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Impact of CSI 300ETF Options on Spot Target

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Abstract: On December 13, 2019, China officially launched the CSI 300 ETF option, which is the second option product after the listing of SSE 50 ETF option. Its launch further improves the development of China's financial derivatives market. This paper takes the daily closing price data of CSI 300 ETF as the research object one year before and after the listing of CSI 300 ETF options. Through ADF test, ARCH test and GARCH model analysis, it is concluded that CSI 300 ETF options can reduce the volatility of spot underlying yield, but the effect is weak. Based on the positive impact of the listing of CSI 300 ETF options on the spot target, this paper puts forward countermeasures and suggestions from the government, financial institutions and investors, in order to provide guidance for the development of financial derivatives.

1. Theoretical Model Research

1.1. ADF inspection

ADF test (Augmented Dickey Full Test) is the unit root test. It judges the stability of the time series by checking whether there is a unit root in the time series. The standard form of ADF test statistics calculation is: $R_t = \sum_{i-1}^{p-1} \alpha_i \Delta R_{t-i} + \rho R_{t-1} + \varepsilon_t$, the assumption is: $\mathrm{H_0}$: $|\rho| \geq 1$, $\mathrm{H_1}$: $|\rho| < 1$.

1.2. ARCH model

Autoregressive Conditional Heteroscedasticity Model (ARCH model) is used to predict the sequence by establishing conditional variance model. The general process of ARCH (p) model is: $\mathrm{R}_t{}^2 = \alpha_0 + \alpha_1 \mathrm{R}_{t-1}{}^2 + \alpha_2 \mathrm{R}_{t-2}{}^2 + \cdots + \alpha_p \mathrm{R}_{t-p}{}^2$ (R_t is the time series yield)[1].

If there is no autocorrelation in the disturbance term, there will be $\mathrm{H_0}$: $\mathrm{R}_t{}^2 = \alpha_0$, at this time

$\alpha_1 = \alpha_2 = \cdots = \alpha_p = 0$, the disturbance term covariance is obtained. The above virtual assumptions can be tested by residual regression of the original equation: $\mu_t{}^2 = \alpha_0 + \alpha_1\mu_{t-1}{}^2 + \alpha_2\mu_{t-2}{}^2 + \cdots + \alpha_p\mu_{t-p}{}^2(\mu_t)$ is the OLS residual estimated by the original regression model at time t).

Check whether the model has ARCH effect through ARCH-LM. Original assumption H_0 is: there is no ARCH effect in the residual until the q order. Regression is performed by the following equation: $\mu_t{}^2 = \beta_0 + \beta_1\mu_{t-1}{}^2 + \beta_2\mu_{t-2}{}^2 + \cdots + \beta_q\mu_{t-q}{}^2 + \varepsilon_t$, Get F statistic and LM statistic ($T \times R^2$ statistic is the number of observations T multiplied by R^2 of regression test)[2].

1.3. GARCH model

The Generalized Autoregressive Conditional Heteroscedasticity Model, or GARCH model, considers both conditional mean and conditional variance compared with ARCH model.

The mean value equation of GARCH (p, q) model is: $R_t = \alpha + \beta R_{t-1} + \varepsilon_t$. Residual: $\varepsilon_t|\Omega_{t-1} \sim N(0, h_t)$

The conditional variance equation of the model is: $h_t{}^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\mu^2{}_{t-i} + \sum_{j=1}^{p}\delta_j h_{t-j}{}^2$(μ_t is the disturbance term of period $\mu^2{}_{t-i}$ is the fluctuation information obtained from the previous i period measured by the lag of the square of the disturbance term of the mean value equation, that is, the ARCH term. $h_{t-i}{}^2$ is the prediction variance of the previous i period, that is, the GARCH term. p and q are the orders of the autoregressive term and the moving average term, respectively, Ω_{t-1} is the information set of t-1)[3].

In order to make the conditional variance of GARCH (p, q) model have a clear meaning, all coefficients of corresponding ARCH (p) must be positive numbers.

2. Data Selection and Description

2.1. Data Selection

The CSI 300ETF options take Harvest CSI 300ETF as the tracking object. In order to reduce the error, this paper studies the daily closing price of Harvest CSI 300ETF fund data as a sample to discuss the impact of CSI 300ETF options on the spot target[4]. The data are obtained from Yahoo Finance database, and the data are processed through Eviews 10.0. This paper selects the closing price data of Harvest CSI 300ETF for 484 trading days from December 24, 2018 to December 23, 2020 for research, of which December 24, 2018 to December 23, 2019 is the range before the listing of CSI 300ETF options, and December 23, 2019 to December 23, 2020 is the range after the listing of CSI 300ETF options [5].

In this paper, the closing price data of Harvest CSI 300ETF is logarithmized and then processed by difference to reduce the error of time series due to the instability of random walk. A new series definition is established as follows:

$$R_t = lnP_t - lnP_{t-1}$$

Where R_t represents the daily yield of Harvest CSI 300ETF, P_t represents the daily closing price of Harvest CSI 300ETF. This means that the original sample yield data is 1 less than the original sample closing price data[6].

This paper analyzes the yield volatility of Harvest CSI 300ETF before and after the launch of CSI 300ETF options. The yield volatility charts are shown in Figure 1 and Figure 2. According to the interval 1 data in Figure 1, the overall volatility of Harvest CSI 300ETF yield series before the option launch is large, the abnormal volatility is large, and the series distribution is relatively unstable. It can be seen from Figure 2 that the volatility of the yield series is large near the time point of the option listing, but the overall abnormal volatility of the interval 2 series is small and the range of volatility is smaller[7]. As can be seen from Figure 1 and Figure 2, the volatility of the return rate shows aggregation, which will fluctuate greatly in a certain period of time and slightly in a certain period of time.

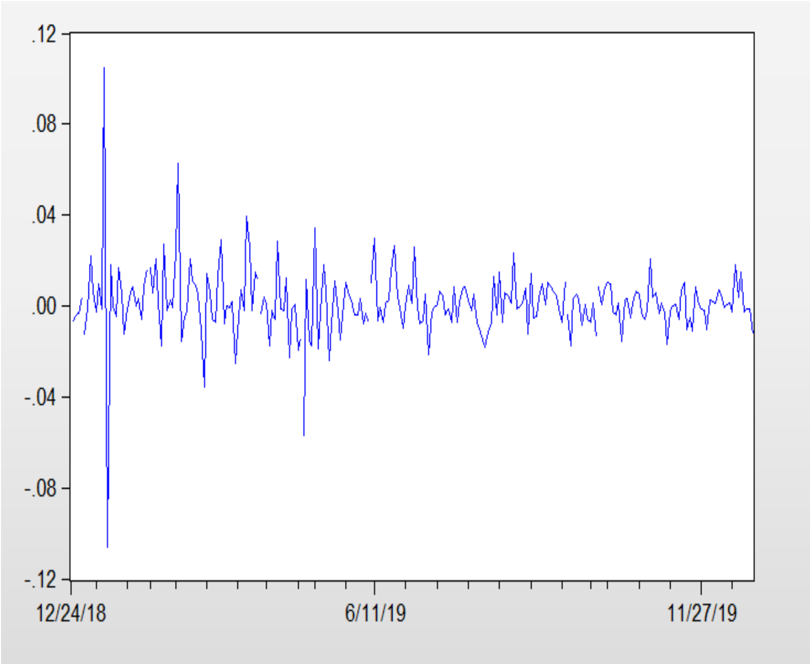


Figure 1. Volatility chart of harvest CSI 300ETF yield in interval 1

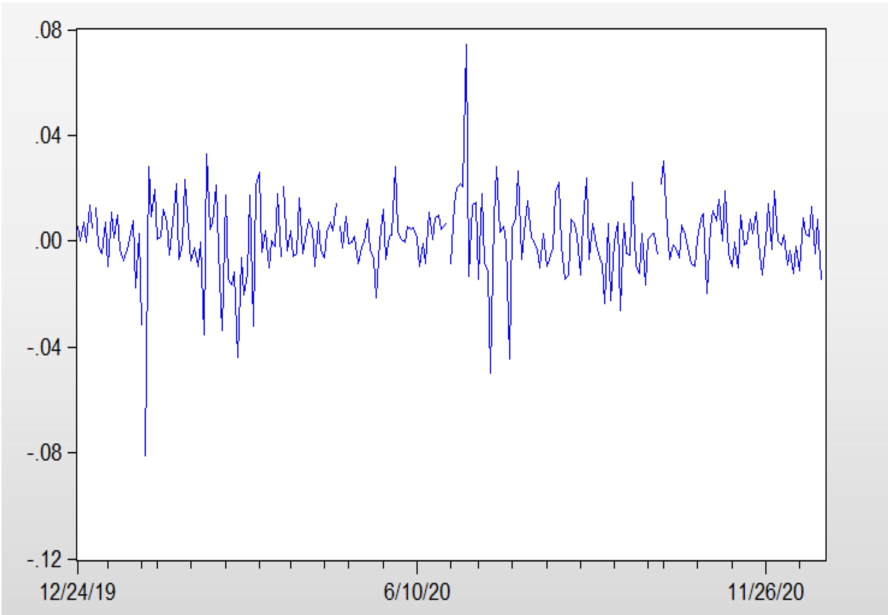


Figure 2. Volatility chart of harvest CSI 300ETF yield in interval 2

2.2. Descriptive Statistics

The descriptive statistics results in this paper are shown in Table 1. It can be seen from Table 1 that after the launch of the CSI 300ETF option, the standard deviation of the underlying spot yield is 0.014641, lower than the total standard deviation of 0.015082, and even lower than the pre launch standard deviation of 0.015544. This shows that the volatility of the underlying spot yield has decreased since the launch of the CSI 300ETF option.

Table 1. This caption has one line so it is centered

Section	Mean value	Standard deviation	Skewness	Kurtosis
Section 1	0.001183	0.015544	0.019015	20.84939
Section 2	0.000854	0.014641	-0.578934	9.579087
Full sample	0.001018	0.015082	-0.252784	15.92746

Figures 3 and 4 are descriptive statistical charts of Harvest CSI 300 ETF yield. Observe descriptive statistics, Skewness is the skewness of sequence distribution, that is, when Skewness value is 0, the sequence is symmetrically distributed; When Skewness value is greater than 0, the sequence distribution is shifted to the right; When Skewness value is less than 0, the sequence distribution is left biased[8]. Kurtosis value is the kurtosis of the sequence. When Kurtosis value is greater than 0, the peak distribution of the sequence can be seen from Figure 3. Skewness value of interval 1 is 0.019015>0, kurtosis value is 20.84939>0, and the sequence shows a right leaning peak distribution, which does not meet the requirements of standard normal distribution. It can be seen from Fig. 4 that the skewness Skewness of interval 2 is -0.578,934<0, the Kurtosis value is 9.579,087>0, and the sequence distribution is peak thick tailed, which does not meet the requirements of standard normal distribution[9]. In addition, the Jarque Brea values of the two intervals are abnormally large, 3186.022 and 449.9692 respectively, and their corresponding P values are 0.000000, indicating that the two sequences reject the original assumption of standard normal distribution. Therefore, F test cannot be used in this study.

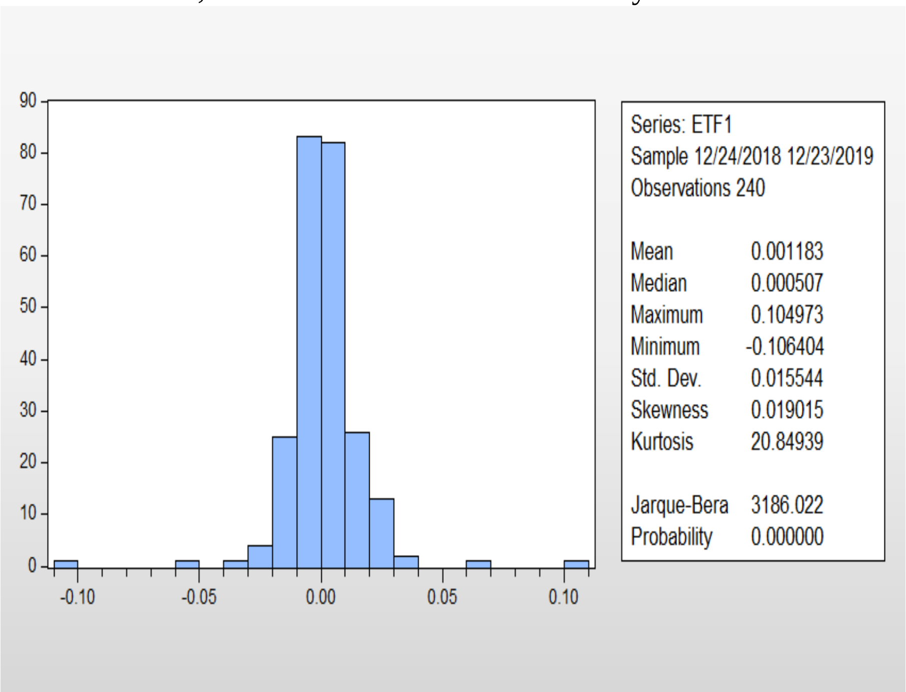


Figure 3. Descriptive statistics of harvest CSI 300ETF yield in interval 1

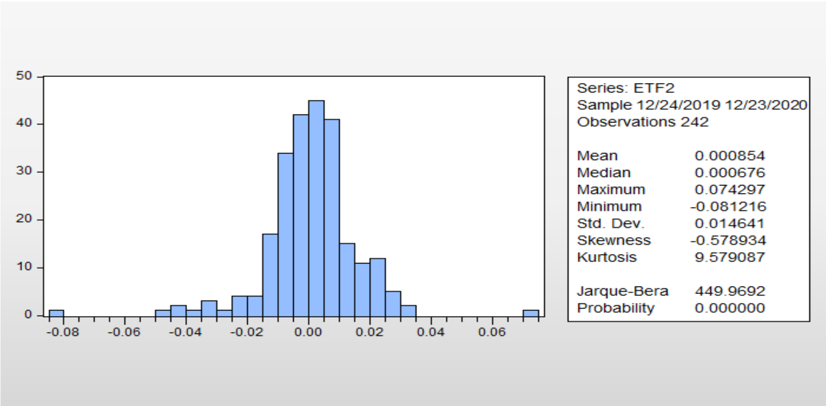


Figure 4. Descriptive statistics of harvest CSI 300ETF yield in interval 2

3. Empirical Analyses

3.1. Stability Test

When conducting time series analysis, it is necessary to ensure that the time series is stable, and the time series in a stable state can ensure that the statistical values obtained are valid. The stability test of the time series is carried out by ADF test (unit root test)[10]. When the ADF value is less than the corresponding t statistical value under the significance level, it means that there is no unit root in the series and the time series is stable; Otherwise, when the ADF value is greater than the t statistic corresponding to the significance level, the time series tested is non-stationary.

Table 2. Harvest CSI 300ETF Yield ADF Test Data

Research interval	t-Statistic				Prob.*	conclusion
	ADF-statistic	1%Level	5%Level	10%Level		
Section 1	-18.71207	-2.574674	-1.942159	-1.615814	0.0000	Unit root does not exist
Section 2	-15.12882	-2.574593	-1.942147	-1.615821	0.0000	Unit root does not exist
Full sample	-23.99582	-2.569779	-1.941483	-1.616257	0.0000	Unit root does not exist

The ADF test results of Harvest CSI 300ETF yield are shown in Table 2. The ADF statistical value of interval 1 is -18.71207, which is significantly less than the value of -2.574674 at the 1% confidence level. The corresponding adjoint probability is 0.0000, then the unit root does not exist, and the interval 1 sequence is stable. Similarly, the ADF statistics of interval 2 and full sample are -15.12882 and -23.99582 respectively, which are significantly less than 1% confidence. The samples in this paper all pass the unit root test, and the sample sequence passes the stationarity test.

3.2. ARCH Effect Test

Before the establishment of GARCH model, the ARCH effect of yield should be tested. Now we construct the autoregressive equation of the yield series:

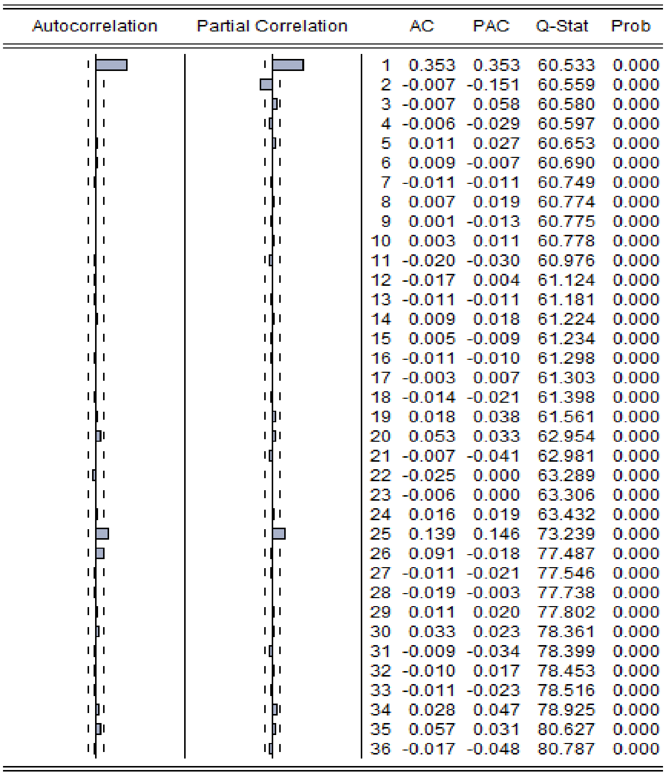
$$R_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i R_{t-i} + \mu_t$$

The first step is to use OLS to make a first-order autoregression on the Harvest CSI 300ETF yield series. The results are shown in Table 3. The regression t value is 174.0972, and the corresponding concomitant probability P value is 0. The 5% significance level test shows that there is a significant autocorrelation in the yield series, and the regression R^2 is 0.984410, indicating that the regression equation has a high degree of fitting.

Table 3. First order autoregression results of yield series

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007070	0.003464	2.041036	0.0418
LOG_E(-1)	0.989089	0.005681	174.0972	0.0000
R-squared	0.984410	Mean dependent var	0.607921	
Adjusted R-squared	0.984378	S.D. dependent var	0.052261	
S.E. of regression	0.006532	Akaike info criterion	-7.220075	
Sum squared resid	0.020480	Schwarz criterion	-7.202739	
Log likelihood	1742.038	Hannan-Quinn criter.	-7.213262	
F-statistic	30309.83	Durbin-Watson stat	2.183173	
Prob(F-statistic)	0.000000			

The second step is to test whether the residual term of the equation has conditional heteroscedasticity. The heteroscedasticity of test conditions can be tested by residual fluctuation chart or ARCH-LM test. In order to reduce the error, this study uses two methods at the same time to test, and the results are the same[11]. The residual fluctuation diagram generated by Method 1 is shown in Figure 5. It can be seen that the autocorrelation AC and partial autocorrelation PAC of the residual sequence occasionally fall outside the dotted line, indicating that the error perturbation sequence has the ARCH effect.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.353	0.353	60.533	0.000
		2	-0.007	-0.151	60.559	0.000
		3	-0.007	0.058	60.580	0.000
		4	-0.006	-0.029	60.597	0.000
		5	0.011	0.027	60.653	0.000
		6	0.009	-0.007	60.690	0.000
		7	-0.011	-0.011	60.749	0.000
		8	0.007	0.019	60.774	0.000
		9	0.001	-0.013	60.775	0.000
		10	0.003	0.011	60.778	0.000
		11	-0.020	-0.030	60.976	0.000
		12	-0.017	0.004	61.124	0.000
		13	-0.011	-0.011	61.181	0.000
		14	0.009	0.018	61.224	0.000
		15	0.005	-0.009	61.234	0.000
		16	-0.011	-0.010	61.298	0.000
		17	-0.003	0.007	61.303	0.000
		18	-0.014	-0.021	61.398	0.000
		19	0.018	0.038	61.561	0.000
		20	0.053	0.033	62.954	0.000
		21	-0.007	-0.041	62.981	0.000
		22	-0.025	0.000	63.289	0.000
		23	-0.006	0.000	63.306	0.000
		24	0.016	0.019	63.432	0.000
		25	0.139	0.146	73.239	0.000
		26	0.091	-0.018	77.487	0.000
		27	-0.011	-0.021	77.546	0.000
		28	-0.019	-0.003	77.738	0.000
		29	0.011	0.020	77.802	0.000
		30	0.033	0.023	78.361	0.000
		31	-0.009	-0.034	78.399	0.000
		32	-0.010	0.017	78.453	0.000
		33	-0.011	-0.023	78.516	0.000
		34	0.028	0.047	78.925	0.000
		35	0.057	0.031	80.627	0.000
		36	-0.017	-0.048	80.787	0.000

Figure 5. Residual sequence fluctuation chart

Method 2: ARCH-LM test for conditional heteroscedasticity of the above equation. The order of ARCH model lag is determined according to AIC and SC criteria. Table 4 shows that when the lag order is 2, the AIC and SC values are relatively minimum, indicating that ARCH (2) has the best fitting effect. Therefore, ARCH (2) model is selected for this study.

Table 4. Regression results of different lag orders

Lag order	AIC	SC
1	-14.71043	-14.69307
2	-14.70117	-14.71700
3	-14.72438	-14.68954

The ARCH-LM test results of the second order lagged residual sequence are shown in Table 5. The P values of the F and LM statistics of the test results are 0.0000. Through the test of 1% significance level, the original assumption that the residual term of the model does not have the ARCH effect can be rejected, and the GARCH model can be established for analysis[12].

Table 5. ARCH-LM inspection results

F-statistic	23.68361	Prob. F(1,479)	0.0000
Obs*R-squared	22.66200	Prob. Chi-Square(1)	0.0000

3.3 Introduction and Construction of GARCH Model

By introducing dummy variable D on the basis of GARCH model, this study further studies the impact of this specific time point segment on the underlying spot volatility before and after the listing of Shanghai and Shenzhen 300ETF options. The dummy variable D is assigned different values according to the time period[13]. D=0 represents the time period before the option listing (December 24, 2018 to December 23, 2019), and D=1 represents the time period after the option listing (December 23, 2019 to December 23, 2020). The expression of GARCH (1,1) model containing dummy variables is:

$$\mathrm{R}_t = \alpha + \beta\mathrm{R}_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, {h_t}^2)$$

$$ {h_t}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i {\varepsilon^2}_{t-i} + \sum_{j=1}^{p} \delta_j {h_{t-j}}^2 + \beta D$$

Where R_t is the yield of Harvest CSI 300ETF at time t, ε_t is the random error obeying the $N(0, {h_t}^2)$ distribution, ${h_t}^2$ is the conditional variance at time t, and D is the introduced time dummy variable, β Is the coefficient of D dummy variable, then $\beta > 0$ means that the option listing has increased the volatility of Harvest CSI 300ETF, $\beta = 0$ means that the option launch has no impact on the fluctuation of Harvest CSI 300ETF, $\beta < 0$ means that the option listing has reduced the volatility of Harvest CSI 300ETF.

GARCH model equation is: GARCH= GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1) + C(4)*D (where GARCH represents conditional variance, GARCH (-1) represents conditional variance of first-order lag, and RESID (- 1) represents first-order lag error term.)

Table 6. Parameter Results of GARCH Model for Yield Series

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	7.84E-06	1.40E-06	5.591839	0.0000
RESID(-1)^2	0.219483	0.027777	7.901649	0.0000
GARCH(-1)	0.663424	0.040875	16.23036	0.0000
D	-2.86E-06	9.01E-07	-3.173216	0.0015

The parameter results of GARCH model output are shown in Table 6. The introduced dummy variable D coefficient is -2.86E-06, which is less than 0, and the corresponding accompanying probability P value is 0.015, which is less than the significance level of 5%. Through the significance level test, it shows that the introduction of CSI 300ETF option reduces the volatility of Harvest CSI 300ETF. However, the coefficient value of D variable is small, indicating that the effect of option listing on Harvest CSI 300ETF is not obvious[14].

In order to ensure that GARCH (1,1) does not have ARCH effect, the equation was tested by ARCH-LM, and the results are shown in Table 7. The concomitant probabilities of F statistic and LM statistic are 0.3455 and 0.3445, respectively, which are greater than 5% of the significance level, so the residual term of the equation does not have ARCH effect. At the same time, the ARCH coefficient output is 0.219483, and the GARCH coefficient output is 0.663424, both of which are greater than 0. The addition of the two coefficients is 0.219483+0.663424<1, which meets the constraint range of GARCH model for each parameter. Then GARCH (1,1) model is used to make the residual series have no ARCH effect, and the yield series of Harvest CSI 300ETF is well fitted.

Table 7. ARCH-LM Test Results of GARCH Model Residual Sequence

F-statistic	0.891554	Prob. F(1,479)	0.3455
Obs*R-squared	0.893613	Prob. Chi-Square(1)	0.3445
R-squared	0.000000	Mean dependent var	1.93E-09
Adjusted R-squared	0.002075	S.D. dependent var	0.006550
S.E. of regression	0.006543	Akaike info criterion	-7.348800
Sum squared resid	0.020637	Schwarz criterion	-7.314129
Log likelihood	1775.061	Hannan-Quinn criter.	-7.335174
Durbin-Watson stat	2.190286		

The empirical research results show that the statistical data of the above tests and models have passed the significance level test, and the model data are valid. It can be concluded that the introduction of the CSI 300ETF option effectively reduced the volatility of the underlying spot, namely the CSI 300ETF, but played a weak role. There are several possible reasons for its weak role. First, Harvest CSI 300 ETF's target stocks are all domestic listed blue chip stocks, and its income level and volatility are more stable than other stocks; Second, market participants and investors are not familiar with options products, and options derivatives belong to the minority, so the impact on the spot target is not obvious[15]; Third, the launch time of CSI 300ETF options is still relatively short, and its trading volume is not as good as other derivative products that have been launched for a longer time, so the corresponding effect on the spot market and the spot target is relatively weak. However, the impact of CSI 300ETF options on the spot target still exists, and with the improvement of the market mechanism, the reasonable guidance of the government, institutions, etc., and the improvement of the quality of investors, its impact will increase.

4. Countermeasures and Suggestions

Based on the empirical research results, that is, the introduction of CSI 300 ETF options reduced the volatility of the underlying cash Harvest CSI 300 ETF, but the impact of options was relatively weak. This paper puts forward corresponding suggestions for the government, financial institutions, investors and other aspects.

(1) Further improve the legal and regulatory mechanisms of the financial derivatives market. At present, China's derivatives market is still an emerging market to be developed, and the market trading mechanism needs to be improved. At the same time, the corresponding laws and regulations also need to be further improved, and the compliance management, internal control and other aspects need to be further strengthened, so as to further protect the rights and interests of market participants and provide them with a sound legal system.

(2) Strengthen the risk control and prevention of CSI 300ETF options. The listing time of CSI 300 ETF options is still relatively short, and its long-term effect on the market is visible but still unknown. Therefore, the government should strengthen the supervision and risk control of such emerging financial products. Specifically, we can: set up early warning about market manipulation to prevent illegal manipulation from disturbing the market order; Establish a real-time monitoring system for option products, and pay attention to abnormal fluctuations and abnormal position changes of options. These controls can effectively supervise the market, reduce market volatility and improve the efficiency of market transactions.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Roll Richard. An analytic valuation formula for unprotected American call options on stocks with known dividends. Journal of Financial Economics, 1977, 5(2):251-258. https://doi.org/10.1016/0304-405X(77)90021-6

[2] Hakansson Nils H. Changes in the Financial Market: Welfare and Price Effects and the Basic Theorems of Value Conservation. The Journal of Finance, 1982, 37(4):977-1004. https://doi.org/10.1111/j.1540-6261.1982.tb03592.x

[3] Damodaran, Aswath, Marti G.Subrahmanyam. The Effects of Derivative Securities on the Markets for the Underlying Assets in the United States A Survey. Financial Markets, Instution, and Instruments, 1992.(5):1-22.

[4] Raman Kumar, Atulya Sarin, Kuldeep Shastri. The impact of index options on the underlying stocks: The evidence from the listing of Nikkei Stock Average options. Pacific-Basin Finance Joumal, 1995, 3(2):303-317. https://doi.org/10.1016/0927-538X(95)00006-7

[5] Sahlstrm P. Impact of stock option listings on return and risk characteristics in Finland. International Review of Financial Analysis, 2002, 10(1):19-36. https://doi.org/10.1016/S1057-5219(00)00046-6
[6] Shinhua Liu. The impacts of index options on the underlying stocks: The case of the S&P 100. The Quarterly Review of Economics and Finance, 2007, 49(3):1034-1046. https://doi.org/10.1016/j.qref.2007.10.001
[7] Julien Chevallier, Yannick Le Pen, Benoî Sévi. Options introduction and volatility in the EU ETSIJI. Resource and Energy Economics, 2011, 33(4):855-880. https://doi.org/10.1016/j.reseneeco.2011.07.002
[8] Peihwang Wei, Percy Poon, Susan Zee. The Effect of Option Listing on Bid-Ask Spreads, Price Volatility, and Trading Activity of the Underlying OTC Stocks. Review of Quantitative Finance and Accounting, 1997, 9(2):165-180. https://doi.org/10.1023/A:1008212525953
[9] George Filis, Christos Floros, Bruno Eeckels. Option listing, returns and volatility: evidence from Greece. Applied Financial Economics, 2011, 21(19):1423-1435. https://doi.org/10.1080/09603107.2011.577005
[10] Roll R. A note on an analytical valuation formula for unprotected American call options on stocks with known dividends. Journal of Financial Economics, 1977, 7(4):375-380. DOI：10.1016/0304-405X(79)90004-7
[11] Gukhal C R. Analytical Valuation of American Options on Jump-Diffusion Processes. Mathematical Finance, 2010, 11(1):97-115. DOI：10.1111/1467-9965.00109
[12] Choi B. Numerical methods for the valuation of American options under jump-diffusion processes. The University of Texas at Austin. 2002.
[13] Toivanen, Jari. Numerical Valuation of European and American Options under Kou's Jump-Diffusion Model. SIAM Journal on Scientific Computing, 2008. DOI：10.1137/060674697
[14] Jun-Ling W U, Wang Y, Wang J X. The Effect of Warrant Listing on Bid Ask Spreads, Price Volatility, and Trading Activity of the Underlying Stocks. Journal of Hubei University of Technology, 2007, 34(6):403-412. DOI：10.1007/s10295-007-0210-z
[15] Ke P, Pei W N, Teo L. Price, volume and volatility effects associated with derivative warrant listing on the Singapore Exchange. 2007.