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Does the ETF Market Overreact in the United States?

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Abstract

This paper aims to investigate the dynamic correlation of liquidities between the ETF market and the stock market in the United States. To accurately capture the characteristics of liquidity distribution and to effectively enhance the reliability of an empirical analysis, this paper adopts the DCC-GARCH Model with normal- and heavy-tailed distribution proposed by Politis [16] to examine whether there is an overreaction to market information in the ETF market. Empirical results show that the liquidities in the two markets exhibit leptokurtic and fat-tailed features and clusters of volatilities. It clearly indicates that a fat-tailed distribution for measuring the residual pattern of the two market liquidities is more suitable and more efficient than a normal distribution. In addition, the correlation coefficients of the two markets also present time-varying characteristics. In particular, a high correlation of the two markets is found in a period of financial crisis, which indicates that ETFs provide a substitute for investment allocation. Conversely, the correlation decreases when there is a financial bull market and the monetary environment is tight, which indicates that the ETF market does not effectively respond to the underlying asset. Our results also suggest that the ETF market information flow is inconsistent with the stock market.

Keywords: Dynamic correlation, liquidity, financial crisis, monetary environment.

1. Introduction

As the globalization of financial markets has accelerated capital flows among different countries, it has improved the links between international capital markets and information transmission. Although such a conditional market has improved the benefits of investment portfolio diversification, it has also increased the difficulty of asset allocation in investments. To effectively reduce investment risk and to enhance investment performance, market investors must be more attuned to the reciprocal effects between different financial markets. In the past decade, major shocks to international financial markets, such as the 2010 European debt crisis, the 2011 Fukushima nuclear incident, and the oil price slump that began in June 2014, caused market investors to suffer serious investment losses. Additionally, for market investors concerned with how to allocate assets and avoid investment risk, the Volatility Index (VIX) as a measurement tool to assess the stock market's expectations for the future may be a good indicator to facilitate investment strategy decisions.

The VIX is one of the most recognized measures of volatility around the world, and is widely used as a daily market indicator to follow a variety of market participants. According to historical data from the Chicago Board Options Exchange (CBOE) for the 2009-2010 European debt crisis, the VIX reached a maximum of 57.36, a minimum of 15.23, and a volatility of 276.62% due to the after-effects of uncertainty in the capital markets. In addition, after the 2011 Fukushima nuclear incident, the global stock markets experienced a crash and quickly dropped more than 3.5%. At the same time, the VIX dropped by as much as 236.37%. Similarly, the 2014 tumble in oil prices and the 2015 Chinese stock market disaster also produced significant VIX volatilities. Consequently, these shocks to the international financial markets led market investors to change their investment portfolios in order to decrease market risk exposures.

Since 2008, the market capitalization of ETF commodities has increased about five-fold and assets have reached a value of four trillion US dollars, accounting for approximately 25% of U.S. stock market transactions. The world's first tiered ETF was the SPDR issued by State Street Asset Management. It tracks the US S&P 500 Index and was formally listed on the New York Stock Exchange in 1993. It opened the door to the global indexed investment that investors are familiar with. In addition, ETF commodities also formally jumped into different asset types such as bonds, currencies, and precious metals. Historical statistics show that the Asian ETF markets have grown at an average annual rate of 26% over the past five years. The growth rate is even higher than that of the United States and Europe. After the 2008 financial crisis, the indexed investment industry moved into the mainstream of global investment. As of the end of 2016, there are more than 900 listed ETF commodities in Asia and the market capitalization has reached 290 billion US dollars. It has become one of the main assets for enhancing investment portfolio efficiency.

Therefore, most of the literature has been devoted to analysing the behaviour of ETF market returns, to capture the tracking errors between the ETF and the underlying asset, and to measuring the hedging function. Rompotis [17] argued that ETF performance can be predicted in a way such that when the stock prices fell and the volatility of stock returns increased, it revealed the bilateral spillover effect of return volatilities between leveraged ETFs and the benchmark index. In addition, Trainor and Gregory [20] also found that options for non-leveraged ETFs or related indices can replace leveraged ETF options. Although previous studies provide different assessments of return patterns, in view of the impact of the existing literature on major events in the market, changes in the role of ETF commodities still need to be covered by ignoring the existence of alternative or complementary products between ETF commodities and tracking assets under different monetary environments. Accordingly, this study attempts to adopt the DCC-GACRH model to capture the dynamic correlation between the two markets. It also considers the heavy-tailed distribution proposed by Politis [16] to correct the GARCH error distribution for empirical analysis to improve the estimation results, which can improve the reliability and the fitness of estimated results. Moreover, this study also controls the relevant variables, including market liquidities, trading volume, interest risk premium and investor sentiment.

This paper is organized in six sections. Section 1 is the introduction, which describes the development of ETF markets and the research purposes and motivations for this paper. In Section 2, we review the relevant literature and build a theoretical framework. Section 3 presents the definitions of key variables and the empirical methodology, followed by the presentation of data sources and basic statistics in Section 4. Section 5 contains a discussion of the empirical results. Lastly, the conclusions are summarized in the closing section.

2. Literature Review

2.1. The relationship between market sentiment and financial market

In the existing literature, market investors usually demonstrate irrational expectations when financial markets transmit new information. Boscaljon and Clark [4] found that investor sentiment was changed by the VIX. The selection between gold ETFs and stocks during the financial crisis would change after considering rates of change in the VIX of 10%, 25%, and 50%. Similarly, Tseng and Lee [11] further analysed the effect of investor sentiment on ETF liquidities in Asian ETF markets. Their results found that variations in market sentiment regarding ETF liquidities play an important role. The volatility-clustering effect exists in the ETF market. In addition, Gilbert, Dongmin and Wu [12] used the Fama-MacBeth cross-sectional regression to investigate whether there are extreme returns in the Chinese stock market. The results show that extreme returns and idiosyncratic volatility was reversed. This implies that market investors may demonstrate under- and over-reactions to new information, thereby changing the relationship between ETFs and stocks. The idea is still not fully understood.

Considering that VIX behaviour can effectively measure variations in market sentiment, Kownatzki [14] argued that the VIX does not provide any meaningful information. It routinely presents over-estimates of actual volatility in normal times and under-estimates during the times of crisis. Similarly, Wu, Pan, and Tai [22] show that the stock market is not efficient using a panel smooth transition autoregressive model. The persistence effects are nonlinear and vary with time and across countries. There are spillover effects from the VIX to stocks. In addition, Yue [23] found that there is negative return premium on VIX futures and VIX exchange-traded products (ETP). It was found that the increase in endogenous volatility will cause the stock price to fall. From the perspective of traditional finance, market investors will require more risk premiums when market risk increases. Similarly, Shaikh and Padhi [16] further investigated the correlation between the VIX and the stock market. The empirical results show that the volatility of the VIX in Asian market will be greater than the impact of positive returns. That is, when a market panic happens, market expectations will make stock prices change more drastically, much larger than when the stock price rises. There is a strong information asymmetry between the VIX and the stock market. Consequently, as concluded by previous studies, they are consistent in supporting market inefficiency.

2.2. Capital market and market condition

On the other hand, some studies such as those by Wang, Tsai and Lu [21] and Eaqueda, Luo, and Jackson [7], argued that there is a positive effect of the VIX on the stock market and ADRs. Observing VIX variations in order to adjust investment portfolios can improve the hedging effect and increase investment returns. A previous study by Bittman [3] also reached the same conclusion that VIX futures can be used to hedge stock market risk. This study's results indicated that the VIX can be used to measure fluctuations in asset prices. Given the relevancy of the above, the return patterns of both ETFs and stocks may demonstrate discrepancies when market conditions change. In other words, a dynamic correlation between the two markets should be expected.

Furthermore, to understand whether there is interaction between the stock market and the macroeconomic environment, Chevapatrakul [6] used the stock returns and interest rates of 30 countries to investigate the impact of international monetary policy environments on stock returns. The results of the quantile regression suggest that higher returns are associated with an expansionary monetary policy. Bhattacharya and OHara [2] demonstrated that ETFs have altered the market efficiency of underlying markets and have accelerated information transmission. Particularly, ETFs also cause a herding effect, driving speculators to trade across markets and resulting in the distortion of individual asset prices. Interestingly, these results clearly state that the relationship between ETFs and underlying assets is one of dislocation; in other words, a substitution or complementary effect. It is important to clarify their characteristics in ETFs and stocks. As previously mentioned, ETFs may suffer from the under- and over-reactions of market investors.

In addition, because of noise traders and market inefficiency, many researchers in recent years have discussed in depth. For example, Tokic [19] explores the question of whether the market manipulation strategy of market spoofing (a 'cancel if close to market' order) is capable of causing a highly volatile event such as the 2010 Flash Crash. The results show that this type of market manipulation can enhance market efficiency under normal market conditions, but when the market is under stress and in a condition of illiquidity, this market manipulation strategy may cause a significant stock market crash. Therefore, considering that market volatility depends on different market conditions and market trading strategies, the correlation between ETFs and stocks under different monetary environments may change. Moreover, Hu, Chang, and Chou [13] investigated whether market conditions moderate the relationship between diversification and mutual fund performance. Their empirical results show that the benefit of diversification increases within down-market conditions. This study points out that a well-diversified portfolio depends on different market conditions. A similar conclusion can also be reached regarding other market activities. Ooi and Liow [15] argued that real estate stock yields are subject to market interest rates and market conditions. Bougatef and Chichti [5] provided evidence of that market timing theory. These authors found that managers tend to issue debt when interest rate are low and reduce debt issuance when equity market conditions are more favourable. tTherefore, the financial or investment decisions depend on market timing considerations. Alexakis, Alexakis and Xanthakis [1] use intraday data to investigate the relationship between stock prices and trading volumes in bull and bear markets. Research suggests that investors will change their trading strategies based on whether the stock market is up or down. In particular, Jansen and Tsai [9] examine asymmetries in the impact of monetary policy surprises on stock returns between bull and bear markets. The authors noted that the impact of a monetary policy surprise is significantly greater for a bear market than for a bull market. Therefore, this study infers that the diversified benefits of ETFs against underlying assets may be affected by different markets, which is further considered by our analysis.

3. Variables Definition and Empirical Models

3.1. Variables definitions

3.1.1. The change rate in ETF, Stock and VIX ($SR, ETFR, VIXR$)

In the calculation of market returns of stock, ETF, and VIX, this study use differentials of natural logarithm of daily closing price to measure for each index's rate of change, it is as follows

$$R_t = \log\Big(\frac{Closing\_Price_t}{Closing\_Price_{t-1}}\Big). \tag{3.1}$$

In equation (3.1), the R_t is denoted as SR_t, $ETFR_t$, and $VIXR_t$. It presents the return rate of stock market, ETF market and VIX at t time, respectively. The $Closing\_Price_t$ is the daily closing price of stock, ETF, and VIX at t time.

3.1.2. Liquidity ($ETFliq, Stockliq$)

This study calculates the market liquidity using the method of Karolyi, Lee and Van Dijk [10]. It is as follows:

$$Stockliq_t = (-1) \times \log\Big(1 + \frac{|SR_t|}{Stock\_Volume_t}\Big) \times 10^6 \tag{3.2}$$

$$ETFliq_t = (-1) \times \log\Big(1 + \frac{|ETFR_t|}{ETF\_Volume_t}\Big) \times 10^6 \tag{3.3}$$

In equation (3.2) and (3.3), $Stockliq_t$ and $ETFliq_t$ denote the liquidities of stock market and ETF market on t day. In addition, $Stock\_Volume_t$ and ETF_Volume_t present trading volume of stock market and ETF market, respectively.

3.1.3. Trading volume and interest rate spread ($ETFVol, StockVol, Spread$)

To isolate the effects of trading volume and bond market, this study further consider the natural logarithm of trading volume of stock market and ETF market and spread of interest rate of long term and short term government bond. It is as follows

$$StockVol_t = \log(Stock\_Volume_t) \tag{3.4}$$

$$ETFVol_t = \log(ETF\_Volume_t) \tag{3.5}$$

$$Spread_t = TB10Y_t - TB3M_t \tag{3.6}$$

In equation (3.4) to (3.6), the signals $StockVol_t$ and $ETFVol_t$ present the natural log value of stock market and ETF market at t time, respectively. In addition, the $Stock\_Volume_t$ and ETF_Volume_t are the trading volume of two markets. Finally, $Spread_t$ presents the spread of interest rate of long term and short term government bond at t time, which is calculated by the difference of ten years ($TB10Y_t$) and three months ($TB3M_t$) government bond.

3.2. Market condition

According to the conclusions of previous literatures as Jansen and Tsai [9] and Hu, Chang, and Chou [12], the market condition affects the behaviors of market returns. In order to distinguish of dynamic correlation of stock market and ETF market in different market conditions, this study separates the periods of expansion and tightness of international monetary environment. The past literature has largely documented changes in stock market returns under different market conditions.

3.3. Model specification

3.2.1. Dynamic conditional correlation GARCH model (DCC-GARCH Model)

The main difference between DCC-GARCH model and CCC-GARCH (Constant Conditional Correlation GARCH model) model is DCC-GARCH model assumes the variances of asset rate of return - covariance matrix as $D_t R_t D_t$, among them

$$R_t = \operatorname{diag}\{Q_t\}^{-1/2} Q_t \operatorname{diag}\{Q_t\}^{-1/2}, \quad \text{and} \quad D_t = \operatorname{diag}\{H_t\}^{1/2} = \begin{bmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{bmatrix},$$

and $\sigma_{1,t}$ estimate value is the estimate square root of GARCH. The Qt in formula $R_t = \operatorname{diag}\{Q_t\}^{-1/2} Q_t \operatorname{diag}\{Q_t\}^{-1/2}$ is to use the standardized residual $Z_t = D_t^{-1} * \varepsilon_t$ with GARCH model is conditional variances covariance matrix. In addition, Q_t is as follows:

$$Q_t = S_0(ii' - A - B) + AoZ_{t-1}Z'_{t-1} + BQ_{t-1}. \tag{3.7}$$

At the function, A and B are parameter, i represent one vector, S is standardized residual unconditional covariance matrix, the math symbol $(\cdot)$ is the Hadamard matrix product formula. Thus, the maximum likelihood estimate function can be expressed as:

$$L = -\frac{1}{2} \sum_{t=1}^{T} (n \ln(2\pi) + 2 \ln |D_t| + \ln |R_t| + z'_t R_t^{-1} \hat{z}_t). \tag{3.8}$$

In addition, θ is the parameter of D_t, ϕ is the R_t parameter, simliar to likelihood function and can be break down into volatility and correlation coefficient two parts, as shown below:

$$L(\theta, \phi) = L_{vol}(\theta) + L_{corr}(\theta, \phi). \tag{3.9}$$

The likelihood function of volatility as:

$$L_{vol}(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t|^2 + \varepsilon_t' D_t^{-2}\varepsilon_t). \tag{3.10}$$

According to Engle [8], the likelihood function of volatility can be written as the sum of individual GARCH model likelihood function, and to solve the parameter of volatility, can be derived from maximum likelihood function of GARCH model, so it can be rewritten as:

$$L_{vol}(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n}\Big(\log(2\pi) + \log(\sigma_{i,t}) + \frac{\varepsilon_{i,t}^2}{\sigma_{i,t}}\Big). \tag{3.11}$$

The likelihood function of correlation coefficient as:

$$L_c(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(\log|R_t| + Z_t' R_t^{-1} Z_t - Z_t' Z_t). \tag{3.12}$$

Because the volatility of some parameter some parameters of correlation coefficient is independent of each other, it can be estimated using two state estimation method, first to estimate volatility of some parameters as follow:

$$\hat{\theta} = \arg\max\{L_v(\theta)\}. \tag{3.13}$$

Under the known θ to estimate ϕ as below:

$$\hat{\phi} = \arg\max_{\phi}\{L_c(\hat{\theta}, \phi)\}. \tag{3.14}$$

After introducing the above DCC-GARCH model, the first step will estimate the conditional variance of two market returns. It can be presented as below equations

$$\begin{aligned}
SR_t &= Constant_s + a_1 Stockliq_{t-1} + a_2 VIXR_{t-1} + a_3 StockVol_{t-1} \\
&\quad + a_4 \Delta Spread_{t-1} + \sum_{i=0}^{1}\varepsilon_{st-i} \\
h_{st} &= \omega_s + \alpha_s \varepsilon_{st-1}^2 + \beta_s h_{st-1} &(3.15)\\
ETFR_t &= Constant_{etf} + a_1 ETFliq_{t-1} + a_2 VIXR_{t-1} + a_3 ETFVol_{t-1} \\
&\quad + a_4 \Delta Spread_{t-1} + \sum_{i=0}^{2}\varepsilon_{etft-i} \\
h_{etft} &= \omega_{etf} + \alpha_{etf}\varepsilon_{etft-1}^2 + \beta_{etf} h_{etft-1}. &(3.16)
\end{aligned}$$

In addition, this study further adopts the GARCH error distribution proposed by Politis [16] to test the GARCH model to match assumptions more appropriately. The modified error distribution can effectively describe the traits of High Kurtosis and Heavy tail. The error obeys the probability density function as shown in equation (3.7) shown below:

$$f(u;a_0,1) = \frac{(1+a_0u^2)^{-3/2}\exp\Big\{-\frac{u^2}{2(1+a_0u^2)}\Big\}}{\sqrt{2\pi}\Big(\phi(\sqrt{\frac{1}{a_0}}-\phi\Big(-\frac{1}{a_0}\Big)\Big)}, \qquad \text{and } u \in R. \tag{3.17}$$

Where $f(u;a_0,1)$ in equation (3.17) represents the Standard deviation it has a value of 1, and f is the probability density function of a standard normal distribution. When the value shape parameter increases, the heavy tail degree will be bigger. Then the model will become the GARCH-HT model. Using BFGS Algorithm to maximize its Logarithmic Likelihood Function to obtain the a_0.

4. DATA

The main purpose of this study is to investigate whether the stock and ETF markets have a dynamic correlation type of variation, namely, alternative and complementary changes due to differences in market conditions. To further capture the actual behaviours between the two markets, investor sentiment is measured by the VIX change rate. In addition, based on the research hypothesis of this study, the sample period from October 19, 2002 to September 27, 2017 is divided into three sub-sample intervals. This was done so that the analysis could align with periods of U.S. monetary policy expansion and tightness. These break points included the 2008 financial crisis , the U.S. Federal Quantitative Policy that started in 2009, and the federal funds rate increase of December 15, 2016. Combined, all of the sample years total 15 years.

In addition, relevant information and data sources were taken from Bloomberg, Yahoo Finance, and the Taiwan Economic Journal (TEJ). The relevant variables include daily closings of the iShares SPY and S&P 500 indices. Daily closing price and total transaction volume are also considered to have a significant impact on the movements of dynamic correlation between stock and ETF markets. Moreover, both long- and short-term interest rates are mainly influencing factors affecting the asset allocation of market participants. If the effects of interest rate spread are ignored, the credibility of the fitting results will decrease. Therefore, our empirical model considers the difference in interest rates between ten-year and one-year government bonds as a proxy for the bond market risk premium.

Empirical data is segmented based on several criteria. First, all the variable data must be in the sample period and both markets must have complete transaction information. If the data is unreasonable or missing information, it will be excluded. Second, when the market date falls on a national holiday or weekend, it is also deleted from our sample. Finally, when there is a lack of human records in the database system, the two markets will be paired in order to reach the same sample period. In addition to the above criteria and the work of merged data collection, the actual transaction dates for the model estimation are the daily frequencies. Furthermore, as proxies for the key variables of the returns and trading volumes of both markets (and referring to practices described in the existing literature), this study assumes that when trading volume and market liquidity increases, which will help improve liquidity and information transfer efficiency, especially in a period of monetary expansion. Thus, investors will tend to invest in stocks rather than in ETFs.

5. Empirical Results

Table 1 presents the basic statistical characteristics of the two markets. First, the mean and standard deviations in the stock and ETF markets are $(0.0002, 0.0114)$ and $(0.0002, 0.0113)$, respectively, revealing no significant difference between the two. The preliminary results imply that the two products have similar trends. This result also supports the research hypothesis of this study that the two commodities have a substitution effect. When the investor wants to invest in the stock market, the ETF commodity can be used as another investment channel of the stock market. In addition, for the liquidity index, there is no significant difference between the average and volatility of liquidities in stock market and ETF market $(-0.0344, 0.0385)$ and $(-0.0342, 0.0379)$. When the maximum value is 0, it means that market liquidity is optimized. A smaller value indicates that the market is less liquid.

According to the basic statistics obtained, there is no significant difference between two markets. Generally, ETF commodities are passive management funds. They intend to track the tendencies of the broader market. Therefore, ETFs can be used as alternative commodities for investing in the stock market. However, they may be used as substitutes for major events or changes in market conditions. The nature of the commodity is likely to change. Unfortunately, the existing literature does not include an in-depth study of this, so a follow-up study will look to detect changes in the correlation between the two markets and whether there are significant changes during the sample period. By observing the VIX change rate, great fluctuations can be seen during the sample period. The maximum value is as high as 49.6%, and the minimum value is -35.05%, showing that investors have a high levels of optimism and pessimism during the sample period. In terms of public interest rate spreads, the sample period included the Fed's implementation of quantitative easing policies and the increase of the federal funds rate. One of the principle objectives of this research is to determine whether capital flows will affect substitution between the stock and ETF markets.

For the purposes of this study, the DCC-GARCH estimation model was adopted to capture the dynamic correlation between the two markets. At the same time, considering the improvement in the fitness of the empirical model, this study further revised the assumption of error distribution adopted by Politis [16]. The assumption of error distribution is estimated. Table 2 presents the estimated results of the two models. First, in terms of the mean equation at a 1% significance level, the sentiments of early market investors have a negatively significant relationship with the two market returns and public debt, presenting -0.0492, -0.0507, -0.0430, and -0.0446. The spread variable has a directional correlation of 0.5141, 0.5686, 0.4859, and 0.4599, with at least 5% significance

Table 1: Basic Statistics of Relevant Variables in ETF Market and Stock Market

Variables	mean	std.	Min.	Max.	skew	kurtorsis	JB	$Q(5)$	$Q(5)^2$
SR	0.0002	0.0114	-0.0935	0.1024	-0.4543***	8.9428***	12372***	23.1870***	1277.5230***
$ETFR$	0.0002	0.0113	-0.0927	0.1105	-0.3935***	9.2057***	13071***	24.5660***	1337.9810***
$Stockliq$	-0.0344	0.0385	-0.4506	0.0000	-3.0872***	16.6803***	48442***	583.1500***	574.0430***
$ETFliq$	-0.0342	0.0379	-0.4860	0.0000	-3.1149***	17.6379***	53579***	558.3740***	623.5670***
$VIXR$	-0.0003	0.0687	-0.3505	0.4960	0.7590***	4.5834***	3569***	36.5250***	297.2610***
$StockVol$	18.4733	0.7019	15.9019	20.5851	0.0574	-0.4499***	33***	381.2180***	60.1920***
$ETFVol$	21.8381	0.4657	19.6906	23.1618	-0.5522***	0.0011	186***	315.7400***	458.6240***
$\Delta Spread$	-0.0000	0.0005	-0.0042	0.0030	-0.1305	4.8530	3616***	7.5630	404.2070***

Notes: *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. The kurtorsis is excess kurtorsis. JB-statistics is normal distribution test of Jarque-Bera. $Q(5)$ and $Q(5)^2$ denote Ljung-Box test for serial correlation in the standardized residuals and squared standardized residuals with n lags.

levels. This result proves that a market panic will cause investors to reduce their willingness to invest. In addition, when the bond market defaults, an extra risk premium may be required for stocks and ETFs, resulting in an acceleration of capital flows and pushing up the prices of stocks and ETFs. In terms of model fitness, at a 1% significant level, both markets are characterized by a volatility-clustering phenomenon and they are close to unity. These results confirm that the DCC-GARCH model can effectively capture market fluctuations. Furthermore, for the dynamic correlation coefficient between stocks and ETFs, the parameters (θ_1, θ_2) present statistically significant results in a 1% level. If the representative model is estimated using the fixed correlation coefficient model as the main model, it will result in biased results and analysis errors. Moreover, with the revised error distribution introduced in this study, the fat-tailed coefficient values (A) are 0.0896 and 0.0875. This is evidence that an assumption of normal distribution will underestimate the tailed risk and result in an incorrect estimation. Our results were also obtained through a likelihood ratio (LR) test.

Finally, the study illustrates the dynamic correlation of the two markets in Figure 1. During periods of financial crisis, quantitative easing, and increases in the federal funds rate, we can see a dramatic change in the correlation between the two markets. When a market panic happens, and federal funds rates rise, there is a low positive correlation. One possible explanation is that market investors tend to transfer their funds to hedge against stock market volatility and to invest in ETF markets as passive investments. Therefore, ETFs provide a complementary advantage. In addition, when the market is in a period of monetary expansion, the high correlation indicates that ETFs will play a substitute commodity role. These results further support arguments of this research. The stock and ETF markets have substitute and complementary interaction characteristics, but changes in the nature of ETFs necessarily depend on different market conditions.

Table 2. Estimated Results from DCC-GARCH model with different distributions.

	DCC-GARCH(1,1)-N		DCC-GARCH(1.1)-HT	
	Coeff. (Std. error)	Coeff. (Std. error)	Coeff. (Std. error)	Coeff. (Std. error)
PANEL-A: Mean Equations				
$constant_s$	0.0004*** (0.0005)		0.00003 (0.0004)	
$constant_{etf}$		0.0009*** (0.0000)		0.0003 (0.0000)
$Stockliq_{t-1}$	0.9934*** (0.0021)		0.9921*** (0.0020)	
$ETFliq_{t-1}$		0.9919*** (0.0005)		0.9909*** (0.0004)
$VIXR_{t-1}$	-0.0492*** (0.0029)	-0.0507*** (0.0029)	-0.0430*** (0.0025)	-0.0446*** (0.0026)
$StockVol_{t-1}$	-0.0000 (0.0000)		-0.0000 (0.0000)	
$ETFVol_{t-1}$		-0.0000*** (0.0000)		-0.0000 (0.0000)
$\Delta Spread_{t-1}$	0.5141** (0.2377)	0.5686** (0.2349)	0.4859*** (0.1789)	0.4599** (0.2018)
$e_{s,t-1}$	-1.0580*** (0.0152)		-1.0583*** (0.0155)	
$e_{s,t-2}$	0.0902*** (0.0150)		0.0908*** (0.0147)	
$e_{etf,t-1}$		-1.0394*** (0.0043)		-1.0293 (0.0031)
$e_{etf,t-2}$		0.0784*** (0.0043)		0.0646 (0.0031)
PANEL-B: Conditional Variances Equations				
ω_s	0.0000*** (0.0000)		0.0000*** (0.0000)	0.0000* (0.0000)
ω_{etf}		0.0000*** (0.0000)		
α_s	0.0801*** (0.0102)		0.0428*** (0.0059)	
α_{etf}		0.0865*** (0.0112)		0.0456*** (0.0126)
β_s	0.8982*** (0.0127)		0.9300*** (0.0091)	
β_{etf}		0.8325*** (0.0135)		0.8886*** (0.0295)

PANEL-C: Fat-Tailed Coefficient and Conditional Correlation Equations				
A			0.0896***	0.0875***
			(0.0070)	(0.0067)
θ_1	0.0069***		0.0062***	
	(0.0006)		(0.0006)	
θ_2	0.9922***		0.9919***	
	(0.0007)		(0.0009)	
PANEL-D:Model adaptability				
LR-test-stock		325.9552***		
LR-test-etf		332.6740***		
Function Value	8103.5054	8123.2723	8266.4813	8289.6093
$Q(5)$	1.0830	1.1010	0.8120	0.6240
$Q^2(5)$	3.5330	2.4930	4.4410	2.8800

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. $Q(n)$ and $Q^2(n)$ denote Ljung-Box test for serial correlation in the standardized residuals and squared standardized residuals with n lags. LR is likelihood ratio test which is K degrees of freedom of chi-square and $K = LL(\theta_1) - LL(\theta_0)$.

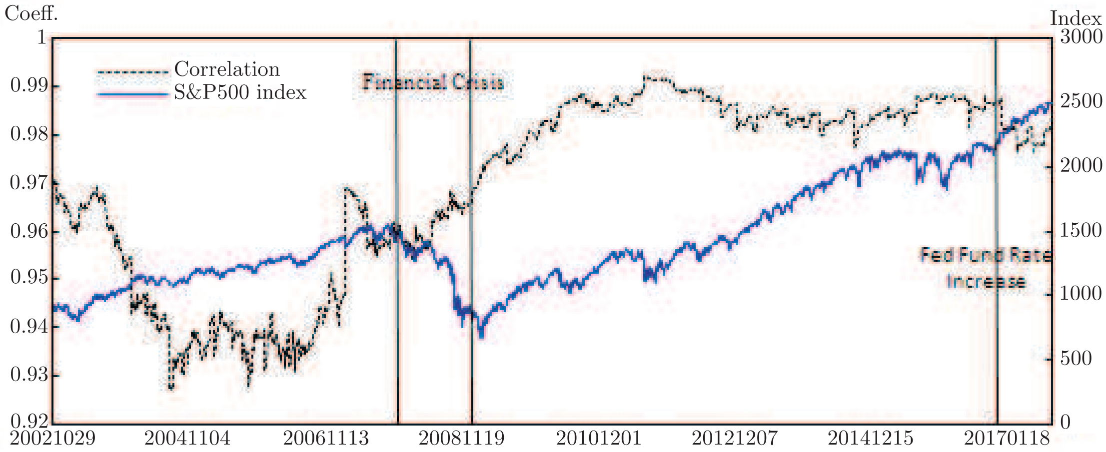

Figure 1: Dynamic Behaviors of Liquidities of Stock Market and ETF Market.

6. Conclusions

The main purpose of this study is to use the DCC-GARCH model to evaluate the dynamic relationship between the stock and ETF markets under different market conditions. We also consider whether market investor sentiment has a significant effect on the two markets. The sample period is October 19, 2002 to September 27, 2017. In addition, this study adopted the error distribution with fat-tailed characteristics proposed by Politis [16] to correct the assumption of normal distribution. Empirical results show that when a market crisis happens and when the monetary environment is in a period of tightness, the nature of ETF commodities will change. A low correlation between the two markets can then be seen. Therefore, this implies that investors will tend to reduce their willingness to invest in the stock market or to accelerate capital flows, which results in an increase in ETF investment. The ETFs have the advantage of hedging market risk. In addition, a highly dynamic correlation is seen during periods of quantitative easing of monetary policy. In other words, optimistic expectations for the future of the economy and international funds flows will drive up both markets. Consequently, ETFs function as substitutes. Our results can provide market investors with a good understanding of investment portfolios and can fill the gaps in the existing literature regarding ETF market characteristics.

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