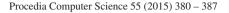






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Volatility Spillovers in the CSI300 Futures and Spot Markets in China: Empirical Study Based on Discrete Wavelet Transform and VAR-BEKK-bivariate GARCH Model

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Abstract

China's introduction of CSI300 futures in 2010 has aroused widespread attention to whether the stock index futures market has effectively stabilized price fluctuations of its spot market in the past four years. Since the prices of CSI300 futures and CSI300 contain numerous noises and fluctuate drastically over time, this paper applies discrete wavelet transform to denoise these series by decomposing and reconstructing their return. Further, a VAR-BEKK-bivariate GARCH model is established to study the volatility spillover effects. Empirical results show that a bi-directional volatility spillover effect exists between CSI300 futures and the spot market, but the former affects the latter in a more obvious way. The introduction of CSI300 futures also contributes to the stabilization of the stock market.

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Keywords: CSI300 futures; discrete wavelet transform; volatility spillovers; VAR-BEEK-bivariate GARCH model

1. Introduction

On April 16th, 2010, China formally launched CSI300 futures, which symbolizes the introduction of a mechanism for short sales of stock, providing an efficient vehicle to disclose market information meanwhile. Theoretically, stock index futures have important functions including price discovery, volatility stabilization, hedging, etc., and serve as a burgeoning but efficient risk management tool. In practice, however, a mass of irrational speculative transactions does exist in the futures market, increasing the risk of short-term fluctuations in the spot market. Bad news magnified by the leverage effect also aggravates the potential jeopardy to the spot market. Thus, it has already become a hot spot in Chinese academy whether CSI300 stock index futures market,

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the "shadow market" of CSI300 stock index market, stabilizes the stock price around its real value, and what the dynamic relation between them is.

This paper chooses the CSI300 futures market and its spot market as subjects, trying to answer the following questions via empirical analysis: what is the volatility spillover relation between CSI300 futures and its spot market? How does information flows between them? Does the introduction of CSI300 futures contribute to its spot market's stability? Should these financial innovations be encouraged in the present Chinese financial market? Exploring these questions allows us to unravel the relationship between CSI300 futures and its stock market for financial regulatory departments and investors concerned, which also helps China's further development of the financial market.

2. Literature review

Most literature applied the GARCH family models to characterize price volatility in the stock index futures and its spot market. These models are known for their consideration in modelling volatility clustering and asymmetry that are typical of stock index and its futures prices. In studying the volatility spillover effect between the stock index futures and its spot market, most researchers agreed that the relation was generally bi-directional, but the direction of volatility spillover may vary with different countries, with well-developed financial markets' stock index futures playing a leading role in spill. Koutmos and Tucker (1996) [1] analysed daily S&P500 index futures and spot prices. They found that the futures' volatility led the spot for one day, and the spillover effect was asymmetric. Tse (1999) [2] analyses DJIA index futures and spot, suggesting bi-directional spillover effect in the two markets, with the future markets' spillover being more evident. Bhar (2001) [3] studied daily Australian stock index futures and spot data and suggested that markets utilized volatility spillover effect to transfer information. In China's academia, Liu et al. (2011) [4] analysed CSI300 and futures with a bivariate EGARCH model, finding that the volatility spillover effect is larger in the spot market than the futures market, and suggested that both good and bad news had leverage effect on market returns. Zhou Pu et al. (2013) [5] applied both linear and nonlinear Granger Causality Test, co-integration test and built a VECM model to analyse information spillover in the CSI300 futures and spot market, discovering only linear variance information spillover from the spot to futures, but remarkable nonlinear variance information spillover between them.

The majority of existing research utilized bivariate ECM-EGARCH model, but this model contains many parameters and may not guarantee the positive definiteness of its residual's variance-covariance matrix, which questioned the validity of the model. To solve this problem, Engle and Kroner (1995) [6] proposed a parametric model with positive definiteness restrictions, namely the BEKK-GARCH model, and thus offered an effective device for volatility modelling. This new type of GARCH is known for its ease in satisfying the positive definiteness of the variance-covariance matrix as well as its efficiency in reducing parameters for estimation. Compared to traditional GARCHs, the BEKK-GARCH has great advantage in analysing the volatility spillover effect of the stock index futures market. Thus in this paper, we utilize a VAR-BEEK-GARCH model to explore the volatility spillover effect between CSI300 stock index futures market and its spot market in China.

3. Data selection and discrete wavelet transform

3.1. Data selection

We choose the 1080 closing prices of CSI300 stock index and CSI300 stock index futures from April 16th, 2010 to September 25th, 2014 (Data sources: Wind Database). To avoid drastic fluctuations of financial prices series, we transform the prices into daily returns using logarithmic difference, namely $R_t = 100 \times \log(P_t / P_{t-1})$, and obtain 1079 return rates since CSI300 futures' introduction in China.

Figure 1 plots the return rates of CSI300 and CSI300 futures together. As the picture shows, CSI300 and its futures share much in common in both trend and volatility, and the volatility clusters in certain periods.

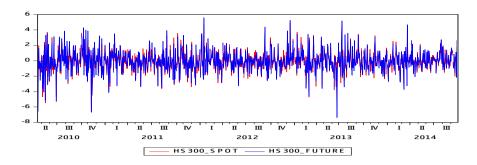


Fig1 returns of CSI300 Spot and CSI300 Futures

3.2. Discrete wavelet transform

Because high-frequency CSI300 and its futures returns include interfering information such as short-term supply and demand fluctuations, innovation shocks, speculation behaviour, etc., data may deviate from their true value and contain great noises. The existence of "Calendar effects" and other cyclical behaviours also makes quantitative analysis based on original data lacks robustness. Thus, this paper applies wavelet analysis to preprocess the returns series.

1. The rationale and superiority of wavelet transform

The rationale of the wavelet transform can be summarized as below: by decomposing the signal into different levels, we obtain the low frequency part of the signal that corresponds to its main characteristics and the high frequency part of the signal that corresponds to its details. With the increase of decomposition layers, we can observe the signal from coarse to fine. The essence of wavelet transform is to decompose signals into low and high frequency parts by using high-pass and low-pass filters.

Wavelet transform provides fine locality for the series in both time and frequency spaces. It can subdivide high-frequency signal in time space and low-frequency signal in frequency space through flexing and translating operations so that we can focus on any detail of the signal. Thus, wavelet transform are widely applied in time-frequency analysis, noise separation, weak signal extraction and signal identification, etc.. Since high-frequency futures and spot returns contain strong noises in high frequency, wavelet transform can effectively remove these noises while retain the low-frequency and stable characteristics of the original signal. Above all, wavelet transform shows enormous superiority in dealing with the high-frequency and noisy futures and spot data.

2. The decomposition and reconstruction of returns series of CSI300 futures and spot

Since Daubechies wavelet (Db wavelet) has superiority in decomposing and rebuilding signals, this paper chooses DbN wavelet function as the wavelet base. Considering both decomposition accuracy and signal smoothness, we choose Db4 wavelet to decompose and rebuild CSI300 futures and spot return series to get the actual trend of the original returns. More precisely, steps are taken as follows:

(1) Decompose the stock index and futures returns. Results are shown in Figure 2 and 3. We denote low-frequency signal with a4 and high-frequency signal with d1, d2, d3, d4.

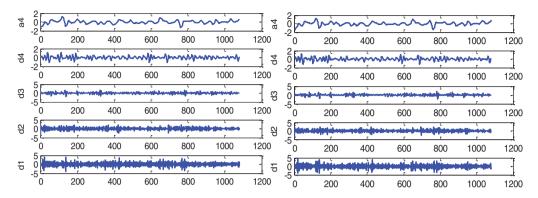
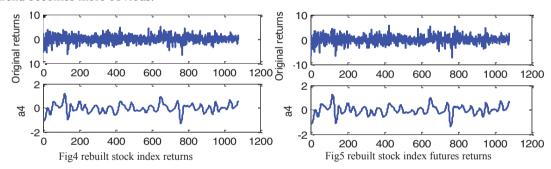


Fig2 decomposed returns of stock index

Fig3 decomposed returns of stock index futures

(2) Retain the low-frequency wavelet coefficients but set the high-frequency wavelet coefficients to 0. Then use the above wavelet coefficients to rebuild the stock index and futures returns. Results are shown in Figure 4 and Figure 5. We denote a4 as the stock index and futures returns after rebuilding, and further named them as Rs_t and Rf_t , respectively. Compared with their original returns series before wavelet transform, the strong noises of the stock index and futures returns have already been removed and their trend becomes more obvious.



4. Empirical analysis

4.1. Stationary test and VAR model establishment

ADF unit root test examines the stationarity of the stock index futures and spot returns series after wavelet decomposition and reconstruction. After taking the ADF test, both CSI300 stock index futures and spot return series prove to be stationary, so a VAR (p) model can be established for empirical analysis. According to Akaike Information Criteria, we choose lag 6 as the order of the VAR model (i.e. building a VAR(6) model). The Granger Causality Test (table 1) shows that stock index futures and their spot are Granger reasons for each other, indicating a bi-directional price guidance between the stock index futures and stock market.

Table1 Granger Causality Test of CSI300 futures and spot

Pairwise Granger Causality Tests			
Null Hypothesis:	Obs	F-Statistic	Prob.
HS300_SPOT does not Granger Cause HS300_FUTURE	1073	3.17174	0.0043
HS300_FUTURE does not Granger Cause HS300_SPOT		3.16883	0.0044

4.2. BEKK-Bivariate GARCH (1, 1) Model

Further examination on the VAR model reveals strong serial correlation between the squared residuals, and this ARCH effect contributes to volatility clustering. A GARCH model can thus be established to further explore the volatility spillover effect between CSI300 and its futures market. Because the BEKK model shows advantages in reducing the number of parameters estimated compared with ordinary GARCHs and can guarantee the positive definiteness of the variance-covariance matrix under weak conditions, this paper selects a BEKK-GARCH (1,1) model (whose ARCH and GARCH terms' orders are widely considered adequate in describing financial market volatility, while multivariate GARCH model can fully portray the correlation of market fluctuation in a dynamic way), and build the VAR-BEKK-bivariate GARCH (1,1) model as follows:

We first introduce the mean equation defined by the VAR model:

$$Rs_{t} = a_{10} + \sum_{i=1}^{p} a_{11,i} Rs_{t-i} + \sum_{i=1}^{p} a_{12,i} Rf_{t-i} + \varepsilon_{1t}$$

$$Rf_{t} = a_{20} + \sum_{i=1}^{p} a_{21,i} Rf_{t-i} + \sum_{i=1}^{p} a_{22,i} Rs_{t-i} + \varepsilon_{2t}$$

Here \mathcal{E}_{1t} , \mathcal{E}_{2t} are conditional residuals. We define $H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}$ as the residual's conditional

variance-covariance matrix with information known at time t-1 and before, and further structure a variance equation as follows:

$$H_{t} = \Omega'\Omega + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A$$

Here $\Omega = \begin{bmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{bmatrix}$ is a lower triangular constant matrix, and its setting guarantees the positive

definiteness of $H_t \cdot A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}$ measures the ARCH effect while $B = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}$ measures the GARCH

effect. The formula is equivalent to:

$$\begin{bmatrix} h_{1,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{bmatrix}' \begin{bmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{22} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}' \begin{bmatrix} \alpha_{21} & \alpha_{22} \\$$

Equivalently, we get:

$$\begin{split} h_{11,t} &= \omega_{11}^{-2} + \beta_{11}^{-2} h_{11,t-1} + 2\beta_{11} \beta_{21} h_{12,t-1} + \beta_{21}^{-2} h_{22,t-1} + \alpha_{11}^{-2} \varepsilon_{1,t-1}^{2} + 2\alpha_{11} \alpha_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \alpha_{21}^{-2} \varepsilon_{2,t-1}^{2} + 2\alpha_{11} \alpha_{21} h_{12,t-1} \\ h_{22,t} &= \omega_{21}^{-2} + \omega_{22}^{-2} + \beta_{12}^{-2} h_{11,t-1} + 2\beta_{12} \beta_{22} h_{12,t-1} + \beta_{22}^{-2} h_{22,t-1} + \alpha_{12}^{-2} \varepsilon_{1,t-1}^{2} + 2\alpha_{12} \alpha_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \alpha_{22}^{-2} \varepsilon_{2,t-1}^{2} \\ h_{12,t} &= \omega_{11} \omega_{21} + \beta_{11} \beta_{12} h_{11,t-1} + (\beta_{12} \beta_{21} + \beta_{11} \beta_{22}) h_{12,t-1} + \beta_{21} \beta_{22} h_{22,t-1} + \alpha_{11} \alpha_{12} \varepsilon_{1,t-1}^{2} + (\alpha_{21} \alpha_{12} + \alpha_{11} \alpha_{22}) \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \alpha_{21} \alpha_{22} \varepsilon_{2,t-1}^{2} \end{split}$$

Here $h_{11,t}$ denotes the conditional variance of the stock index returns; $h_{22,t}$ denotes the conditional variance of the stock index futures returns; $h_{12,t}$ denotes the conditional covariance of spot and futures returns. Examining the volatility spillover effect that the futures market has on the spot market is equivalent to examining whether

 β_{21} and α_{21} are significantly zero, so we can set the null hypothesis as $H_0: \beta_{21} = \alpha_{21} = 0$. Similarly, we can examine the volatility spillover effect that spot has on futures returns, and set the null hypothesis as $H_0: \beta_{12} = \alpha_{12} = 0$. If there is no direct relationship between spot and future market, the conditional variance of futures and spot returns will only be determined by their own past values, and thus the non-diagonal elements of the matrix are all 0. The associate null hypothesis will be H_0 : $\alpha_{12} = \beta_{12} = \beta_{21} = \alpha_{21} = 0$. Based on the discussion above, we solve the BEKK-bivariate GARCH (1,1) model by applying Marquardt

algorithm in estimation, and choose $l(\theta) = -T \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} (\ln|H_t|) + \varepsilon_t' H_t \varepsilon_t$ as the likelihood function.

According to AIC, lag 2 is chosen as the order of the VAR model, and this indicates that an VAR(2) model is used as the mean equation of the GARCH model.

Table2 the variance equation and Wald restriction tests on volatility spillover effect

Coefficient matrix Ω		Coefficient matrix A		Coefficient matrix B	
$\omega_{11} = 0.0011^{***}$		$\alpha_{11} = -0.1858$	$\alpha_{12} = 0.7581^{***}$	$\beta_{11} = 0.9320^{***}$	$\beta_{12} = -0.0987^{**}$
(0.0001)		(0.1152)	(0.1122)	(0.0332)	(0.0318)
$\omega_{21} = 0.0010^{***}$	$\omega_{22} = 0.0000$	$\alpha_{21} = -0.8829^{***}$	$\alpha_{22} = 1.4573^{***}$	$\beta_{21} = 0.1685^{***}$	$\beta_{22} = 0.6660^{***}$
(0.0001)	(0.0000)	(0.1198)	(0.1205)	(0.0314)	(0.0310)
$H_0: \beta_{21} = \alpha_{21} = 0$, no volatility spillover from the futures market to the spot market $\chi^2(2) = 46.2347^{***}$			H_0 : $\beta_{12}=\alpha_{12}=0$, no volatility spillover from the spot market to the futures market $\chi^2(2)=57.9130^{***}$		

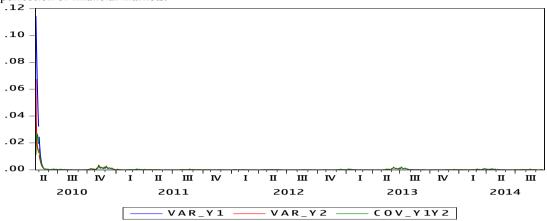
 $H_0: \alpha_{12} = \beta_{12} = \beta_{21} = \alpha_{21} = 0$, no volatility spillover between the two markets $\chi^2(4) = 227.0764^{***}$ Note: +, P<0.10; *, P<0.05; **, P<0.01; ***, P<0.001. In brackets are S.E. of the estimated parameters.

Table 2 shows the estimated result of the variance equation. We find that α_{22} , β_{11} , β_{22} are significantly different from zero at 1% level, which means that the time-varying variance characteristic of the stock index and the time-varying variance as well as volatility persistence characteristics of stock index futures are well described. This implies that the volatility of the stock index can be explained by innovations in its market, while the volatility of the stock index futures can be explained by both innovations in the futures market and the futures' previous volatility, and both of them suggest positive correlations. Meanwhile, the estimated parameters $\alpha_{21} = -0.8829$, $\beta_{21} = 0.1685$, $\alpha_{12} = 0.7581$, $\beta_{12} = -0.0987$ shows obvious bi-directional volatility spillover effect between stock index futures and spot market. However, the former coefficients are much larger than the latter for both alpha and beta, which means that the effect the futures market has on the spot market is much larger than the spot market does on the futures market, confirming the leading position of futures market relative to the spot market.

Investigating the three hypotheses using Wald restriction test, we can also confirms this volatility spillover effect between the stock index and its futures market. Results show that all these hypotheses are refused at 1% level, substantiating the bi-directional volatility spillover effect between the two markets. Additional examination shows no ARCH effect in residuals, proving the validity of applying BEKK-GARCH models to further delineate the VAR model.

Based on the above model, figure 10 shows a synergic trend of stock index futures and spot market volatility in a more intuitive way. We observe that since the introduction of CSI300 futures in April, 2010, the volatility of both the stock index and its futures' markets plunged dramatically, and the fluctuation became mild at a low level after only a month, characterized by a synergic fluctuation trend in the two markets. This further illustrates the

synergy of two markets' fluctuation, and shows the ability of the markets to react concurrently to common information. At the same time, the result highlights the advantage of the futures market in stabilizing the fluctuation of the stock index's price, suggesting diversified financial instrument's function in the development and perfection of financial markets.



5. Conclusion

Fig 6 synergic volatility of stock index and futures market

This paper utilizes four years' CSI300 and its futures' returns data since April 16th, 2010 to date. We first apply discrete wavelet transform to denoise, decompose and reconstruct the returns for further analysis. Then we establish a VAR-BEKK-bivariate GARCH model to study volatility Spillovers. Empirical results are as follows:

First, there is a bi-directional but asymmetric volatility spillover effect between CSI300 futures and its spot market, with the influence of the futures' volatility to the spot's volatility stronger than that of the spot's to the futures's. This conclusion substantiates the leading role played by the futures market to the spot market in China. By comparing the volatility spillover effect between the two markets, we can have a better understanding about how information flows and amplifies in the process, and effectively control risks in advance. Financial regulation agencies should pay attention to the linkage between the spot and futures markets and keep alert to volatility transmission between them especially when prices fluctuate violently, so that they can better regulate and ensure the balance and stability of CSI300 futures market and its spot market.

Second, the introduction of CSI300 futures can lead to an immediate and significant volatility decrease in the stock market, and can also succeed in keeping the volatility at a low level thereafter. This underline the importance of diversified financial instrument for the stabilization and perfection of Chinese existing financial markets, pointing out the necessity for China to embrace powerful financial tools for future development.

The introduction of CSI300 stock index futures represents a milestone of China's financial market reform in achieving multi-level development of China's capital markets. It provides diversified investment strategies for investors, improves the capital leverage of the financial institution, promotes the financial market's liquidity and efficiency, and expands the breadth and depth of the financial market. With the opening of China's financial markets, together with a better regulation system and a macro environment, complementary futures and spot will attract more capital into the stock market, and this promote its prosperity and liquidity. With the gradual maturity of the futures market, its leading position to the spot will become more significant, and its hedging, risk management function will also be brought into full play, thus effectively reducing the volatility of the stock market and further promoting the development of China's financial market.

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