to calculate the return-implied volatility. The return-implied volatility relation is not significant and the asymmetric return sometimes was positive for the currency market.

A few study focused on fixed income ETFs, for example Houweling (2012) researched the return of fixed income (plain vanilla) ETFs tracking treasury bonds, corporate and non-corporate bonds. The results showed that tracking the benchmarks ability of treasury ETFs was higher than others, and the performances of (non) corporate bonds ETFs were lower than their benchmarks. They also expressed that the transaction costs of the underlying bonds impacted on the return of ETFs. To extend the issue of ETFs, Johnson (2009) evaluated the tracking errors between 20 foreign ETFs and the underlying home index returns. The variable of positive foreign indexes returns relative to the US index was a significant source of tracking error among the ETFs and the underlying indexes. Wong and Cheong (2010) disclosed the performances of 15 ETFs worldwide in bearish and bullish markets from 1999 to 2007. They validated that ETFs always generated underperformance in a bearish market than in a bullish market.

There is an abundance of literature exploring the returns of ETFs using different methodologies and data sets, with various conclusions being drawn. Therefore, forecasting and modeling financial market volatility have been the topic of recent theoretical researches in academia as well as in financial markets. On the basis of theories of model building, financial price forecasting models divided into two types. In the first type is models based on statistical theories, such as Autoregressive Integrated Moving Average (ARMA), General Autoregressive Conditional Heteroskedasticity (GARCH), Smooth Transition Autoregressive Model (STAR), Markov Switching Model (MS) and Stochastic Volatility Model (SV). In the second type is models based on artificial intelligence, such as the Artificial Neural Network (ANN) and the Support vector Machine (SVM). The study of Kumah (2011) applied Markov-Switching (MS) model to measure exchange market pressure (EMP) in the Kyrgyz Republic from 1996 to 2006. In light of the recent findings reported by Zhu and Wei (2013) used autoregressive integrated moving average (ARIMA) model and the Least Squares Support Vector Machine (LSSVM) to predicate carbon prices under the EU Emissions Trading Scheme (EU ETS). Above past studies can know many methods seek accurate trend forecasting.

[2] Data retrieved from www.ici.org, on November 30, 2013.

Indeed, several studies have shown that forecasting models are subject to instabilities, leading to imprecise and unreliable forecasts. Guo and Wohar (2006) that evidenced multiple structural breaks in the volatility indexes were published by the Chicago Board Options Exchange. The available data series for the VIX is from 1990 to 2003 and for the VXO[3] is from 1986 to 2003. The empirical study confirmed that the means of lowest market volatility during 1992-2007 is the lowest volatility. Covarrubias et al. (2006) exercised multiple structural changes to recognize the switches in the volatility of the interest rate shifts on the 10-year Treasury bond. Time points of shifts in volatility and the endogenously determined by time series utilizing iterated cumulative sums of squares (ICSS) algorithm proposed by Inclan and Tiao (1994) provided an important conclusion of correct predicting model with structural breaks. In addition, Ewing and Malik (2013) used gold and oil futures data to identify the volatility dynamics cover the period 1993:1 to 2010:1. They also employed ICSS approach to calculate volatility shifts. The results showed statistically significant structural breaks in volatility.

In this context, Gadea et al. (2004) advocated the risk of neglecting structural breaks and found that long memory phenomenon for identifying non-linear dependence in the conditional mean and variance was significantly affected in the face of structural breaks. They not only emphasize structural breaks, but also confirm long memory phenomenon. Moreover, Sadique and Silvapulle (2001) explored the presence of long memory in the stock returns for seven countries. The result expressed that equity market with long memory will generate nonrandom walk occurrence, implying long memory in the time series is associated with the high autocorrelation function.

There are numerous studies explaining the sources of long memory observed in different market. Recently, Huskaj (2013) illustrated the present of long memory in the VIX futures returns, and applied three models to evaluate the predicating power in the volatility process. The models included the GARCH, Asymmetric Power ARCH (APARCH), Fractionally Integrated GARCH (FIGARCH) and FIAPARCH models. This article showed that statistically significant results of the best out-of-sample VaR (value at risk) forecasts are FIGARCH and FIAPARCH models. To analyze the presence of structural breaks in financial time series, Fernandez (2005) combined ICSS and GARCH models to examine four stock indices[4] and interest rates series by Chilean banks. The study provided that the importance of mixing model could offer significant results which were better than testing for variance homogeneity. Further, Kang et al. (2009) explored Japanese and Korean stock markets covering the 1986–2008 period to examine whether the persistence of volatility in variance or not. They used ICSS-GARCH and ICSS-FIGARCH models and corroborated incorporate sudden changes and volatility in variance models which can enhance forecasting ability. The green ETFs did not exist in long memory process, but non-green ETFs existed long memory process in volatility were provide by Chen and Diaz (2013). The methodology of the study applied the ARFIMA and FIGARCH models.

## 3. Data and Methodology

The CBOE published the volatility Index (VIX) in March 2004. Later, some relative instruments such as ETFVIX and individual equity VIX based on volatility were developed in the financial market. This study investigates the return and volatility of VIX-ETFs. In the work employs the multiple structure breaks model measured by ICSS to evaluate structural breaks and applies ARFIMA-FIGARCH estimate long memory. Finally, this study performs the models to evaluate the return and volatility dynamics of VIX-ETFs.

### 3.1. Data

The paper considers VIX-ETFs closing prices as shown in Table 1. The study utilizes daily ETF price data from October 3, 2011 to December 31, 2013. The data were obtained from Yahoo Finance, for five popular VIX-ETFs (i.e. ProShares VIX Mid-Term Futures ETF (VIXM), ProShares VIX Short-Term Futures ETF (VIXY), PowerShares S&P 500 Low Volatility Portfolio (SPLV), ProShares Trust Ultra VIX Short Term Futures ETF (UVXY), and ProShares Short VIX Short Term Futures ETF (SVXY)).

Table 1. The Sample Size and Period of VIX-ETFs

| ETF Name | Symbol | Track delivery | Period |
|---|---|---|---|
| ProShares VIX Mid-Term Futures ETF | VIXM | S&P 500 VIX Mid-Term Futures Index | 2011/01/03 |
| ProShares VIX Short-Term Futures ETF | VIXY | S&P 500 VIX Short-Term Futures Index | 2011/01/03 |
| PowerShares S&P 500 Low Volatility Portfolio | SPLV | S&P 500 Low Volatility Index | 2011/05/05 |
| ProShares Trust Ultra VIX Short Term Futures ETF | UVXY | S&P 500 VIX Short-Term Futures Index | 2011/10/03 |
| ProShares Short VIX Short Term Futures ETF | SVXY | S&P 500 VIX Short-Term Futures Index | 2011/10/03 |

Source: Yahoo Finance-various dates up to December 31, 2013.

[3] VXO was based on S&P 100 Index (OEX) option prices volatility.
[4] Four countries include Emerging Asia, Europe, Latin America, and North America.

### 3.2. Structural break: The Iterated Cumulative Sums of Squares (ICSS)

The methodology used in this study to identify sudden shifts in the variance of a time series is on the basis of the iterated cumulative sums of squares (ICSS) algorithm developed by Inclan and Tiao (1994).
The analysis supposes that the time series shows a stationary variance over an initial period until a sudden shift in variance occurs. The break in the variance specification is proposed by Inclan and Tiao (1994). The variance is still stationary again during the time until the next abrupt shift. The process is repeated over time, yielding a time series of observations with an unknown number of changes in the variance.

Let $\varepsilon_t$ be a series with zero mean and with unconditional variance $\sigma_t^2$. The variance in each interval is denoted by $\sigma_j^2$, $J = 0,1,\ldots,N_T$, where $N_T$ is the total number of variance changes in $T$ observations. By letting $1 < k_1 < k_2 < \ldots K_{NT} < T$ are the change points.

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < k_1 \\ \sigma_1^2, & k_1 < t < k_2 \\ \vdots & \\ \sigma_{NT}^2, & k_{NT} < t < T \end{cases} \quad (5)$$

To estimate the number of changes in variance and the point in time of each variance shift. The cumulative sum of the squared observations from the start of the series to the *k*th point in time is expressed as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \quad \text{where } k=1,\ldots,T. \quad (6)$$

The $D_k$ statistic is defined as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \quad k=1,\ldots,T, \; D_0=D_t=0, \quad (7)$$

where $C_T$ is the sum of the squared residuals from the entire sample period.

If there are no shifts in variance for the sample period, the $D_k$ statistic waves around zero and it can be drawing as a horizontal line against $k$. However, if there are abrupt variance changes in the series, the statistic values fluctuate up or down near zero. Based on the distribution of $D_k$ calculated the critical values under the null hypothesis of homogeneous variance provide upper and lower boundaries to distinguish a significant change in variance with a known level of probability. In this context, the null hypothesis of constant variance is accepted if the maximum absolute value of $D_K$ is smaller than the critical value. So, if $\max_k \sqrt{(T/2)}|D_k|$ surpasses the predetermined boundary, then the value of $k$ is taken as an estimate of the change point. The critical value at the 95th percentile is 1.36; therefore the boundaries can be set at ±1.36 in the $D_k$ draw.
In the context of multiple change points, the $D_k$ operation lonely is not enough to recognize the breakpoints. Therefore, Inclan and Tiao (1994) developed an algorithm that uses the $D_k$ operation to systematically seek for change points at different points of the series. The algorithm functions by estimating the $D_k$ operation for different time periods and those different periods are determined by breakpoints, which are recognized by the $D_k$ plot. Once the shift points are recognized using the ICSS algorithm, the periods of shifts in volatility are tested with potential factors.

### 3.3. ARFIMA-FIGARCH

Long memory generalizations of model short-memory time series models are suitable for the ARFIMA and FIGARCH model. With the previous findings of Baillie et al. (1996) who suggested the modeling of conditional variance of high frequency financial data associated with Fractionally Integrated GARCH (FIGARCH) model.

#### 3.3.1. ARFIMA

The ARFIMA ($p,d,q$) model is a common parametric method to examine the long memory property in financial time series (Granger and Joyeux, 1980; and Hosking, 1981). The ARFIMA ($p,d,q$) model can be expressed as a generalization of the ARIMA model as follows:

$$\varepsilon_t = z_t\sigma_t, \quad z_t \sim N(0,1), \quad (8)$$

$$\psi(L)(1-L)^{\xi}(y_t - \mu) = \Theta(L)\varepsilon_t, \quad (9)$$

where $\varepsilon_t$ is independent and identically distributed (*i.i.d*) with variance, and $L$ denotes the lag operator. $\xi$, $\mu$, $\psi_i$ and $\theta_i$ are the parameters of the model. $\psi(L)=1-\psi_1 L-\psi_2 L^2-\cdots-\psi_n L^n$ and $\Theta(L)=1+\theta_1 L+\theta_2 L^2+\cdots+\theta_s L^s$ are the Autoregressive (AR) and Moving Average (MA) polynomials with standing in outside of unit roots, respectively. The fractional differencing operator, $(1-L)^{\xi}$, is described by the binomial series formation:

$$(1-L)^{\xi}=\sum_{k=0}^{\infty}\frac{\Gamma(k-\xi)}{\Gamma(k+1)\Gamma(-\xi)}L^k$$
$$=1-\xi L-\frac{1}{2}\xi(1-\xi)L^2-\frac{1}{6}\xi(1-\xi)(2-\xi)L^3-\cdots, \tag{10}$$

where $\Gamma(\bullet)$ denotes the gamma function. Following Hosking (1981), when $-0.5<\xi<0.5$, the $y_t$ process is stationary and invertible. For such processes, the effect of shocks to $\varepsilon_t$ on $y_t$ decay at a slow rate to zero. If $\xi=0$, the process is stationary, the the effects of shocks to $\varepsilon_t$ on $y_t$ decay geometrically. For $\xi=1$, the process follows a unit root process. If $-0.5<\xi<0.5$, the process presents negative dependence between far observations, so named anti-persistence.

### 3.3.2. FIGARCH

Engle (1982) proposed the Autoregressive Conditional Heteroscedasticity (ARCH) to describe the variance of the residuals changes over time. And time series variable has a phenomenon with volatility clustering. Bollerslev (1986) proposed the Generalize Autoregressive Conditional Heteroscedasticity (GARCH model) and set conditional variance not only influenced by the square of prior residual, but also the prior variance. In modeling conditional variance, GARCH is more flexible than ARCH.
The Fractional Integrated Generalized Autoregressive Conditional Heteroskedasticity model (FIGARCH) to capture the long memory in volatility return was proposed by Baillie et al. (1996). The FIGARCH ($p,d,q$) can be expressed as follows:

$$\varphi(L)(1-L)^d\varepsilon_t^2=\omega+[1-\beta(L)]\nu_t, \tag{11}$$

where $\varphi(L)\equiv\varphi_1 L+\varphi_2 L^2+\cdots+\varphi_q L^q$, and $\beta(L)\equiv\beta_1 L+\beta_2 L^2+\cdots+\beta_p L^p$ and $\nu_t\equiv\varepsilon_t^2-\sigma_t^2$. The $\{\nu_t\}$ process can be expressed as the innovations for the conditional variance, and it has zero mean sequentially uncorrelated. All the roots of $\varphi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle. Where $0<d<1$, and all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle. Thus, the characteristic of the FIGARCH model is that, $0<d<1$, it is adequately flexible to allow for an intermediate range of persistence. The FIGARCH model offers greater flexibility for modeling the conditional variance, because it conforms with the covariance stationary GARCH model ($d=0$) and the nonstationary IGARCH model $(d=1)$.

## 4. Empirical Results

### 4.1. Summary Statistics

Table 2 shows the descriptive statistics properties of the returns from the five VIX-ETFs. Over the sample period, the UVXY is the most volatile with the standard deviation at 7.42% followed by the VIXY with 3.08%, while SPLV displays to be most stable with standard deviation being 0.35%. The analysis shows that they do not correspond with the assumption of normality. The return series tend to have a fatter-tail distribution and a higher peak than a normal distribution which was verified by the kurtosis statistics.

**Table 2. Descriptive Statistics of Variables for VIX-ETFs**

| | RVIXM | RVIXY | RSPLV | RUVXY | RSVXY |
|---|---|---|---|---|---|
| Mean | -0.08187 | -0.05899 | 0.018913 | -0.05531 | 0.089851 |
| Std. Dev. | 0.864121 | 3.082134 | 0.346635 | 7.421735 | 2.139912 |
| Skewness | 0.495906 | 15.3332 | -0.40921 | 9.659103 | -5.07858 |
| Kurtosis | 5.611043 | 344.7322 | 7.820725 | 121.6383 | 67.79446 |
| Jarque-Bera | 244.7637*** | 3693506*** | 666.4692*** | 339533.8*** | 101085*** |
| Obs. | 753 | 753 | 669 | 564 | 564 |

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Before testing for the long memory property, all series are checked by applying Augmented Dickey Fuller (ADF) test. The empirical results shows in the Table3, the stationary test reject the null of a unit root in the logarithm of price series at the 1% significance level. The results imply VIX-ETFs are stationary processes I (0). Additionally, the study employs that the minimum value of AIC (Akaike information Criterion) is used to identify the optimal model of ARMA. After selecting the optimal ARMA, the work applies the Breush-Godfrey LM test to investigate whether the residuals have series correlation or not. The work also examines ARCH effect, showing that all series do not have the auto-correlation, but VIXM and SPLV exist in ARCH effect. So VIXM and SPLV must further estimate the GARCH model.

**Table 3. Summary Statistics of Unit Root, LM, and ARMA-LM tests for VIX-ETFs**

| VIX-ETF | ADF | ARMA | AIC | LM | ARCH-LM | GARCH | AIC | ARCH-LM |
|---|---|---|---|---|---|---|---|---|
| VIXM | -27.8541*** | (1,2) | 2.5401 | 0.6103 | 4.756047*** | (1,3) | 2.4547 | 0.00541 |
| VIXY | -26.6363*** | (1,2) | 5.0939 | 0.4103 | 0.0004 | - | - | - |
| SPLV | -28.2862*** | (2,2) | 0.6786 | 1.1178 | 14.38395*** | (3,3) | 0.4445 | 0.0008 |
| UVXY | -22.6005*** | (3,3) | 6.8310 | 26.8075 | 0.0503 | - | - | - |
| SVXY | -24.6038*** | (3,3) | 5.7891 | 0.5554 | 0.0001 | - | - | - |

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively.

**4.2 Sudden Change in Volatility**

The return series of a shift in volatility as detected by the ICSS algorithm are given in Table 4. Another, the return graphs presented in Figure 1, several volatility periods can clearly be observed. There are two change points were detected in among VIXM, VIXY, UVXY and one shift also was detected in SPLV and UVXY. Referring to Table 4, the time points of sudden shift in volatility are correlated to a perceived degree with domestic and foreign economic events. As for instance, there was a significant increase in volatility detected by ICSS algorithm at the end of 2011 in the SPLV, UVXY, and SVXY. This could be due to the fact that the Eurozone’s debt crisis deeply and extensively spread to other Europe countries. Another, Tohoku earthquake and tsunami and Standard & Poor’s downgrades the US credit rating from AAA to AA+ also were a significant impact shift in 2011 for VIXM and VIXY. Some events that occurred around the time of these change points in volatility are presented in the last column of Table 4. For instance, the Federal Reserve System decided to extend Operation Twist in order to provide and have a “modest” impact on helping the economy achieve a better rate of growth at the end of Jun in 2012. There was shocking news that United States federal government shutdown has impacted on financial market and produced a sudden change for VIXY and UVXY.

**Table 4. Structural Breaks in Volatility**

| Variables | Change points | Interval | Events |
|---|---|---|---|
| VIXM | 2011.03.21 | 2011/01/04-2011/06/13 | Tohoku earthquake and tsunami |
| | 2012.07.02 | 2011/06/14-2013/01/31 | The Federal Reserve System extends Operation Twist |
| VIXY | 2011.08.05 | 2011/01/04-2013/06/07 | Standard & Poor’s downgrades the US credit rating from AAA to AA+ |
| | 2013.10.17 | 2013/06/10-2013/12/31 | United States federal government shutdown of 2013 |
| SPLV | - | 2011/08/09-2013/03/11 | - |
| | 2011.12.21 | 2013/06/20-2013/07/02 | The Eurozone’s debt crisis |
| UVXY | 2011.11.10 | 2011/10/04-2012/03/07 | The Eurozone’s debt crisis |
| | - | 2012/03/08-2012/09/06 | - |
| | - | 2012/09/07-2013/06/07 | - |
| | 2013/10/17 | 2013/06/10-2013/12/31 | United States federal government shutdown of 2013 |
| SVXY | 2011.11.10 | 2011/10/04-2012/10/04 | The Eurozone’s debt crisis |
| | 2013.04.23 | 2012/10/05-2013/12/31 | Boston Marathon bombings |

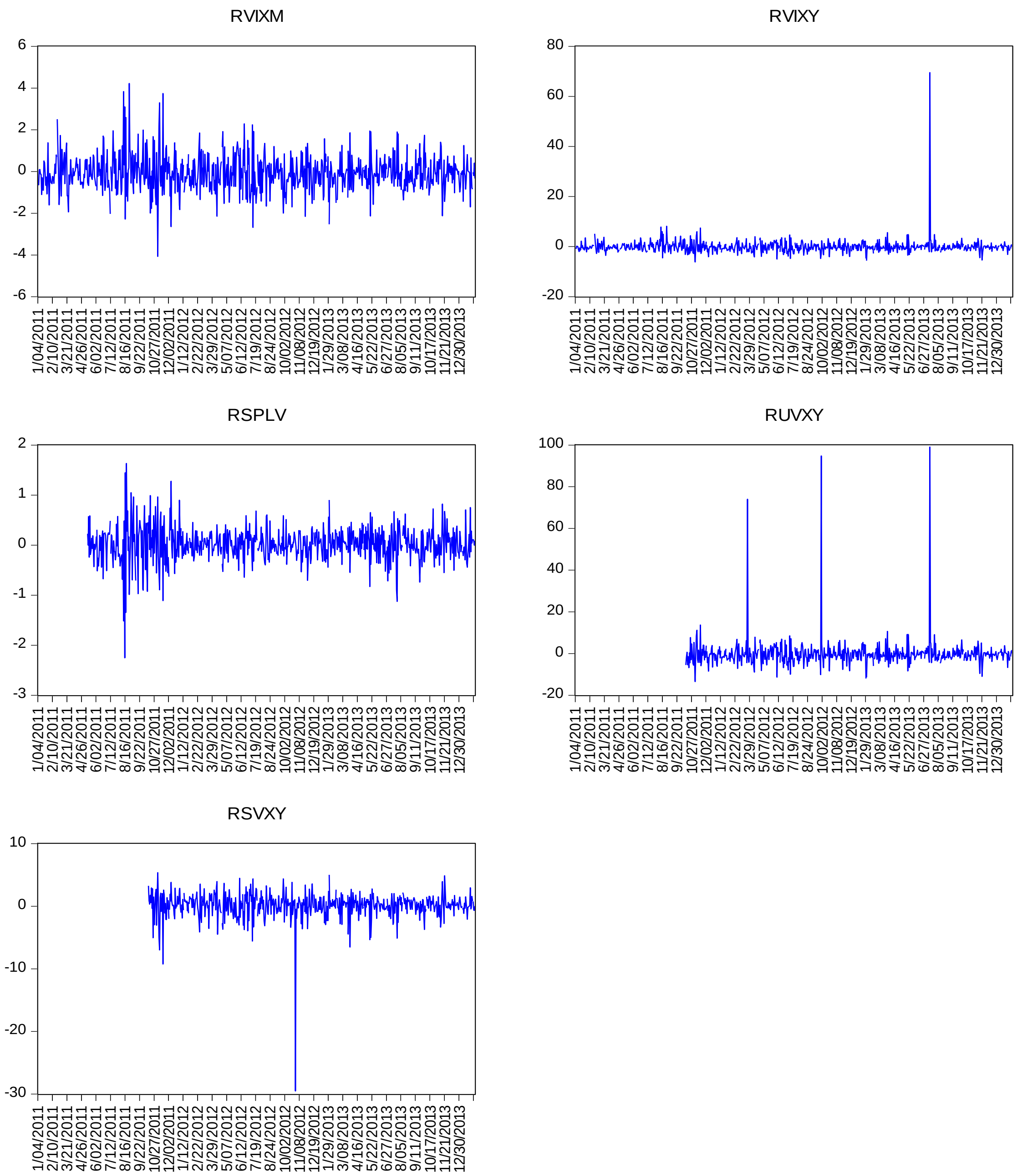


Figure 1. The Returns for VIX-ETFs

### 4.3 ARFIMA and ARFIMA-FIGARCH models

The next step explains these sudden changes in variances via dummy variables in the ARFIMA and ARFIMA-FIGARCH models. The results of long memory are summarized in Table 5. Firstly, the results of the ARFIMA model without sudden changes in panel A illustrated that all series do not have long memory effect. It clearly indicates that there is no evidence of long memory in among VIX-ETFs. It implies the return series shows weak-form market efficiency. Furthermore, the research investigates if there is dual long-term memory in mean return and conditional variance exists for VIX-ETFs by applying ARFIMA-FIGARCH model.

**Table 5. ARFIMA and ARFIMA-FIGARCH without and with Dummy Variables for Sudden Changes in Variance**

| VIX-ETF | ARFIMA | | | ARCH-LM | ARFIMA-FIGARCH | | | |
|---|---|---|---|---|---|---|---|---|
| | model | d-coeff. | AIC | | d-coeff. | model | d-coeff. | AIC |
| Panel A: Without Dummy Variables for Sudden Changes in Variance | | | | | | | | |
| VIXM | (1,2) | -0.0319 [0.474] | 2.5440 | 4.5178 [0.0339]* | -0.0122 [0.8190] | (2,3) | 0.2096 [0.1589] | 2.4619 |
| VIXY | (2,2) | 0.0061 [0.845] | 5.0976 | 0.0005 [0.9830] | - | - | - | - |
| SPLV | (3,3) | -0.0569 [0.130] | 0.6892 | 14.902 [0.0001]** | -0.0805 [0.0302]* | (2,3) | 0.5477 [0.0000]*** | 0.4291 |
| UVXY | (1,0) | -0.034 [0.394] | 6.8473 | 0.0127 | - | - | - | - |
| SVXY | (1,0) | -0.0703 [0.248] | 4.3673 | 3.0645e-005 [0.9956] | - | - | - | - |
| Panel B: With Dummy Variables for Sudden Changes in Variance | | | | | | | | |
| VIXM | (1,2) | -0.0371 [0.416] | 2.5491 | 4.3442 [0.0375]* | -0.0206 [0.6628] | (2,3) | 0.1964 [0.0093]** | 2.4662 |
| VIXY | (2,2) | 0.0060 [0.848] | 5.1032 | 0.0005 [0.9827] | - | - | - | - |
| SPLV | (3,3) | -0.0463 [0.121] | 0.7272 | 16.444 [0.0001]** | -0.1153 [0.0000]*** | (2,3) | 0.5111 [0.0000]*** | 0.4430 |
| UVXY | (2,1) | -0.9933 [0.000]*** | 6.8653 | 0.0270 [0.8695] | - | - | - | - |
| SVXY | (1,0) | -0.0749 [0.231] | 4.3760 | 2.5398e-005 [0.9960] | - | - | - | - |

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

The finding reveals that VIXM does not exhibit long memory or persistence, as *d* parameter is statistically insignificant; but SPLV shows long memory or persistence as *d* parameter is statistically significant for mean returns while it does for conditional variance.

From an extensive analysis of the ARFIMA model with sudden changes in panel B; the result of UVXY present that the process is not mean-reverting in the sense that any shock to the process will displace it from its starting point. We also join the structure breaks in mean return and conditional variance by ARFIMA-FIGARCH model. The results revealed that VIXM and SPLV existed long memory, as *d* parameter is statistically significant. An important implication of this finding is that considering structure breaks can provide the return series existing in inefficient market, so one can use past price to predicate their future price for VIXM and SPLV.

This article showed statistically significant results of dual long memory in VIXM and SPLV. VIXM tracks S&P 500 VIX mid-term futures index and SPLV tracks S&P 500 low volatility index but VIXY, UVXY, and SVXY track S&P 500 VIX short-term Futures Index. The finding implies that VIX short-term volatility trend cannot predicate in opposition different period and pattern. In other words, VIX measure the volatility of the Standard and Poor's 500 (S&P 500) so it caused VIX possess weak-form efficiency market in short-term VIX-ETFs.

## 5. Conclusion

This study investigated sudden shifts of volatility and examined long memory for VIX-ETFs. The results of ARFIMA model displayed that there was no long memory property in the VIX-ETF returns, implying the weak-form efficiency market. Next, this study also tested the long memory property in conditional variance series of VIX-ETFs. The estimation results indicated that ARFIMAR-FIGARCH with structure breaks model have better exposes long memory property in conditional variance of return series.

Roughly speaking, the work failed to reject weak-form market efficiency, because the presence of long memory in the volatility appears, and VIXM and SPLV presented reverting to its mean. The returns of VIXM and SPLV can be predicted due to the facts that dependence between distant observations was evident. Thus, fund managers and investors may apply the empirical results by possessing a position on VIXM and SPLV.

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