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Testing for the Long Memory and Multiple Structural Breaks in Consumer ETFs

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Abstract

This research examines the consumer exchange-traded funds (ETFs) in several industries based on long memory and multiple structural breaks. The autoregressive fractionally integrated moving average (ARFIMA) model indicates that consumer ETF returns in the media, consumer service, food and beverage, and consumer goods industries can be accurately predicted. The autoregressive fractionally integrated moving average and fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) model reveals that only the gaming and consumer goods industries have a long memory in volatility. This study establishes that through the iterated cumulative sum square test, multiple structural breaks exist in consumer ETF industries. Results prove that the consumer goods industry has a long memory and multiple structural breaks. Finally, the structural breaks in consumer ETFs have strong asymmetrical effects, indicating that all of the consumer ETF industries are generally unstable.

Keywords: The Long Memory, Multiple Structural Breaks, Consumer ETFs, Iterated Cumulative Sums Squares Test.

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1. Introduction

A long memory is the main indicator determining the nonlinear dependence of the conditional mean and variance of financial time series. Long memory is generally identified to capture the time series, in which the price returns and volatilities can influence portfolio investment.

The presence of long memory in financial asset returns signifies that the market does not directly respond to financial market news (Chen and Diaz, 2013; Trang, 2014), which is inconsistent with the efficient market hypothesis (EMH) proposed by Fama (1970). The market efficiency implies that the information directly influences the price, which cannot be predicted.

The performance of data for time series returns related to the influence of long memory dynamic and historical data is utilized to predict future returns. The possibility of consistent expected returns enhances the weakness of EMH. In contrast, the presence of long memory in volatility suggests uncertainty or risk in security prices. Consequently, the long-memory properties of returns and volatilities are considered the right approach in this financial issue. To measure the long memory of the behavior of equity trading volume and volatility for single companies, Bollerslev and Jubinski (1999) noted the superiority of using fractionally integrated processes in describing the long memory for temporal dependencies in both series. In particular, using the fractional integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model can properly explain the volatility and long memory in the finance area.

Brunetti and Gilbert (2000) employed the FIGARCH model and discovered fractionally integrated processes on the New York Mercantile Exchange (NYMEX) and International Petroleum Exchange crude oil markets. Likewise, Baillie et al. (1996) captured the long memory in volatility return. Cochran et al. (2012) investigated the existence of the volatility processes as long-memory parameters on metal return. They suggested that the volatility index should be considered in any future modeling of metal returns and volatility return (Cochran et al., 2012). However, Beine et al. (2002) concluded that central bank interventions exert an imperfectly signed effect on the intensities of exchange rates, which tends to increase their volatility in the short term. Bentes (2014) determined that the FIGARCH model is the best model to measure the persistence in stock market volatility. Moreover, Chortareas et al. (2011) forecasted the volatility of various euro exchange rates using high-frequency data. They stated that one to use in determining the long memory specification in high-frequency applications (Chortareas et al., 2011).

Numerous studies have extensively used the ARFIMA-FIGARCH model to investigate the long memory of returns and volatility. Beine and Laurent (2003) estimated the four daily exchange rates from 1980–1996 and revealed that the long memory related to the conditional variance is decreased when the observed jumps showed in the exchange rate dynamics. They also noted that this model could estimate the persistence of volatility shocks. Lux and Kaizoji (2007) investigated the predictability of volatility and volume in Japanese stocks and discovered that the FIGARCH and ARFIMA models have better results than GARCH and ARMA models.

Kang and Yoon (2013) examined the volatilities and their predicting capacities for petroleum futures contracts transacted on the NYMEX. They found that the ARFIMA-FIGARCH model best captures the long-memory properties of returns and volatility (Kang and Yoon, 2013). Mensi et al. (2014) analyzed the long memory, structure change, and forecasting volatility of foreign exchange markets for oil-exporting countries. A few indications of the long memory in the conditional mean exist, but they are strongly significant for the long memory in conditional volatility of the Saudi Arabia exchange rates versus major currencies (Mensi et al., 2014).

Non-stationary time series variables possibly occur in a structural break or multiple structural breaks. The ICSS test suggested by Inclán and Tiao (1994) can recognize sudden changes to the unconditional volatility of a series. Similarly, Wang and Moore (2009) noted a structural break in volatility in the stock markets of the new European Union (EU) members. Meanwhile, McMillan and Wohar (2011) used the ICSS algorithm and revealed that the financial, technology, and telecommunications sectors in the UK have a structural break in volatility.

To identify time points of structural changes in a financial time series, Huang (2012) demonstrated that no common structural change exists in variances in the UK, Japan, and the US futures returns. In addition, volatilities in the UK, Japan, and the US stock index futures markets are directly affected by their own lagged volatilities (Huang, 2012). Moreover, asymmetric volatility transmission effects are evident between Japan and the UK as well as between Japan and the US. Chang and Chen (2014) applied the ICSS to test market panics' timing and found significant evidence for the existence of a contagion in the global real estate investment trust returns worldwide during the 2007–2009 Global Financial Crisis.

The current study primarily aims to present certain unique experimental pieces of evidence of the long memory and multiple structural breaks in consumer ETFs. This paper examines the asymmetric effects on consumer ETFs by using the ARFIMA and ARFIMA-FIGARCH models and the ICSS to test the long memory and analyze multiple structural breaks, respectively.

This study also aims to evaluate the long memory and multiple structural breaks in consumer ETFs, which are categorized by industries, such as retail, gaming, automotive, media, consumer service, leisure and entertainment, food and beverage, and consumer goods. We then selected consumer ETFs associated with individual needs and wants. Based on the physiological, personal, or socioeconomic perspective, human needs are required for humans to live and function, whereas wants are a means to fulfill human needs. For example, transportation is a need for modern urban people to obtain work, food, and other daily life necessities.[3] By such

[3] "Economic Needs and Wants: Definition, Lesson & Quiz." (study.com/academy/lesson/economic-needs-and-wants-definition-lesson-quiz.html.)

a definition, "needs" may thus influence consumer behavior.

Consumer ETFs have a great opportunity to generate profit. Hence, selecting consumer ETFs boosts the confidence of investors and increases their capability to explore outstanding returns. This research's important contributions provide clear evidence for consumers to analyze the long memory and multiple structural breaks. The results of both ARFIMA-FIGARCH models analyzing consumer goods signify long memory. Applying ICSS helped identify multiple structural breaks in consumer ETFs, which are connected to similar changes in different industries. This research can contribute to the investor with a new resource for obtaining better investing decisions. The academician can close the gap of research from the consumer ETFs. For the consumer industry, this research can provide analysis to enrich knowledge in the consumer area. This study enriches our understanding of consumer ETFs because, to the best of our knowledge, no previous research has discussed the long memory and multiple structural breaks in consumer ETFs.

This study's findings can help investors understand consumer ETFs and provide a reference for practitioners and scholars. Consumer ETFs are a promising investment instrument; therefore, the results may not only encourage investors to examine which selected industries have potential benefits, but also help them estimate consumer ETFs for diversifying and hedging strategies.

The first part of the study explains the introduction and the purposes of the research. The second part reviews the related literature and describes consumer ETFs, which are categorized by industry. The third part presents the sample data and the research methodology, including the ARFIMA-FIGARCH models and the ICSS algorithm used to examine the long memory and multiple structural breaks in consumer ETFs. The last part analyzes and explains the empirical results and presents the conclusion.

2. Related Literature

The experienced long memory in stock returns in the US by the rescaled variety statistic of Hurst (1951) was then adopted by Greene and Fielitz (1977). Similarly, Wright (1988) discovered that long memory in stock returns is evident in emerging markets. Henry (2002) also revealed that long memory could be established in the South Korean, German, Japanese, and Taiwanese stock markets.

Several studies noted the long memory using the ARFIMA-FIGARCH models. Kang and Yoon (2007) specifically discovered the Korean stock market's dual long-memory properties related to long-memory dynamics in returns and volatilities. Diaz (2012) disclosed that currency exchange-traded notes have non-stationary and non-invertibility properties, while Kasman et al. (2009) revealed strong evidence of long memory in both conditional mean and variance in the central and eastern stock markets of eight European countries. Similarly, Lux and Kaizoji (2007) examined the certainty of equal volatility and volume in a large sample of Japanese stocks and found that pooled estimates have considerably better results than an individual estimated model. Using both the regime-switching stochastic volatility model and the efficient method of moments estimation, Liu (2000) noted long memory in the volatility with heavy tails.

Bollerslev and Mikkelsen (1996) used the FIGARCH and exponential GARCH models to characterize financial market volatility and prove a long-term dependence on the US stock market volatility, which is associated with a mean-reverting fractionally integrated procedure. Meanwhile, Charfeddine (2014) found strong evidence of long memory in the volatility of energy futures.

Ellis and Wilson (2004) revealed the effective use of the ARFIMA specification, as a forecasting tool for Standard & Poor's (S&P) 500 and Dow Jones Industrial Average daily returns. In contrast, Xiu and Jin (2007) noted that the ARFIMA algorithm is ineffective in forecasting the Hang Seng Index. However, Bhardwaj and Swanson (2006) presented strong evidence that the ARFIMA model can well predict the S&P 500 in the US. Lahiani and Scaillet (2009) concluded that the threshold ARFIMA model provides significant results in the US unemployment rate data's long-memory features. Baillie (1996) utilized the ARFIMA-FIGARCH model and highlighted that a long memory volatility process could be applied in economic and financial data. Granger and Joyeux (1980) used the ARFIMA model and noted the long memory in the monthly index of consumer food price index from January 1947 to June 1978 in the US. Arouri et al. (2012) examined the long memory in precious metals, and revealed that ARFIMA-FIGARCH model has better performance in terms of forecast accuracy compared with other general volatility models.

Lanouar and Dominique (2011) applied the structural change model and noted that the break dates coincided with several economic and financial events, such as the Vietnam War and the two oil price shocks. Moreover, the existence of breaks can provoke spurious long-memory behavior. Malik (2003) used ICSS and discovered the structural changes in the British pound and the Japanese yen. Covarrubias et al. (2006) discovered regime shifts in the volatility of the 10-year treasury interest rates in the US. Finally, utilizing the ICSS model, Wang and Morre (2009) confirmed that the volatility in returns of the stock markets of new EU members appeared to be successfully recognized for transition economies.

Chen and Malinda (2014) and Chen and Huang (2014) used ICSS method and ARFIMA-FIGARCH model to investigate the long memory and structural breaks for travel and tourism indices at New Zealand, the UK, and the USA stock exchanges and for Volatility Index (VIX)-ETFs returns. The empirical results found that about 90% of indices have multiple structural breaks, while a long memory process could be observed at the US stock exchange. Furthermore, it is a better estimation for performing structural breaks model to incorporate with dual long memory in VIX-ETFs. Chen and Malinda (2015) studied the room occupancy rates of hotels in Bali. The results revealed that a long memory process existed at rates of 2-star~4-star hotels during the same structural break time.

3. Data and Methodology

This study used daily closing prices on eight consumer ETF industries, including retail, gaming, automotive, media, consumer service, leisure and entertainment, food and beverage, and consumer goods in the US. The study period begins with the inception dates of the varying indices. Table 1 summarizes the consumer ETFs used in this research. The data were obtained from the ETF Database and Yahoo! Finance websites on April 28, 2014.

Table 1: Summarized of ETFs for the Long Memory and Multiple Structural Breaks

Industry	Consumer ETFs	Code	Inception period	Assets (Mil USD)	Average Volume
Retail	SPDR SandP Retail ETF	XRT	6/23/2006	$677,029	3,411,663
Gaming	Market Vectors Global Gaming Index	BJK	1/25/2008	$79,408	28,374
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	5/11/2011	$58,935	18,245
Media	PowerShares Dynamic Media Portfolio	PBS	6/24/2005	$177,764	256,002
Consumer Service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	6/30/2000	$418,545	53,658
Leisure and Entertainment	PowerShares Dynamic Leisure and Entertainment Portfolio	PEJ	6/24/2005	$174,130	80,060
Food and Beverage	PowerShares Dynamic Food and Beverage Portfolio	PBJ	6/24/2005	$437,115	161,184
Consumer Goods	iShares Dow Jones U.S. Consumer Goods Sector Index Fund	IYK	6/19/2000	$458,565	28,611

Source: http://etfdb.com/ETF.

The research methodology used the ARFIMA-FIGARCH models to examine the long memory. The ICSS test was applied for multiple structural breaks analysis.

3.1 ARFIMA

Box and Pierce (1970) proposed the ARMA model (*p, q*) to illustrate stationary time series, where *p* explains the autoregressive item and *q* stands for the moving average item. The mean, auto-covariance, and variance of the ARMA model are all constant and are not affected by the time. However, most of the financial time series are non-stationary; hence, the time series have non-stationary mean and auto-covariance. The ARIMA model (*p, d, q*) proposed by Box and Jenkins (1970) uses parameter *d* to differentiate the time series variables and make the variables stationary. To observe the time series data with a long-memory effect, Engle and Granger (1987) demonstrated that an unsatisfactory parameter *d* with a value of either zero or one could indicate the equilibrium error, thus restricting the ability to control a long-memory effect. Granger and Joyeux (1980) proposed the AFIRMA model (*p, d, q*), which allows the parameter *d* to be the non-integer or fraction. If 0<d<0.5, the time series has a long-memory effect. The mathematical model is defined as:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Psi(L)\varepsilon_t \quad , \tag{1}$$

where *d* stands for the fractional integration real number parameter, L and ε_t are the lag operator and a noise residual, respectively. In addition, $\Phi(L)=1-\Phi_1 L-\cdots-\Phi_p L^p=1-\sum_{j=1}^{p}\Phi_j L^j$ are the polynomials in the lag operator of order *p*; $\Psi(\mathrm{L})=1+\sum_{\mathrm{j}=1}^{\mathrm{p}}\Psi_{\mathrm{j}}\mathrm{L}^{\mathrm{j}}$ are the polynomials in the lag operator of order *q*, where both *p* and *q* are integers; ε_t is a white noise residual; and μ_t is the mean of $\mathrm{y_t}$. The fractional differencing lag operator $(1-L)^d$ can be further illustrated using the expanded equation given by the following:

$$(1-L)^d=1-dL+\frac{d(d-1)}{2!}L^2-\frac{d(d-1)(d-2)}{3!}L^3+\ \ldots. \tag{2}$$

The ARFIMA model uses the parameter *d* to capture the long memory of the time series variable. When d = 0, the variable represents a short memory and the effect of market shocks to the ε_t geometrically decays. When *-0.5 < d <0.5*, the variable is stationary, and the effect of market shocks to ε_t gradually decays near zero (i.e., hyperbolic decay). When *d = 1*, a unit root process is present (Styger et al., 2009). Generally, the empirical results reveal that the ARFIMA model shows improved accuracy in forecasting volatility.

3.2 FIGARCH

Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model to illustrate the variance of the residual changes over time as well as a phenomenon with volatility clustering. Moreover, Bollerslev (1986) proposed the use of the GARCH model and argued that conditional variance is not only manipulated by the square of prior residual, but also influenced by the prior

variance. In modeling conditional variance, the GARCH model is more flexible than the ARCH model.
To capture the long memory in volatility returns, Baillie et al. (1996) proposed the use of the FIGARCH model. The volatility decays at a gradual rate to zero (i.e., hyperbolic decay). If the variables have long memory, the random external shock of each period may take a longer time to react to them. A faster decay can be obtained for stationary variables (i.e., geometric decay) to measure the random external shock.
The model is high elastic in modeling the conditional variance, capturing both the covariance stationary GARCH for $\bar{d} = 0$ (Bollerslev, 1986) and the non-stationary IGARCH for $\bar{d} = 1$ (Engle and Bollerslev, 1986). The FIGARCH model can be illustrated as follows (Bollerslev and Mikkelsen, 1996; Beine et al., 2002; Bentes, 2014):

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]vt, \tag{3}$$

where $\phi(L) \equiv \phi_1 L + \phi_2 L^2 + \cdots + \phi_q L^q, \beta(L) \equiv \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p,$

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(d+1)L^k}{\Gamma(k+1)\Gamma(d-k+1)}, \tag{4}$$

$$(1-L)^d = 1 - dL - 2\frac{1}{2}d(1-d)L^2 - \frac{1}{6}d(1-d)(2-d)L^3 + \cdots \tag{5}$$

$$(1-L)^d = \sum_{k=1}^{\infty} C_k(d)L^k, \tag{6}$$

and $0 \leq d \leq 1$ is the fractional differencing parameter, that is, $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$. The process of υ_t can be interpreted as the innovation for the conditional variance; it has a zero mean and is serially uncorrelated. All of the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle. The FIGARCH model explains $0 < d < 1$, which refers to the intermediate range of persistence. When $-0.5 > d > 0.5$, the series is stationary, and the effect of market shocks decays at a gradual rate to zero. If $d = 0$, the series has short memory and the effect of market shocks decays geometrically. When $d = 1$, a unit root process is present.
Beine et al. (2002) and Bentes (2014) reported that the forecasting power of the FIGARCH model is better than those of the GARCH and the IGARCH models. Pelinescu and Acatrinei (2014) discovered a long-memory process in the RON[4]-Euro exchange rate and indicated persistence in the data.

[4] RON - Romanian new leu.

3.3 Multiple structural breaks

Under economic structural changes, economic variables can be influenced by external shock, such as oil crises and monetary policy changes. In such cases, an unstable and non-stationary parameter exists.

Non-stationary time series variables may exist in a structural break or multiple structural breaks. The ICSS test proposed by Inclán and Tiao (1994) is designed to identify sudden changes in the unconditional volatility of a series. Kang et al. (2009) demonstrated that ICCS examines the persistence of volatility in Japanese and Korean stock markets. Structural change is normally connected with international financial and political events. The variance of a series is assumed to continue constantly until a sudden change in volatility occurs. After this point, the variance is assumed to remain constant until another sudden change in variance occurs. This series must be unrelated with mean zero and variance σ_t^2, which is expressed as follows:

$$
\begin{aligned}
\Sigma_t^2 &= \xi_0 \quad 1 < t < \textit{k}_{\textit{k}} \\
&= \xi_1 \quad \textit{k}_1 < t < \textit{k}_3 \\
&= \xi_{N\xi} < t < \textit{k}_T,
\end{aligned}
$$

where $1 < \textit{k}_1 < \textit{k}_1 < \cdots < \textit{k}_{NT} < T$ are the various points where the changes in variance occur; N_T is the total number of changes; and ξ_j presents the variance within each of the periods $(j = 0,1, \ldots, N_T)$.

Inclán and Tiao (1994) proposed the statistic $D_{\textit{k}}$ based on the cumulated sum of the square of the series, in order to detect the amount and the time point at which these changes happen. This is expressed as follows:

$$C_{\textit{k}} = \sum_{t=1}^{\textit{k}} X_t^2, \tag{7}$$

$$D_{\textit{k}} = \left(\frac{C_{\textit{k}}}{C_T}\right) - \frac{\textit{k}}{T}, \qquad \textit{k} = 1, \ldots, T;\ D_0 = D_T = 0, \tag{8}$$

where $C_{\textit{k}}$ and C_T are the mean centered cumulative sums of squares designed for the $\textit{k}$ and T observations, respectively. If no variance changes are evident over the sample period, then the series $D_{\textit{k}}$ oscillates around zero; $D_{\textit{k}}$ also drifts up or down from zero when a variance shift occurs. The quantity $(\left(\frac{T}{2}\right) D_{\textit{k}})^{\frac{1}{2}}$ converges in distribution to a standard Brownian motion. The change point of variance over the interval t=1,…, T, is the point $\textit{k}_0$, in which $(\left(\frac{T}{2}\right) D_{\textit{k}})^{\frac{1}{2}}$ reaches its maximum and $(\left(\frac{T}{2}\right) D_{\textit{k}})^{\frac{1}{2}} > C_\alpha$, where C_α is a breaking value. At the 5% level, the breaking value is 1.358 (Inclán and Tiao, 1994). For any time t_1 and t_2 with $t_1<t_2$, the notation X $[t_1 : t_2]$ is adopted to indicate the extracted series $X_{t1}, X_{t+2},\ldots,X_{t2}$ and $D_{\textit{h}}$ (X[t_1 : t_2]), which is denoted by the value of $D_{\textit{h}}$ calculated from

$X_{t1}, X_{t+2},\ldots,X_{t2}$. First, we set t_1=1. To compute D_k(X [t_1: T]), we let k^*(X [t_1: T]) denote the point where $\max_k|D_k[t_1{:}T]|$ is reached. Then, we set the following:

$$M(t_1{:}T) = \max_{t_1 \le k \le T} \left(\frac{T-t_1+1}{2}\right)^{\frac{1}{2}} |D_k[t_1{:}T]|. \quad (9)$$

If M (t_1: T) >$C_{0.05}$, then k^*(X[t_1:T]) can be considered as a structural break point, and if M(t_1:T) < $C_{0.05}$, then no variance change is evident in the series.

Steeley and Tsorakidis (2009) found that the ICSS method can identify periods of high and low exchange volatility. Lanouar and Dominique (2011) illustrated in an experiential study that the long memory behavior is spurious and can lead to the presence of breaks in the data.

3.4 GARCH model estimations with changes in variance

Lamoureux and Lastrapes (1990) and Glosten et al. (1993) combined the GARCH model with dummy variables to demonstrate changes in variance. The modified GARCH model cited by Arago and Izquierdo (2003) incorporates the identified changes in unconditional variance, and are expressed as follows:

$$H_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2, \quad (10)$$

$$h_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2 + \gamma S_{t-1}^{-} \varepsilon_{t-1}^2, \quad (11)$$

where D_i refers to the dummy variables (i.e., break) that reflect the changes in variance; the parameters that accompany these variables (F_i) reflect the differences with respect to α. In addition, S_{t-1} is equal to the unit if ε_{t-1}<0 (innovation in t=1), and zero if ε_{t-1}>0. The asymmetrical effect is captured if γ>0. The different effects on volatility depend on the sign of innovation in t-1. Lamoureux and Lastrapes (1990) reported the occurrence of high persistence when the GARCH models are applied because of incorrect specification, thereby disregarding the possible deterministic changes in the unconditional variance.

4. Empirical Results

Table 2 demonstrates that all of the consumer ETFs have negative means and positive standard deviations. These conditions explain that consumer ETFs in all of the industries have high volatility. In terms of skewness, all the consumer ETF industries have a negative value, indicating that the future data will be less than the mean. The results of kurtosis help determine the risk. Here, most of the data exhibited for kurtosis have a leptokurtic distribution because all of the values are higher than three. With a leptokurtic distribution, the index has a relatively low quantity of variance, because the returns are usually close to the mean, suggesting that large and erratic swings in portfolio returns can be avoided. The Jarque-Bera statistic for residual normality indicates that most of the data are significant at the 1% level, signifying an abnormal distribution. Hence, the consumer ETFs in all of the industries are under an abnormal distribution. With a significant Q (10) correlation coefficient, all the consumer ETFs have no serial correlation.

Table 2: The Descriptive Statistics of Variables

Industry	Index	Code	Inception Period	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera	Q(10)
Retail	SPDR S&P Retail ETF	XRT	6/23/2006	2014	-5.6245	0.7796	-0.2321	4.9243	2052.9***	22.0645 [0.014]**
Gaming	Market Vectors Global Gaming Index	BJK	1/25/2008	1630	-6.9239	0.9168	-0.1300	10.4470	7417.6***	26.2685 [0.0033]**
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	5/11/2011	719	-5.3434	0.7507	-1.0993	8.5620	2341***	21.4687 [0.0180]**
Media	PowerShares Dynamic Media Portfolio	PBS	6/24/2005	2216	-4.3525	0.6722	-0.3911	6.3107	3733.6***	16.5711 [0.0844]*
Consumer service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	6/30/2000	3469	-3.9773	0.5836	-0.0887	5.0472	3686.6***	18.7112 [0.0440]*
Leisure & Entertainment	PowerShares Dynamic Leisure & Entertainment Portfolio	PEJ	6/24/2005	2230	-3.4458	0.6845	-0.0479	5.4916	2803***	20.5078 [0.0247]**
Food and Beverage	PowerShares Dynamic Food & Beverage Portfolio	PBJ	6/24/2005	2203	-2.8830	0.4619	-0.4148	4.5180	1936.8***	35.8901 [0.0001]***
Consumer goods	iShares Dow Jones U. S. Consumer Goods Sector Index Fund	IYK	6/19/2000	3462	-3.1226	0.4349	-0.1643	7.2123	7519.1***	63.8187 [0.0000]***

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

Sources: Yahoo Finance- Various Inception date up to 21 July 2014.

Table 3 presents the outcome of the unit root test of the best-fitted ARMA model, Lagrange multiple (LM) test and the ARCH-LM method proposed by Engle (1982); then, the GARCH model is applied. For the Augmented Dickey Fuller (ADF) test suggested by Dickey and Fuller (1979), all of the data significantly reject the null hypothesis, suggesting that all the data are stationary and appropriate for further testing. This study used the minimum Akaike Information Criterion (AIC) to obtain the best-fitted ARMA model. After establishing the model, we conducted the serial correlation with the LM test to determine whether the result is insignificant. If the result is insignificant, no serial correlation exists. All of the LM tests are insignificant, indicating no serial correlation between all of the variables. After testing the serial correlation, this study continued to process the heteroscedastisity test using the ARCH-LM method (Engle, 1982). The ARCH-LM test results illustrate that the null hypothesis can be accepted if no ARCH effect exists. Otherwise, the null hypothesis can be rejected when the ARCH effect exists and then further applied to the GARCH model to remove the ARCH error. The results of the ARCH-LM are significant (Table 3), and the null hypothesis is rejected, thus indicating that all of the samples have the ARCH effect. Hence, the GARCH model should be applied to all of the consumer ETFs. The results of the ARCH-LM test establish that the GARCH-ARMA models can eliminate ARCH errors in the residuals.

Table 3: Summary Statistics of Unit root, ARMA, LM, ARCH-LM and GARCH

Industry	Index	Code	ADF	ARMA	AIC	LM	ARCH-LM	GARCH	AIC	ARCH-LM
Retail	SPDR S&P Retail ETF	XRT	-46.5148***	(2,2)	2.3365	2.0411	228.6981***	(3,3)	1.9163	0.6085
Gaming	Market Vectors Global Gaming Index	BJK	-40.5780***	(3,2)	2.6399	2.7113	221.4194***	(1,3)	2.1743	0.2178
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	-28.9506***	(3,3)	2.2568	1.2361	36.54656***	(3,2)	1.8463	0.5265
Media	PowerShares Dynamic Media Portfolio	PBS	-46.4284***	(2,3)	2.0430	0.7230	255.2238***	(2,2)	1.6033	0.0939
Consumer service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	-44.1242***	(0,2)	1.7594	1.1210	432.7357***	(2,3)	1.3491	0.9995
Leisure & Entertainment	PowerShares Dynamic Leisure & Entertainment Portfolio	PEJ	-45.5742***	(3,3)	2.0781	0.8954	519.0434***	(1,2)	0.9878	1.0797
Food and Beverage	PowerShares Dynamic Food & Beverage Portfolio	PBJ	-36.9089***	(3,3)	1.2860	1.7654	312.4372***	(2,2)	0.9723	0.0844
Consumer goods	iShares Dow Jones U. S. Consumer Goods Sector Index Fund	IYK	-46.1507***	(3,3)	1.1591	0.1384	780.0513***	(3,3)	0.8142	0.2804

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

This study further runs the ARFIMA and ARFIMA-FIGARCH models. The ARFIMA (0, *d*, 1) to ARFIMA (3, *d*, 3) is examined based on the minimum AIC to obtain the optimal model. Parameter *d* is measured to estimate the existence of long memory.

Table 4 presents ARFIMA and ARFIMA-FIGARCH models. The *d*-coefficient in the ARFIMA model indicates that PBS, IYC, PBJ, and IYK are $-0.5 < d < 0.5$. A long memory is significant at 1% and 5% levels. Therefore, the consumer ETF returns in the media, consumer service, food and beverage, and consumer goods industries can be predicted or estimated in the long term. Other studies have confirmed the existence of a long memory through the ARFIMA model (Nouira et al., 2004; Kang and Yoon, 2007; Choi and Hammoudeh, 2009; Tan and Khan, 2010; Chen and Diaz, 2013; Chen and Malinda, 2014). The ARFIMA-FIGARCH model revealed that only the gaming and consumer goods industries have long memory in volatility for Consumer ETFs, suggesting that the gaming and consumer goods industries can be accurately predicted. Similarly, Baillie (1996) and Arouri et al. (2012) determined the long memory for price index and commodities index. Other industries have an intermediate range of persistence. Those of the consumer service, leisure and entertainment, food and beverage, and consumer goods industries are stationary. Hence, the effect of market shocks decays at a gradual rate to zero. Long memory does not exist in return for these industries.

Table 4: Summary Statistics of ARFIMA and ARFIMA-FIGARCH Models with All Period

Industry	Index	Code	ARFIMA				ARFIMA-FIGARCH				
			Model	**d-coeff.**	**AIC**	**ARCH-LM**	**d-coeff. (return)**	**Model**	**d-coeff. (volatility)**	**AIC**	**ARCH-LM**
Retail	SPDR S&P Retail ETF	XRT	(3,3)	0.0847 (0.201)	2.3380	60.582 [0.0000]**	-0.0172 (0.8482)	(3,3)	**0.7748 (0.0000***)**	1.9177	0.6193 [0.6851]
Gaming	Market Vectors Global Gaming Index	BJK	(3,3)	0.1222 (0.110)	2.6569	209.89 [0.0000]**	0.0032 (0.9763)	(3,0)	**0.4722 (0.0011***)**	2.1732	0.1431 [0.9821]
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	(3,3)	0.0691 (0.550)	2.2593	28.038 [0.0000]**	-0.0244 (0.4778)	(3,2)	**0.9145 (0.0000***)**	1.8425	0.5437 [0.7432]
Media	PowerShares Dynamic Media Portfolio	PBS	(3,3)	**0.1494 (0.022**)**	2.0435	50.277 [0.0000]**	0.0533 (0.4711)	(3,2)	**0.6864 (0.0000***)**	1.6003	0.5074 [0.7709]
Consumer service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	(2,3)	**-0.0391 (0.059**)**	1.7580	111.82 [0.0000]**	**-0.0814 (0.0052***)**	(3,3)	**0.6743 (0.0000***)**	1.3521	0.3023 [0.9117]
Leisure & Entertainment	PowerShares Dynamic Leisure & Entertainment Portfolio	PEJ	(2,0)	-0.0080 (0.797)	2.0809	43.624 [0.0000]**	**-0.0719 (0.0496**)**	(3,2)	**0.7856 (0.0000***)**	1.6578	0.6258 [0.6801]
Food and Beverage	PowerShares Dynamic Food & Beverage Portfolio	PBJ	(2,2)	**-0.0541 (0.002***)**	1.2859	91.478 [0.0000]**	**-0.1119 (0.0004***)**	(3,3)	**0.6880 (0.0000***)**	0.9749	0.1987 [0.9630]
Consumer goods	iShares Dow Jones U. S. Consumer Goods Sector Index Fund	IYK	(2,3)	**-0.0419 (0.065**)**	1.1605	221.32 [0.0000]**	**-0.0997 (0.0000***)**	(2,3)	**0.2877 (0.0000***)**	0.8162	0.3245 [0.8985]

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

Table 5 reveals the effects of multiple structural breaks. This study uses the ICSS to recognize sudden changes to the unconditional volatility of a series for endogenous events. When the value is higher than 1.358, a structural break exists. All the variables have multiple structural breaks. On April 28, 2003, the consumer service and consumer goods industries had significantly similar structural breaks, clearly demonstrating a correlation with severe acute respiratory syndrome (SARS) disease. According to the World Health Organization (WHO), SARS spread from Hong Kong to infect individuals in 37 countries in early 2003; it had peaked in all of the affected countries except People's Republic of China (Smith, 2006). These countries include Canada, Hong Kong, Singapore, and Vietnam.[5] SARS is only the fourth disease after the plague, yellow fever, and cholera among the diseases that countries are compulsory to report to the WHO. The SARS epidemic is likely caused by the people’s means of eating and living, which are highly connected with consumer goods and service (Eichelberger, 2007).

On December 31, 2007, leisure and entertainment and consumer service industries had an equivalent break time. People possibly prefer more leisure and enjoy entertainment and service activities during their vacation. On July 22, 2008, the media and consumer goods industries had an identical break. According to the US Food and Drug Administration (FDA), the same salmonella strain was responsible for the US salmonellosis outbreak from Mexico-grown jalapeño peppers in 2008.[6] The FDA and the Centers for Disease Control and Prevention focused their investigation to certain farms in Mexico held responsible for the contaminated produce. From April 10 to July 31, 2008, a minimum of 1329 cases of salmonellosis food harming was reported in 43 states in the US and in the District of Columbia. This epidemic has been the largest informed salmonellosis outbreak in the US since 1985.[7] On June 1, 2009, the retail, gaming, consumer service, and leisure and entertainment industries had similar breaks. Air France passenger Flight 447 from Rio de Janeiro, Brazil to Paris, France, crashed into the Atlantic Ocean on that day, killing all people including aircrew, cabin crew, and the 228 passengers aboard.[8] On December 20, 2011, the retail, gaming, media, food and beverage, and consumer service industries experienced an identical structural break. This break is strongly connected with issuing payroll tax in the US. By the end of December, house speakers opposed the Senate’s plan to extend the payroll tax cut in the US for two months.

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[5] “The World Health Organization announces that SARS has peaked in all affected countries except the
People's Republic of China.” (Wikipedia.org. en.wikipedia.org/wiki/April_2003.)

[6] “United States Salmonellosis Outbreak.” (Wikipedia.org.en.wikipedia.org/wiki/2008/).

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an Active Outbreak.”

[8] Paris: Bureau d'Enquêtes et d'Analyses pour la sécurité de l'aviation civile (BEA). July 2, 2009. Retrieved
July 4, 2009.

Determined by the value obtained through the ICSS method, this research uses the GARCH model with the dummy variable (Fi). The F_i exposes the differences with respect to its variance in the study period. When F_i is higher than the criteria value of 1.358, a structural break exists. An asymmetrical effect exists if the *r* is significant and positive based on the AIC for selecting a well-fitted model. Furthermore, the outcome is consistent with the findings of Malik (2003) and Covarrubias et al. (2006), in which structural changes in the British pound and Japanese yen are noted, respectively. Similarly, McMillan and Wohar (2011) revealed that financial, technology and telecommunications sectors in the UK had structural breaks in volatility.

Table 5: The Results of Multiple Structural Breaks

Industry	Variables	Code	Change Points	Interval	$\boldsymbol{max_k\left(\left(\frac{T}{2}\right)\lvert D_k\rvert\right)^{1/2}}$
Retail	SPDR S&P Retail ETF	XRT	7/15/2009	6/29/2006-7/21/2014	16.4838
	P_1		10/31/2007	6/29/2006-9/17/2008	9.2649
	P_2		**6/1/2009**	**9/18/2008-6/9/2011**	**12.1966**
	P_3		**12/20/2011**	**6/10/2011-7/21/2014**	**11.8859**
Gaming	Market Vectors Global Gaming Index	BJK	8/10/2009	1/30/2008-7/21/2014	17.1524
	P_1		7/10/2008	1/30/2008-9/29/2008	5.2203
	P_2		6/4/2009	9/30/2008-7/20/2011	12.6372
	P_3		**12/20/2011**	**7/21/2011-7/21/2014**	**11.2009**
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	12/14/2011	5/12/2011-7/21/2014	11.7986
	P_1		8/1/2011	5/12/2011-8/4/2011	3.0086
	P_2		12/14/2011	8/8/2011-7/21/2014	11.7946
Media	PowerShares Dynamic Media Portfolio	PBS	**7/22/2008**	**6/29/2005-7/21/2014**	**14.1255**
	P_1		**7/22/2008**	**6/29/2005-11/26/2008**	**14.0754**
	P_2		4/29/2009	11/28/2008-4/7/2010	8.0014
	P_3		9/7/2010	4/8/2010-7/13/2011	6.8232
	P_4		**12/20/2011**	**7/14/2011-7/21/2014**	**11.5730**
Consumer service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	**4/28/2003**	**7/14/2000-7/21/2014**	**16.3043**
	P_1		**4/28/2003**	**7/14/2000-9/15/2006**	**16.3080**
	P_2		**12/31/2007**	**9/18/2006-10/13/2008**	**9.3594**
	P_3		**6/1/2009**	**10/14/2008-7/11/2011**	**12.3180**
	P_4		**12/20/2011**	**7/12/2011-7/21/2014**	**11.6881**
Leisure & Entertainment	PowerShares Dynamic Leisure & Entertainment Portfolio	PEJ	**12/31/2007**	**6/29/2005-7/21/2014**	**14.3198**
	P_1		**12/31/2007**	**6/29/2005-11/24/2008**	**13.5505**
	P_2		**6/1/2009**	**11/25/2008-7/21/2011**	**10.9956**
	P_3		**11/30/2011**	**7/22/2011-3/7/2013**	**9.3564**
	P_4		1/22/2014	3/8/2013-7/21/2014	4.0684
Food and Beverage	PowerShares Dynamic Food & Beverage Portfolio	PBJ	**11/30/2011**	**6/30/2005-7/21/2014**	**12.3728**
	P_1		7/23/2007	6/30/2005-11/12/2008	12.2170
	P_2		4/17/2009	11/13/2008-8/2/2011	10.8162
	P_3		**12/21/2011**	**8/3/2011-7/21/2014**	**10.9409**
Consumer goods	iShares Dow Jones U.S. Consumer Goods Sector Index Fund	IYK	**7/21/2008**	**7/10/2000-7/21/2014**	**15.7268**
	P_1		5/1/2001	7/10/2000-4/2/2002	6.3260
	P_2		**4/28/2003**	**4/3/2002-6/10/2004**	**9.0460**
	P_3		**7/21/2008**	**6/14/2004-11/12/2008**	**15.7832**
	P_4		7/23/2009	11/13/2008-7/21/2014	13.1130

$$max_k\left(\left(\frac{T}{2}\right)|D_k|\right)^{1/2}$$

Table 6 presents the effects of structural breaks on consumer ETFs. Nearly all of the consumer ETF industries are significant. For example, the estimated coefficients of F_1 for the retail industry are significant, proving an increased value of the unconditional variance obtained from the retail industry. In the gaming industry, the estimated value of F_3 is significant, revealing a decrease compared to the unconditional value of F_3 in the third sub-period. The result reveals that nearly all of the consumer ETF industries' coefficients of F_1 are positive and significant, except for the food and beverage industry. Therefore, the value of unconditional variance obtained from nearly all of the consumer ETF industries increases. Moreover, the retail, gaming, automotive, consumer service, and food and beverage industries have positive *r* in terms of asymmetrical effect. Similar to Huang (2012), the current study noted asymmetric volatility effects between Japan and UK futures returns. All of the consumer ETF industries are unstable. Therefore, investors should be aware of the financial, political, and economic issues.

Table 6: The Effect of Structural Breaks with Whole Period

Industry	Variables	Code	ARMA	GARCH	AIC	F & r
Retail	SPDR S&P Retail ETF	XRT	(2,2)	(1,2)	1.9112	F_1=0.9006(0.000***)
	P_1					F_2=-0.0030(0.1772)
	P_2					F_3=-0.0049(0.0028***)
	P_3					r=0.0791(0.0044***)
Gaming	Market Vectors Global Gaming Index	BJK	(3,2)	(3,1)	2.1628	F_1=0.5763(0.000***)
	P_1					F_2=-0.0357(0.0057***)
	P_2					F_3=-0.0477 (0.0018***)
	P_3					r=0.297 8(0.000***)
Automotive	First Trust NASDAQ Global Auto Index Fund	CARZ	(3,3)	(3,1)	1.6023	F_1=0.6459(0.000***)
	P_1					F_2=-0.0460(0.0325**)
	P_2					r=0.0848(0.1744)
Media	PowerShares Dynamic Media Portfolio	PBS	(2,3)	(3,1)	1.6042	F_1=0.504542(0.000***)
	P_1					F_2=0.0041(0.00181***)
	P_2					F_3=0.0036(0.0201**)
	P_3					F_4=0.0016 (0.032**)
	P_4					r=-0.2944(0.0001***)
Consumer service	iShares Dow Jones US Consumer Services Sector Index Fund	IYC	(0,2)	(1,2)	1.3471	F_1=0.8923(0.000***)
	P_1					F_2=0.0015 (0.0848**)
	P_2					F_3=0.0009(0.2722)
	P_3					F_4=0.0002(0.7582)
	P_4					r=0.1703(0.000***)
Leisure & Entertainment	PowerShares Dynamic Leisure & Entertainment Portfolio	PEJ	(3,3)	(1,2)	1.6491	F_1=0.8625(0.0000***)
	P_1					F_2=0.0029 (0.1485)
	P_2					F_3=-0.0016(0.4164)
	P_3					F_4=-0.0008(0.6608)
	P_4					r=-0.2894(0.0000***)
Food and Beverage	PowerShares Dynamic Food & Beverage Portfolio	PBJ	(3,3)	(3,3)	0.9670	F_1=-0.2533(0.0762*)
	P_1					F_2=0.0017(0.1492)
	P_2					F_3=-0.0001(0.9712)
	P_3					r=0.3928(0.0003***)
Consumer goods	iShares Dow Jones US. Consumer Goods Sector Index Fund	IYK	(3,3)	(3,2)	0.8039	F_1=0.3687(0.0019***)
	P_1					F_2=-0.0037(0.0159**)
	P_2					F_3=-0.0042(0.0049***)
	P_3					F_4=-0.0040(0.0182**)
	P_4					r=-0.4501(0.0000***)

5. Conclusions

The empirical results present several findings. First, the ARFIMA model illustrates that the significant results of PBS, IYC, PBJ, and IYK have a long memory. The consumer ETF returns in the media, consumer service, food and beverage, and consumer goods industries can be predicted. The investors can notice the investment performance and become aware of the market condition changes, especially for consumer activities. Second, the ARFIMA-FIGARCH results reveal that only gaming and consumer goods industries have long memory in volatility for Consumer ETFs. Both industries can be accurately predicted. Third, similar to Malik (2003) and Covarrubias et al. (2006), using the ICSS method, the present study notes that most of the variables have structural breaks, which are connected to similar changes in different industries. For instance, the SARS issue in April 2003 affected the consumer service and consumer goods industries. On July 22, 2008, the media and consumer goods industries had similar breaks possibly caused by the salmonella strain. On June 1, 2009, the retail, gaming, consumer service, and leisure and entertainment industries had equal breaks. Air France 447, a scheduled passenger flight from Brazil to France, crashed on the same date. This accident directly influenced these consumer industries. On December 20, 2011, the payroll tax issue influenced retail, gaming, media, food and beverage and consumer service industries. These examples indicate that changes in circumstances can include disease and economic and political issues that have an effect on consumer industries. Similarly, Lanouar and Dominique (2011) discovered that the breaks date coincides with a number of economic and financial events.

The structural breaks in Consumer ETFs, which are caused by strong asymmetrical effects, indicate that all of the consumer ETF industries are generally unstable. Therefore, investors must be sensitive to volatile shocks related to news and political and economic issues. The implications of this research can help investors and practitioners have more confidence in predicting the gaming and consumer goods industries. For scholars, this research enriches the theory, especially in the financial market. For governments and policymakers, maintaining peaceful political circumstances play a major role in obtaining a remarkable improvement in the financial market.

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