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The Return and Volatility Dynamics of VIX-ETFs: An Empirical Study of Structural Breaks

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A B S T R A C T

This study examines the existence of multiple structural breaks in the Volatility Index (VIX) – Exchange-traded Fund (ETF) returns. This paper also confirms structural changes in testing VIX-ETFs series means through the Bai and Perron procedure. The work demonstrates the significance of structural changes in the VIX-ETF volatility clustering valuation practice. The results found that the stock market possessed structure breaks and indicated that the stock market was a weak efficient market. These breakpoints will then be incorporated into the GARCH-based models to measure the effect of a given change in the length of volatility, including BP-ARFIMA and BP-ARFIMA-FIGARCH models.

Keywords: VIX-ETFs, Multiple Structural Break, Long Memory

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1. Introduction

In analogy to previous works on the stock market indexes worldwide (Engle and Sarkar, 2006), bonds (Houweling, 2012), futures (Padungsaksawasdi and Daigler, 2014), and real estate markets (Ivanov, 2012). The volatility index (VIX) was regarded as the short-term market volatility index and offerred profits through its negative relationship with the S&P 500. Next, ETF and Exchange-traded Notes (ETNs) estimate asset classification for investors. The VIX can track the underlying ETF because of the latter's relationship with the S&P 500.

The academic studies on ETFs reflects their popularity in investment leads (Ivanov et al., 2013). Previous studies mostly investigated ETFs using forecasting techniques. It is an import process if the forecasting models are not taking into account structural breaks, and the results show more unstable predictions than models for structural breaks (Bai and Perron, 2003). Jouini and Boutahar (2005) employed an inflation rate to examine structural numbers. The results demonstrated that models with multiple structural breaks perform better than those with a single structural break. The cornerstone of empirical inquiry has demonstrated that structural breaks impact time series behaviors and estimation accuracy.

Many previous studies such as Huskaj (2013), Stengos and Yazgan (2014), Arouri et al., (2012), Kyongwook and Shawkat (2009), Kang and Yoon (2007), and Henry (2002) have analyzed long memory and financial return series dynamics, like the VIX, commercial, the stock market, and exchange rate. In an empirical study, Herzberg and Sibbertsen (2004) advocated that financial derivatives pricing, which displays an excellent prediction performance, must be thought over financial time series related a long memory.

As noted above, the VIX and ETFs can help investors handle risk management and diversification. The ARCH and GARCH models cannot generate much memory in time series. This paper was motivated by applying the ARFIMA and FIGARCH models to validate the financial time series for long-memory characteristics. In this paper, we expand the previous work of Chen and Huang (2014) by investigating the relevance of structural gaps and long memory in modeling and forecasting the conditional volatility of the VIX-ETFs. The Iterated Cumulative Sums of Squares Test (ICCS) approach had the overshoot showing the iid assumption that is not satisfied when the volatility follows a GARCH-type process (Valentinyi-Endrész, 2004). Thus, the present study observes VIX-ETFs that apply multiple structural breaks offered by Bai and Perron (1998), which evaluated long memory models planned by Baillie et al. (1996), Granger and Joyeux (1980), and Hosking (1981). These breakpoints will then be input in ARFIMA-FIGARCH model in order to calculate an impact of a given breakpoint on the persistence of volatility.

To display the efficient market hypothesis, this study is the first to inspect the structural break associated with long memory process of the VIX-ETFs. We examine the relations between VIX-ETFs and S&P 500, and evaluate their structure breaks and long memory. The survey seeks to examine whether VIX-ETFs and S&P 500 possess the weak efficient market to offer investors gains from their abnormal return. The current work has three contributions: (1) the work adds to the existing literature on VIX-ETFs, (2) it offers recommendations for academic and market experts to help them decide on whether to use the EMH, and (3) it tests and verifies structural break dates that conform to significant economic shocks.

2. Related Literature

Several studies have issued the performance of ETFs in tracking the equity indexes of different countries (Bum, 2011; Blitz et al., 2012), fixed income/bonds (Houweling, 2012), and other underlying instruments (Ivanov, 2012; Daigler et al., 2014).

A large volume of works connected with commodity ETFs. For instance, Padungsaksawasdi and Daigler (2014) used commodity option VIXs for gold, the euro, and oil to assess the return-implied volatility. The findings indicated that the gold ETF has a significant positive relation with returns. There exists a contemporaneous price change relationship between option VIX changes and the commodity ETFs. By using the euro ETFs and the euro option VIX, Daigler et al. (2014) found that the return-implied volatility relation is weak, and the asymmetric return was occasionally positive for the foreign exchange market. Little surveys have centered on fixed income ETFs. Houweling (2012) confirmed that treasury ETFs' benchmarking ability was better than others, and the performance of bonds ETFs was less than their benchmarks. The study examined the return of fixed income ETFs following corporate, treasury, and non-corporate bonds.

Previous works have explored the returns of ETFs applying different methods and data sets, having various conclusions. Pesaran and Timmermann (2004) suggested that forecasting models that neglect structural breaks generate poor results compared with models with structural breaks. The structural break issue has many significant applications. In this context, Guo and Wohar (2006) reported that the CBOE publishes multiple structural breaks in the VIX. The study confirms that the means of the lowest market volatility were the lowest during 1992–2007.

In this context, Bai (1997) and Bai and Perron (2006) reported that based on the period of multiple breaks, the tests for a single shift could be rather low. As with previous studies, Gadea et al. (2004) supported the risk of ignoring structural breaks and revealed that a long memory occurrence for recognizing non-linear dependence based on the conditional mean and variance. Their study centered on structural breaks and the long memory phenomenon.

Numerous studies have explained the sources of long memory in different markets. Cajueiro and Tabak (2004) reported that long memory circumstances occur in asset returns, thus opposing the weak form of market efficiency. Implied historical information can help investors obtain excess profits. Huskaj (2013) showed the presence of long memory for VIX futures returns, and used the GARCH, asymmetric power ARCH (APARCH), FIGARCH and FIAPARCH models, to assess the predicting power in the volatility process. The study reported hat the best out-of-sample for value at risk (VaR) forecasts generated through the FIGARCH and FIAPARCH models. Chen and Diaz (2013) evidenced that non-green ETFs have long memory processes in volatility utilizing the ARFIMA and FIGARCH models. However, Banerjee and Urga (2005) debated that sudden shifts or structural breaks may allow spurious long memory of conditional variances. Thence, it is necessary to re-examine the issue of sudden breaks and long memory in the volatility of the VIX-ETFs returns. Like, Zainudin and Shaharudin (2011) marked the multiple structural changes in the commodity market in Malaysian and used the GARCH-type model to investigate the long memory process. They affirmed that the accuracy of the structural breaks is considered into account through the shifts in volatility.

3. Data and Methodology

The work investigated the return of VIX-ETFs and employed the multiple structural breaks model measured by BP[2] to estimate structural breaks, as well as the ARFIMA-FIGARCH to estimate long memory. The current study used mixture models to assess the return and volatility dynamics of the VIX-ETFs, such as BP-ARFIMA and BP-FIGARCH. The paper examined

[2] The BP method was developed by Bia and Perron to identify sudden shifts in the mean of an observed time series based on the multiple structural breaks model.

closing VIX-ETFs[3], as shown in Table 1.

Table 1. VIX-ETFs Name

ETF Name	Symbol	Track delivery	Period
ProShares Short VIX Short Term Futures ETF	SVXY	S&P 500 VIX short-term Futures Index	2011/10/04
ProShares Trust Ultra VIX Short Term Futures ETF	UVXY		2011/10/04
ProShares VIX Mid-Term Futures ETF	VIXM		2011/01/03
ProShares VIX Short-Term Futures ETF	VIXY		2011/01/03

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

3.1 Structural Break

The mean specification change is prepared by using the Bai and Perron (1998, 2003). They recommended three statistics for consistent estimation of the number and position of break dates and the parameters: and the parameters $(\delta_1^{'}, \delta_2^{'}, \ldots, \delta_{m+1}^{'})$:

Ⅰ. $SupF_T(k)$ Test: $SuF_T(k)$ denotes the F statistic.

H_0: no structure shift.

H_1: a fixed number of breaks k.

Ⅱ. Double maximum Tests (UD_{max}): the maximum number of breaks allowed

H_0: no structure break.

H_1: an unknown number of breaks based on some upper bound (M).

Here, UDmax is an equal-weighted statistic, $UD_{max} F_T(M,q) = \max_{1\le m\le M} F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q)$, and WDmax refers to the weights that depend on the number of individual tests. It reveals that the marginal p-values are equivalent across values of m $WD_{max} F_t(M,q) = \max_{1\le m\le M} F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q)$.

Ⅲ. A test of l versus l+1 breaks: a sequential test $\sup F_T(l+1|l)$.

H_0: no structure.

H_1: a single change.

The breaks was estimated using the modified Schwarz criterion (LWZ) and the Bayesian information criterion (BIC), which was planned by Liu et al. (1997).

3.2 ARFIMA-FIGARCH Models

Standard short-memory time series models for long memory generalizations can be linked with the Autoregressive Fractionally Integrated Moving Average and Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (ARFIMA-FIGARCH) frameworks. Previous findings include those of Ding et al. (1993) and Baillie et al. (1996), who advised modeling the conditional variance of high-frequency financial data related to the FIGARCH model.

The ARFIMA model is the long memory property (Granger and Joyeux, 1980; Hosking, 1981), in which d is allowed to be a fraction of a whole number. The ARFIMA (p,d,q) model stated as the ARIMA model given by

[3] We test two diverse close prices, viz., close prices and adjust close prices to detect change points of structural breaks. To save space, we only list the result of adjusting close price because the result of close price reduces superior breakpoint. We do not list the testing result; however, the result is available upon request.

$$\varepsilon_t = z_t \sigma_t, \quad z_t \sim N(0,1), \tag{1}$$

$$\psi(L)(1-L)^{\xi}(y_t - \mu) = \Theta(L)\varepsilon_t, \tag{2}$$

where is independent and identically distributed (i.i.d) connected with variance; L is the lag operator; ξ, μ, ψ_i and θ_i are the parameters of the model; and $\psi(L) = 1 - \psi_1 L - \psi_2 L^2 - \cdots - \psi_n L^n$ and $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_s L^s$ are the AR and MA polynomials associated with standing inside and outside of unit roots, respectively. The fractional differencing operator, $(1-L)^{\xi}$, is showed as the binomial series expansion given by

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

where $\Gamma(\cdot)$ is the gamma function. Based on Hosking (1981), when -0.5<ξ<0.5, the y_t process stands for stationary and invertible. The shocks to ε_t on y_t decay approaches zero at a slow rate. If ξ=0, the process is stationary and the effects of shocks to ε_t on y_t decay occur geometrically. For ξ=1, the process tracks a unit root process. If -0.5<ξ<0, the process displays a negative dependence for distant observations entitled anti-persistence.

Engle (1982) proposed the ARCH model to describe the variation of the residual changes over time, in which the time series variable is a phenomenon with volatility clustering. Moreover, Bollerslev (1986) offered the GARCH model and put a conditional variance not just determined by the second power of prior residuals, but likewise by the prior variance. GARCH is more flexible than the ARCH in modeling conditional variance.

Baillie et al. (1996) planned the FIGARCH model to get long memory in volatility returns. The FIGARCH (p, d, q) stated as:

$$\varphi(L)(1-L)^d \varepsilon_t^2 = \omega + [1 - \beta(L)]v_t, \tag{4}$$

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 $v_t \equiv \varepsilon_t^2 - \sigma_t^2$ .The $\{v_t\}$ process can be inferred as the innovation of the conditional variance, which has zero serially uncorrelated means. All the roots of φ(L) and [1-$\beta(L)$] lie outside the unit root circle, where 0< d < 1. Therefore, the FIGARCH model's appeal is that 0<d<1, which allows for the persistence of intermediate-range with more flexibility. Hence, the FIGARCH model has greater flexibility to model the conditional variance because it accommodates for d=0: the covariance stationary GARCH model and for d=1: the non-stationary IGARCH model.

4. Empirical Results

The present study applied the augmented Dickey-Fuller (ADF) test to inspect whether the variables were stationary or non-stationary. The stationary test rejects the null hypothesis of a unit root (Table 2). The results imply that the VIX-ETF returns are stationary processes I(0). Furthermore, we use the minimum value of AIC to recognize the optimal model of ARMA. After choosing the optimal ARMA, this study also uses the Breush-Godfrey LM test to examine whether the residuals have a series correlation. The consequences indicate that all series are auto-correlation.

Engle (1982) proposed the Lagrange Multiplier Test (ARCH-LM) to test whether time series has ARCH effects. If the ARCH-LM rejects the null hypothesis, then the variables have the ARCH effect. The present report examines the ARCH effect, which evidences that all VIX-ETFs exhibit the ARCH effect (Table 2). Thus, the paper must further estimate the GARCH model. Likewise, the study also employed the minimum value of AIC to find the optimal GARCH model. Following the procedure of the GARCH model, the study performed the

ARCH-LM test again. All of the variables accept the null hypothesis, implying that an optimal GARCH model does not have the ARCH effect.

Table 2. Summary Statistics for the return of VIX-ETFs

VIX-ETF	ADF	ARMA	AIC	LM[a]	ARCH-LM	GARCH	AIC	ARCH-LM
VIXM	-24.988***	(2,2)	4.123	0.4745 (0.789)	12.176*** (0.0005)	(2,2)	4.027	0.3306 (0.5653)
VIXY	-25.335***	(3,3)	5.569	1.0333 (0.597)	12.8417*** (0.0003)	(3,3)	5.469	0.5741 (0.4486)
UVXY	-25.128***	(3,3)	6.949	0.4708 (0.790)	21.4123*** (0.0001)	(3,3)	6.853	0.0106 (0.9182)
SVXY	-25.331***	(3,3)	5.578	3.5267 (0.1725)	5.9503** (0.0147)	(3,2)	5.492	0.0496 (0.8237)

Note: *, ** and *** are significance at 10%, 5%, and 1% levels, respectively. a. X^2 value of Breusch-Godfrey Serial Correlation LM Test.

4.1 Multiple Sudden Changes

We performed multiple structural breaks in the VIX-ETFs. The analysis explored structural breaks in the variance process of the series. Multiple structural breaks have been put on to the daily adjusted close price series of VIX-ETFs. This work applies the following set of Bai and Perron Test tests proposed by Bai and Perron (1998, 2003) to detect multiple structural breaks: the double maximum tests, the $SupF_T(k)$ test, and the $SupF_T(l+1|l)$. Following Bai and Perron (2003), we used 15%, trimming, such that the maximum number of breaks allowed under the alternative hypothesis is five. The results of the double maximum tests, the $SupF_T(k)$ test, and the $SupF_T(l+1|l)$ test are presented in Tables 3 and 4, respectively.

As can be seen, first, the $UD_{\max}$ and $WD_{\max}$ tests exhibit the result of structural breaks at the 5% significance level, implying that the time series has multiple structural breaks. The $SupF_T(5)$ test results are significant for all sample series (Table 3). The results indicate at least five breaks for VIX-ETFs. In addition, the $SupF_T(l+1|l)$ tests were used to illustrate the number of structural breaks. The results show that only SVXY has no significant break (Table 4). However, the $SupF_T(3|2)$ statistic rejects the two breaks for the null hypothesis and accepts the three-break alternative hypothesis, implying that VIXM ha three structural breaks. This result indicates that $SupF_T(1|0)$ statistic rejects the zero break for the null hypothesis and accepts one break for the alternative hypothesis in UVXY. Next, the BIC and LWZ tests were employed to estimate the number of breaks.

Table 3. Structural Breaks in Mean for VIX-ETF

Test		VIX-ETFs	H_0	H_1	F-statistic	Criteria
$D_{\max}$ test	$UD_{\max}$	VIXM	m=0	m>0	64.0595**	8.8800
		VIXY			35.1466**	
		UVXY			30.0844**	
		SVXY			53.0303**	
	$WD_{\max}$	VIXM	m=0	m>0	140.5704**	9.9100
		VIXY			60.4323**	
		UVXY			44.8836**	

	SVXY			91.1823**	
$SupF$	VIXM	m=0	m=1	27.7763**	8.5800
		m=0	m=2	48.7422**	7.2200
		m=0	m=3	49.6893**	5.9600
		m=0	m=4	28.3643**	4.9900
		m=0	m=5	64.0595**	3.9100
	VIXY	m=0	m=1	18.9628**	8.5800
		m=0	m=2	25.1640**	7.2200
		m=0	m=3	30.5083**	5.9600
		m=0	m=4	35.1465**	4.9900
		m=0	m=5	27.0777**	3.9100
	UVXY	m=0	m=1	30.0843**	8.5800
		m=0	m=2	21.6396**	7.2200
		m=0	m=3	21.1301**	5.9600
		m=0	m=4	18.1814**	4.9900
		m=0	m=5	20.4540**	3.9100
	SVXY	m=0	m=1	2.5573	8.5800
		m=0	m=2	12.1050**	7.2200
		m=0	m=3	26.7481**	5.9600
		m=0	m=4	53.0302**	4.9900
		m=0	m=5	33.3880**	3.9100

Note: ** Significant at the 0.05 level.

Table 4. Structural Breaks for in Mean for VIX-ETF ($SupF_T(l+1|l)$)

Test	H_0	H_1	VIX-ETF	F-statistic	Criteria
$SupF(l+1\|l)$	m=(0|0)	m=(1|0)	VIXM	27.7763**	8.5800
	m=(1|1)	m=(2|1)		25.9447**	10.1300
	m=(2|2)	m=(3|2)		11.5877**	11.1400
	m=(3|3)	m=(4|3)		4.5624	11.8300
	m=(0|0)	m=(1|0)	VIXY	18.9628**	8.5800
	m=(1|1)	m=(2|1)		16.9526**	10.1300
	m=(2|2)	m=(3|2)		21.4077**	11.1400
	m=(3|3)	m=(4|3)		17.1371**	11.8300
	m=(0|0)	m=(1|0)	UVXY	30.0843**	8.5800
	m=(1|1)	m=(2|1)		9.8215	10.1300
	m=(2|2)	m=(3|2)		-	-

m=(3|3)	m=(4|3)		-	-
m=(0|0)	m=(1|0)	SVXY	2.5573	8.5800
m=(1|1)	m=(2|1)		-	-
m=(2|2)	m=(3|2)		-	-
m=(3|3)	m=(4|3)		-	-

Note: ** Significant at the 0.05 level.

Table 5 presents the different results between sequential, BIC, and LWZ tests. Bai and Perron (2003) suggested that selecting the breakpoint using a sequential procedure results well when the numbers of breaks present are similar. Therefore, the results show that VIXM has three structural breaks, UVXY has one structural break, and VIXY has four structural breaks.

The structural break approach estimated the multiple structural shifts located at different unknown dates and a different number of breaks. Table 5 summarizes the structure break dates and means over each segment, and for VIXM, three structural breaks are located on 3/12/2012, 9/07/2012, and 1/14/2013, with confidence intervals of 2/17/2012–4/04/2012, 8/03/2012–10/15/2012 and 1/08/2013–1/23/2013, respectively. The mean estimation model exhibits means of 74.9689, 56.3654, 37.6301, and 24.6404 in the sub-period.

On the contrary, VIXY has four breaks located on 2/03/2012, 7/13/2012, 1/10/2013, and 7/17/2013, with confidence intervals of 12/30/2011–3/12/2012, 7/03/2012–7/26/2012, 12/21/2012–1/31/2013 and 6/24/2013–8/12/2013 at the 5% significance level, respectively. The analysis estimated that in 2012 and 2013, the US fell into fiscal tightening, resulting in the Federal Reserve Board implementing monetary policies that affected equity market volatility. This result is in line with previous studies, which documented the importance of volatility in the equity market (England, 2003; Guo et al., 2011).

Table 5. Multiple Structural Break Model Estimates for VIX-ETF

Test	VIXM	VIXY	UVXY	SVXY
Sequential	3	4	1	0
BIC	5	4	2	4
LWZ	5	3	2	4
Estimates with Breaks				
$\hat{\delta}_1$	74.9689 (4.1341)	418.3946 (56.39192)	40036.32 (6765.27)	34.64406 (34.8815)
$\hat{\delta}_2$	56.3654 (3.4820)	210.1865 (30.4750)	2391.261 (1156.318)	-
$\hat{\delta}_3$	37.6301 (2.2576)	102.2041 (15.7275)	-	-
$\hat{\delta}_4$	24.6404 (1.5200)	56.0811 (1.8839)	-	-
$\hat{\delta}_5$	-	36.6728 (4.1410)	-	-
Break Date	3/12/2012	2/03/2012	2/03/2012	-
Confidence Intervals	2/17/2012 ~ 4/04/2012	12/30/2011 ~ 3/12/2012	1/23/2012 ~ 2/21/2012	-
Break Date	9/07/2012	7/13/2012	-	-

Confidence Intervals	8/03/2012 ~ 10/15/2012	7/03/2012 ~ 7/26/2012		-
Break Date	1/14/2013	1/10/2013	-	-
Confidence Intervals	1/08/2013 ~ 1/23/2013	12/21/2012 ~ 1/31/2013		-
Break Date	-	7/17/2013	-	-
Confidence Intervals		6/24/2013 ~ 8/12/2013		-

Note: Numbers within the parentheses are standard deviations.

4.2 ARFIMA and ARFIMA-FIGARCH models

Long memory are shortened in Table 6. This work calculates the long memory model with orders (p, q) using the minimum value of AIC to select the best-fitted model. First, panel A shows the ARFIMA model results without sudden changes to illustrate three significant results. The results reveal that long memory parameter (d) is significant from zero for VIXY, UVXY, and SVXY. Hence, the ARFIMA model exhibited a stationary and invertible process, meaning that the return series has intermediate memory effects (Hosking, 1981). This result specifies that there is no proof of long memory for VIX-ETFs; therefore, the return series shows weakness-form market efficiency. The ARFIMA model does not conform to the ARCH effect, suggesting that the variance equation is essential for modeling long memory features. Thus, the present research investigates whether a dual long-term memory exists in mean returns and whether the conditional variance occurs for VIX-ETFs by using the ARFIMA-FIGARCH model. The results show that all of the VIX-ETFs have long memory effects in the variance equation, consistent with the findings of Choi and Hammoudeh (2009) and Chen and Diaz (2013). The results also explore the remaining ARCH effects in the residuals, which explain the absence of ARCH effect in all VIX-ETFs.

The effects of structural breaks and long memory are shown in panel B of Table 6, demonstrating that the ARFIMA model with sudden switches in mean produces four significant results. In contrast to the results mentioned above without sudden changes, the VIXM and VIXY establish a stationary but non-invertible process, whereas the UVXY presents a stationary and invertible process, suggesting that UVXY has an intermediate memory effect. The valuation of the ARFIMA-FIGARCH model shows that VIXM and VIXY are statistically significant with a stationary but non-invertible process in the mean equation, while in the variance equation, VIXM, VIXY, and UVXY have long memory effects. Based on this evidence, investors can earn abnormal returns from analyzing the past price.

In sum, the results of the present study suggest that the predictable behavior of VIX-ETFs is inconsistent with the efficient market hypothesis, with or without structural breaks. Based on the analysis results of the ARFIMA-FIGARCH model, long memory parameter ξ in return is not strongly significant for the return series of the VIX-ETFs. However, the parameter d in the variance is statistically significant for all VIX-ETFs (Turkyilmaz and Balibey, 2014). Furthermore, the result suggests a significant ARCH effect in the standardized model, implying that merely modeling the level of return is insufficient to capture the absence of long memory traits in the VIX-ETFs. Finally, the ARFIMA-FIGARCH model extracts more significant results from the combination of structural breaks.

Table 6. ARFIMA and ARFIMA-FIGARCH for Sudden Changes

	ARFIMA					ARFIMA-FIGARCH			
	model	d-coeff.	AIC	ARCH-LM	d-coeff.	model	d-coeff.	AIC	ARCH-LM
Without Dummy Variables for Sudden Changes									
VIXM	(2,0)	-0.1290 (0.1640)	4.1536	5.8755** (0.0157)	-0.1253 (0.1694)	(1,0)	0.2028* (0.0845)	4.0854	0.0239 (0.9764)
VIXY	(1,0)	-0.1511** (0.0160)	5.58508	12.9060*** (0.0004)	-0.2039 (0.2226)	(1,0)	0.26777*** (0.0063)	5.4927	0.2384 (0.7880)
UVXY	(1,0)	-0.1476** (0.0160)	6.9738	20.07 00*** (0.0000)	-0.3006 (0.5579)	(1,0)	0.2556** (0.0354)	6.8689	0.1927 (0.8248)
SVXY	(1,0)	-0.1508** (0.0210)	5.6109	5.9652** (0.0149)	-0.1535 (0.1851)	(1,0)	0.2922** (0.0198)	5.5186	0.23476 (0.7908)
With Dummy Variables for Sudden Changes in Mean									
VIXM	(2,0)	-0.8920*** (0.000)	4.1429	5.0864** (0.0245)	-0.9151*** (0.0000)	(1,0)	0.1243** (0.0289)	4.0558	0.1863 (0.8301)
VIXY	(2,1)	-1.0000*** (0.0000)	5.5839	13.723*** (0.0002)	-1.0612*** (0.0000)	(1,3)	0.0905*** (0.0096)	5.4690	0.4211 (0.6565)
UVXY	(1,0)	-0.1519** (0.0180)	6.9773	20.1900** (0.0000)	-0.3211 (0.4582)	(1,0)	0.2514** (0.0437)	6.8711	0.20807 (0.8122)

Note: *, ** and *** are significance at 10%, 5% and 1% levels, respectively; p-values are in parentheses. SVXY did not find structural breaks in the mean.

5. Conclusions

The present work examines ETFs that track the CBOE's market VIX daily. This paper re-examines the strong existing evidence that the US equity market is an efficient marketplace. Therefore, the ARFIMA-FIGARCH model is employed to test long memory merging with multiple structural breaks. VIX-ETFs have two features, namely, equity return and volatility. Thus, multiple structural breaks in mean and in the variance are studied using the Bai-Perron test.

Interestingly, VIX-ETFs present significant structural breaks in mean, except for SVXY. This outcome is in accord with the findings of Guo and Wohar (2006) and Esteve et al. (2013). However, the paper also highlights the need for time series stability to avoid imprecise and unreliable forecasts (Pástor and Stambaugh, 2001). The key objective here is to test for the presence of breaks in two-price, close price, and adjusted close price conditions. The results show that if researchers do not identify the difference between close prices and adjusted close prices, they will obtain incorrect breaks. Hence, the break dates may be dividends and splits of ETFs in the essential breaks.

However, the present work uses VIX-ETFs to confirm long memory effects, revealing the existence of multiple structural breaks and long memory. First, the result of the ARFIMA model indicates no long memory effect in the VIX-ETF returns. The presence of long memory in asset returns implies the weak form of the efficient market hypothesis (Coakley et al., 2011; Huskaj, 2013). Subsequently, the ARFIMA-FIGARCH model is juxtaposed with the VIX-ETFs to examine long memory effects in the return and variance of the VIX-ETFs. The study findings do not corroborate dual long memory effects.

Moreover, the results show long memory with structural breaks in variance. The ARFIMA model with sudden switches in mean implies VIXY, UVXY, and SVXY have an intermediate memory effect. For the rest, the work also considers the dual long memory in variance. In the variance equation, all samples of VIX-ETF carry a long memory effect, implying an inefficient market.

The samples of the study track that measures S&P 500 volatility, namely VIX, are observed. An important implication of this finding is that long memory dynamics in volatility emerge in an important place in the property. By doing so, investors take into account of invest strategies not only the volatility of the S&P 500 index but also long memory dynamics in VIX. The limitation of this study mainly focused on the early stage of VIX-ETFs for analysis of the dynamics and structural breaks. Future research can extend the period and select more VIX-ETFs for further analysis. A report from Diebold and Inoue (2001) and Kapetanios (2006) argued that nonlinear regime switches inferred long memory, so future research could further detect the linkage between nonlinear regime switches and the long memory effect.

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