Empirical analysis of short-term and long-term volatility of SSE 50 ETF—— based on the ARMA-GARCH Model

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Abstract: This paper studies the volatility of short-term and long-term return of SSE 50ETF option after listing. By analyzing the daily closing price of SSE from February 9, 2012 to February 9, 2021, it is found that it is consistent with GARCH model. Then, the two interval return volatility is modeled by arma-garch model, and the long-term and short-term return volatility is compared by Monte Carlo simulation. It is found that after the listing of SSE 50 ETF options, the volatility increases compared with that before the listing, and the short-term return volatility is greater than the long-term volatility.

1. Introduction

It can be observed that the launch of new financial products is often accompanied by the sharp rise and fall of the market, and often brings severe fluctuations to the market due to imperfect product design, irrational investors and lack of regulatory experience, such as the 327 treasury bond futures event in the 1990s. After the launch of stock index futures, there has also been a sharp decline in the spot market, as well as the sharp rise and fall of the warrant market. Therefore, whether the introduction of financial derivatives will have an impact on the market and whether its function can be effectively played after the introduction is a problem worthy of our study. This paper selects SSE 50 ETF as the research object, which is the subject of the first stock index option launched in China, and studies the fluctuation of its price and yield, which can provide reference value for the launch of stock index futures. Taking February 9, 2015 as the dividing point, this paper explores the price and fluctuation changes of SSE 50 ETF before and after the listing of SSE 50 ETF options, divides its interval since the listing into long-term and short-term intervals, models its mean and variance through arma-garch model respectively, and explores the fluctuation of its long-term and short-term yield series.

2. Literature Review

For the impact of option listing on the underlying asset market, some studies use the event research method to analyze the change of the cumulative excess return of the underlying securities. In 1982, Hakansson found that option listing can increase the cumulative abnormal return of the underlying assets, and have a positive impact on the price of the underlying securities [1]. And some studies are based on the GARCH family models. In 2005, Wu Weiguo used the GARCH model and TGARCH model to study the impact of the listing of SSE 50 ETF options on the volatility of the underlying index. The results show that the listing and trading of options can reduce the volatility of the stock market and have a positive impact on China's stock market [2]. In 2016, Su Zhiwei found that the listing of SSE 50 ETF options can reduce the volatility of the underlying index, but increase the asymmetry of its volatility [3]. Zhang Jing used garh model and TGARCH model to analyze the impact on the liquidity and volatility of the constituent stocks of SSE 50 index when SSE 50 ETF was announced and officially listed [4].

3. Theoretical Models

3.1 ARMA model

ARMA (p,q) model is also called autoregressive moving average model. It is obtained by the combination o autoregressive model AR (p) model and moving average model MA (q) model. The model is often applied to the analysis of stationary time series, such as interest rate fluctuation, yield change and exchange rate change. It is usually a stationary series, or it can become a stationary time series through differential or logarithmic processing. ARMA (p,q) model is as follows:

$$r_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad , \tag{1}$$

Where p and q are the lag orders of AR (p) model and MA (q) model, r_{t-i} is the yield of lag i period, ε_{t-i} is the disturbance direction of lag phase i, ε_t is the mean value is 0 and the variance is σ^2 white noise sequence.

3.2 ARMA-GARCH model

In the actual financial time series, the variance of many time series changes with the change of time. For example, there is often the phenomenon of volatility agglomeration in the return series of assets, so it is necessary to establish a volatility model for its residual series, namely GARCH model. By comprehensively applying ARMA (p,q) model and GARCH (p,q) model, the mean variance model of arma-garch model is as follows:

$$r_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \quad , \tag{2}$$

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad , \tag{3}$$

Where σ_t^2 is the conditional variance, μ_{t-i}^2 is the measurement of volatility information obtained from the previous period, σ_{t-j}^2 is the prediction variance of period t-1.

4. Samples, data and descriptive statistics

SSE 50 ETF is the first trading open-end index fund in China. On February 9, 2015, SSE 50 ETF options were officially listed on Shanghai Stock Exchange.

The price trend of SSE 50 ETF is shown in Figure 1. It can be observed that the price change is divided into three stages: in the first stage, that is, before the listing of SSE 50 ETF option, the price of SSE 50 ETF is between 1.5 and 2. In the second stage, that is, after the listing of SSE 50 ETF, the price fluctuates greatly, first rising sharply and then falling sharply. In the third stage, that is, after February 9, 2016, the price shows an upward trend as a whole, and the decline in 2018, Mainly affected by the Sino US trade war, the stock market fell continuously. At the beginning of 2020, affected by the epidemic, the price fell slightly.

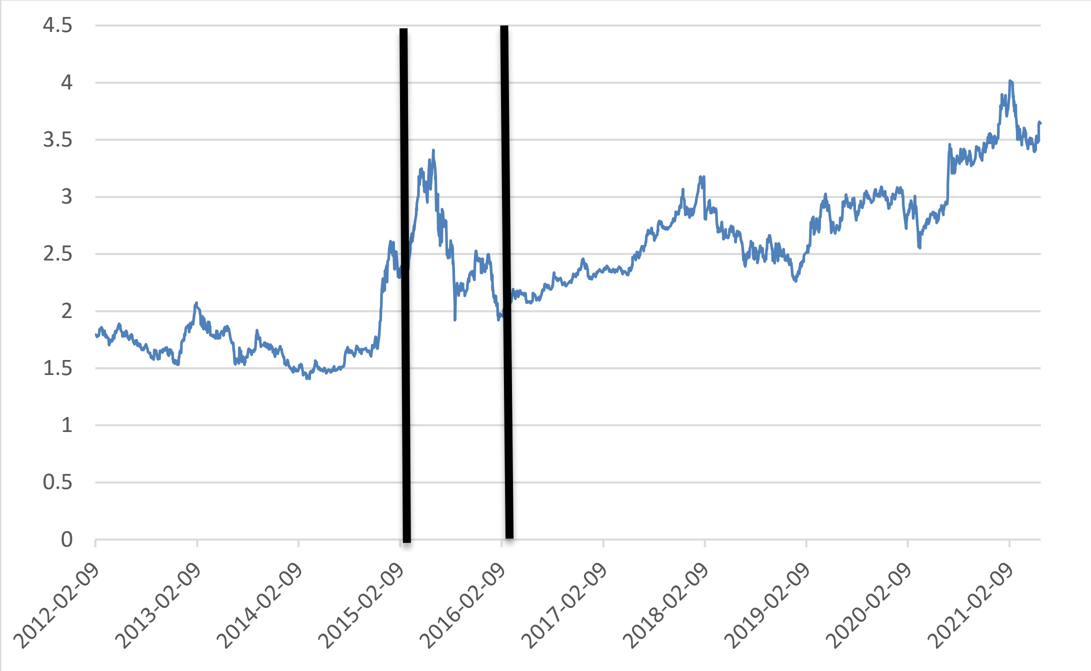

Figure 1. SSE 50 ETF price trend

This paper chooses to divide the sample interval into two stages to study the long-term and short-term fluctuations of SSE 50 ETF return after the listing

Table 1. Sample range and capacity after option listing

	Sample interval	Sample size
Full sample	2012.02.09 – 2021.02.09	2453
Pre marketing: sub sample C0	2012.02.09 – 2015.02.09	736
Short term: subsample C1	2015.02.09 – 2016.02.09	244
Long term: subsample C2	2015.02.09 – 2021.02.09	1473

The logarithmic rate of return method is used to describe the two-stage Shanghai 50 ETF price data, and the logarithmic rate of return is taken as the research object. The calculation formula of daily rate of return is:

$$R(t) = \ln (P_t / P_{t-1}) = \ln (P_t) - \ln (P_{t-1}) \tag{4}$$

Where R(t) is the daily yield of SSE 50 ETF, and P_t and P_{t-1} are the closing prices on day t and t-1 respectively.

See Table 2 for the descriptive statistics of the daily rate of return. It can be seen from table 2 that the average price of SSE 50 ETF is negative before and within one year after the listing of SSE 50 ETF, and the average price of long-term sample interval is positive, indicating that the price of long-term SSE 50 ETF is significantly higher than that before and in the short term; The standard deviation after option listing is greater than that before option listing, and the short-term volatility increases significantly; In addition, the skewness of the short-term interval and the long-term interval is less than 0, and the kurtosis is greater than 3, indicating that the yield series is left biased, with a peak and a tail, and its jb test result is equal to 1, indicating that the long-term and short-term daily yield series before and after listing do not obey the assumption of normal distribution.

Table 2 descriptive statistical results of yield of SSE 50 ETF

Sample	Obs.	Mean	Max	Minimum	Std.	Skewness	Kurtosis	JBtest
C0	736	-0.00035	0.0576	-0.0942	0.0144	0.0148	8.0068	ans=1
C1	244	-0.00062	0.0741	-0.0978	0.0251	-0.6559	5.1391	ans=1
C2	598	0.00037	0.0741	-0.0987	0.0147	-0.7017	9.6649	ans=1

See Figure 2 and figure 3 for the fluctuation of return rate in the two intervals.

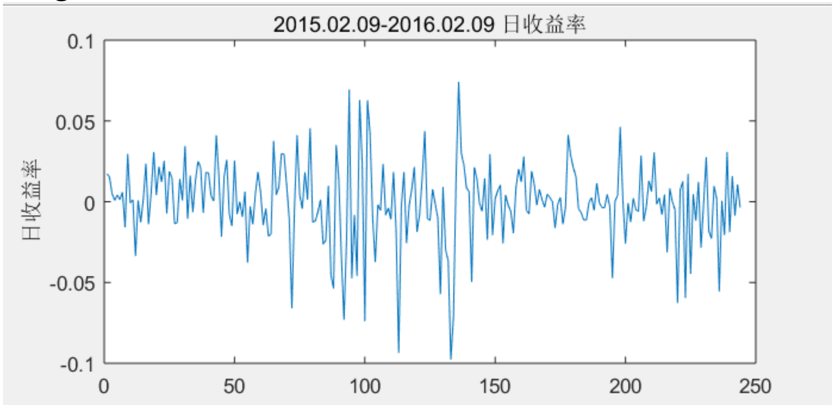

Figure 2. short term daily yield fluctuation

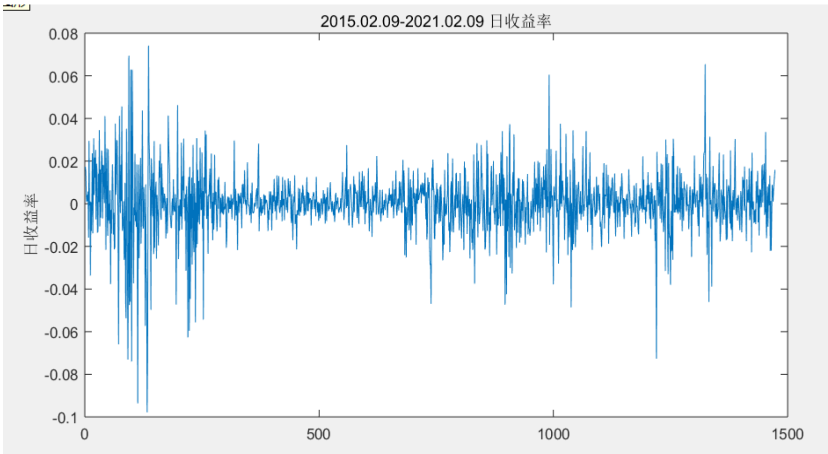

Figure 3. long term yield fluctuation

5. Empirical analysis

5.1 Unit Root Test

The primary premise of time series data modeling is to ensure the stability of data. ADF test method is mainly used to test the stability of return series in short-term interval and long-term interval. In this test, the "ADFtest" function in MATLAB is used to judge whether the return series data is stable. The "ADFtest" function of the two intervals returns "1", indicating that the long-term and short-term yield series are stable.

5.2 Test of the ARCH Effect

Firstly,the mean value model of return series is constructed, by using "autocorr" function and "parcorr" function to determine the time series model and model order.

For the short-term yield series, ARMA (2,4), ARMA (2,2), ARMA (4,2) and ARMA (4,4) models are fitted respectively according to the regression results of ACF and PACF. According to the AIC criterion, the AIC value of ARMA (4,4) model is the smallest, the AIC value is -7.4215, the final prediction error FPE value is 0.0005983 and the mean square error MSE value is 0.0005696. That is, ARMA (4,4) model is finally determined as the mean model of short-term yield series.

For the long-term yield series, ARMA (2,6), ARMA (2,2), ARMA (6,2) and ARMA (6,6) models are fitted respectively according to the regression results of ACF and PACF. According to the AIC criterion, the AIC value of ARMA (6,6) model is the smallest, the AIC value is -8.4698, the final prediction error FPE value is 0.0002097 and the mean square error MSE value is 0.0002063. That is, ARMA (6,6) model is finally determined as the mean model of short-term yield series.

After the mean equation is obtained, the residual sequence of the equation needs to be tested for white noise. If the residual sequence is not white noise, it indicates that there is still useful information in the residual sequence that has not been extracted, and the model needs to be further improved.

Next, the residual sequences of ARMA (4,4) model of short-term yield series and ARMA (6,6) model of long-term yield series are tested by white noise. The arch effect is tested by using the "archtest" function in MATLAB. The output results of short-term time series model and long-term time series model "archtest" are "1", indicating that the residual series of the time series model of the two interval models have arch effect, so it is necessary to further establish GARCH model.

5.3 The Construction of GARCH Model

GARCH (1,1), GARCH (1,2) and GARCH (2,1) models are established for the residual series of ARMA (4,4) of short-term return series. The results show that only GARCH (1,1) model passes the significance test, and the results of GARCH (1,2) and GARCH (2,1) models are not significant. The fitting results of GARCH (1,1) model are shown in Table 3.

Table 3 fitting results of GARCH (1,1) model in short-term interval

Parameter	Value	Standard Error	T Statistic
Constant	4.78028e-05	0.000001	2.24903
GARCH {1}	0.810818	0.0529921	15.3007
ARCH {1}	0.102944	0.0353366	2.91324

As can be seen from table 3, the regression coefficient of short-term arch term is 0.102944, and the regression coefficient of GARCH term is 0.810818. The GARCH term coefficient is relatively large, indicating that the impact of old information on price volatility is relatively long-lasting, and more than 80% of the impact still exists in the next period; The sum of the coefficients of GARCH term and arch term is 0.913762, which satisfies the parameter constraint of less than 1.

GARCH (1,1), GARCH (1,2) and GARCH (2,1) models are also established for the residual series of ARMA (6,6) of long-term yield series. Finally, according to AIC criterion and BIC criterion, the conditional variance model is GARCH (2,1) model. The fitting results of GARCH (2,1) model are shown in Table 4.

Table 4 fitting results of GARCH (2,1) model in long-term interval

	Value	Standard Error	T Statistic
Constant	2.20849e-06	8.85586e-07	2.49381
GARCH {1}	0.422315	0.129018	3.27329
GARCH {2}	0.444473	0.122521	3.62774
ARCH{1}	0.128705	0.0108095	11.9067

It can be seen from table 4 that the sum of GARCH term coefficient is 0.866788, indicating that the impact of more than 80% of the variance in the current period will still have a great impact in the next period. The coefficient sum of GARCH term and arch term is 0.995493, which satisfies the parameter constraint condition less than 1.

Then the "simulate" function in MATLAB is used to simulate the short-term and long-term daily return series respectively, so as to explore the fluctuation of the two intervals. The number of paths in Monte Carlo simulation is 1000. See Fig. 3 for short-term Monte Carlo simulation results and Fig. 4 for long-term Monte Carlo simulation results.

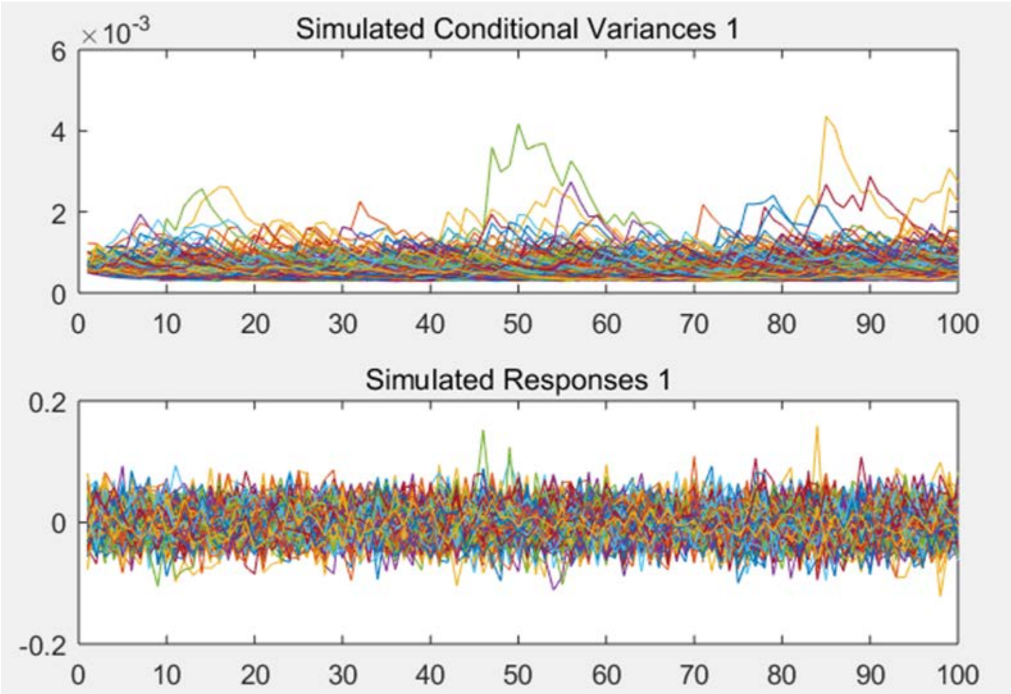

Fig. 3 Monte Carlo simulation results of short-term yield

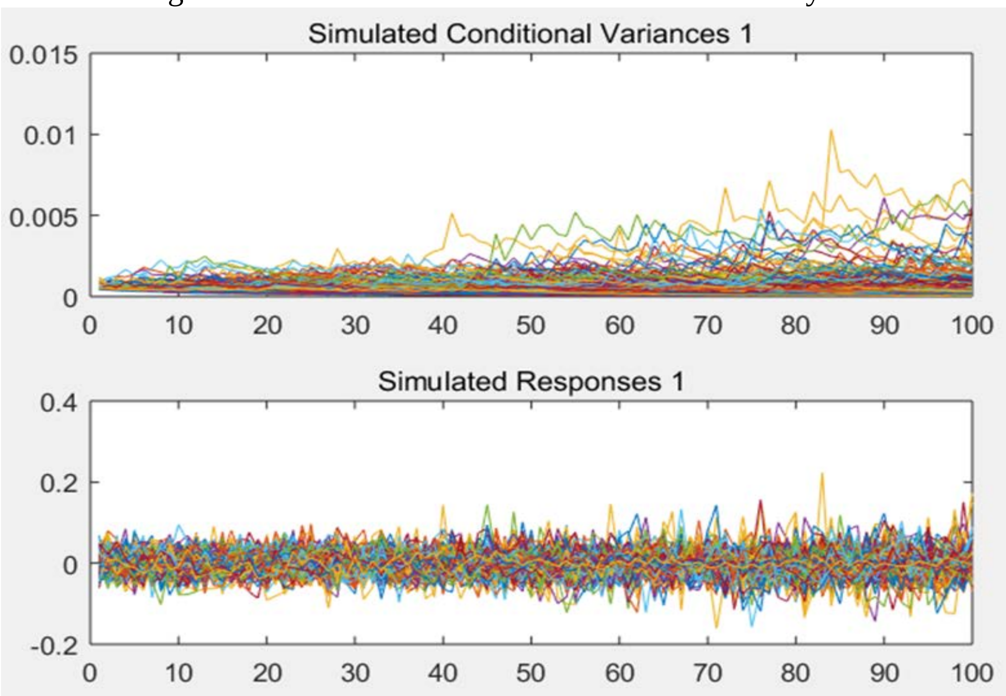

Fig. 4 Monte Carlo simulation results of long-term yield

It can be seen from the Monte Carlo simulation yield results that the long-term volatility is less than the short-term volatility, indicating that after the listing of SSE 50 ETF options, the short-term volatility of SSE 50 ETF market increases, but its long-term volatility decreases.

6. Summary

This paper finds that after the listing of SSE 50 ETF options, the short-term volatility of its underlying securities increases. However, the long-term fluctuation decreases.The results show that the introduction of option products can stabilize the index volatility. China's financial market should constantly enrich the types of financial derivatives, gradually promote the development of option trading platform, establish a multi-level capital market system, provide more options for investors to avoid risks, hedge and other rational trading behaviors, and constantly improve the risk prevention and control mechanism of derivatives, so as to promote the benign and effective development of the financial market.

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