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The Impact of Stock Index Futures on Stock Market Volatility: A Quantitative Test of Daily Data from Different Markets

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Abstract: Using the daily closing price data of four stock indexes in mature markets and emerging markets, the impact of stock index futures on the volatility of different stock markets before and after listing is examined based on the node of futures listing time and asymmetric TGARCH model. The results show that the conditional variance of stock index returns reacts asymmetrically to external shocks; in the leveraged stock market, the bearish news has a greater impact on the stock market than the good news; at the same time, the introduction of stock index futures has a promoting or inhibiting effect on the volatility of the stock market and the existing leverage effect, and there is no obvious difference between mature markets and emerging markets.

1. Introduction

The introduction of stock index futures has a positive or negative effect on stabilizing the financial market, and this topic is still controversial in the academic and practical fields. Therefore, although in principle the content on how to study volatility is rich and informative, in the process of writing practical articles, many of the previous research conclusions are inconsistent and cannot be effectively applied. The purpose of this article is to examine the differences in the impact of stock index futures on stock index volatility between mature and emerging markets. Compared with existing research, it directly combines mature markets and emerging markets, which is more comparable than previous research work and more comprehensive inspection results. Moreover, in the selection of samples and models, the data of the same length of period before and after the stock index futures are selected as nodes, and the asymmetric TGARCH model is fitted, which not only simplifies the calculation, but also forms a better contrast effect. Of course, this method is not the "standard answer" to the study of volatility, and its application still requires model innovation, content innovation, theoretical innovation, and a lot of research work. However, the application of this method can help scholars complete an important task in the process of writing empirical articles, that is, to position a paper in a way that allows readers to clearly understand its contribution to theory and practice.

2. Literature Review

In the process of financial innovation, the emergence and development of stock index futures has been a great success, which not only increases the liquidity of individual stocks that make up the benchmark index, but also improves the market efficiency of index derivatives. Some scholars believe that the introduction of stock index futures has increased the volatility of the stock market. For example, Schwert studied the monthly data of the S&P 500 and argued that the futures market would alter the original stability of the spot market and further enhance its volatility [1]. In other markets, Chang et al. split the volatility of stock indexes into the average yield volatility of interface discreteness, and found that trading in stock futures in the Japanese market caused a small increase in the volatility of the stock market [2]. With the innovation and development of research methods, recent studies have studied the phenomenon of volatility transmission between futures markets and spot markets using high-frequency data, and obvious two-way dependence has been found in the process of research [3].

On the other hand, some scholars believe that the introduction of stock index futures has reduced the volatility of the stock market. Harris studied the impact of derivatives trading on stock market volatility through cross-sectional analysis, arguing that the impact of stock index futures on stock indexes is unstable, especially economically, and has no significant effect [4]. Gulen and Mayhew studied the stock markets of 25 countries around the world and found that in most countries, the introduction of stock index futures has a volatility-suppressing effect on the stock market [5], while also reducing the variance of conditions. Scholars such as Xie and Mo believe that the introduction of stock index futures in the Chinese market does not seem to affect the spot market price for a long time [6], while Fan and Du further discovered the positive spillover effect between the futures market and the spot market in the study of Chinese stock index futures [7].

At the same time, some scholars believe that there is no relationship between stock index futures and stock market fluctuations. In an early study of S&P 500 futures, scholars such as Darrat and Rahman argued that the launch of stock index futures was not the cause of the volatility in the spot market [8]. Outside the U.S., Jochum and Kodres used the SWARCH model to estimate volatility and found that while there was a strong link between the Mexican, Brazilian, and Hungarian markets, futures markets did not have a significant explanation for the volatility that existed in the spot market [9]. Dennis and Sim combined asymmetric ARCH models to study the volatility of stocks and stocks, and similar conclusions were found in the Australian market [10]. Finally, Chen and Zhang found that although there is a certain relationship between the two, there is no significant impact in the analysis of the impact of Chinese stock index futures on stock indices [11].

3. Data and Methods

3.1. Data

Our sample data contains 4 representative daily closing price observation data of stock indexes and collects historical data for 5 years before and after the corresponding stock index futures listing time node. Among them, the US S&P 500 Index (SPX.GI) and the German DAX Index (GDAXI.GI) are from mature markets, the Hong Kong Hang Seng Index (HSI.HI) and the China CSI 300 Index (CSI300) are from emerging markets, and all data are from the Wind database (see Table 1 for sample data characteristics). In order to analyze the fluctuations of the data in empirical research, and in order to reduce the correlation effects of unevenness and heteroscedasticity, the data is often logarithmicized and differentially processed to take the yield as the analysis object, so the collected daily closing price data of the stock index is treated as follows:

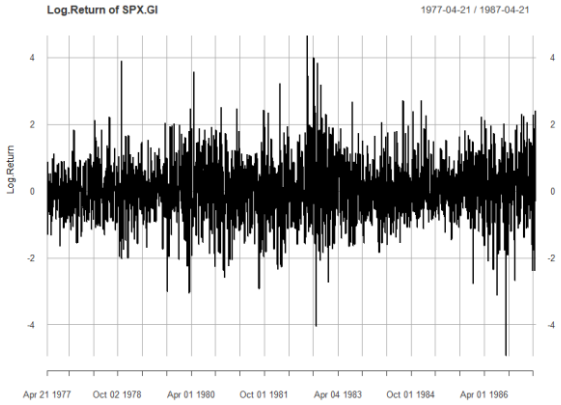
$$R_t = 100 \times \ln(\frac{P_t}{P_{t-1}}) \quad (1)$$

Where P_t represents the daily closing price of the stock index at time t, and R_t represents 100 times the logarithmic return of the stock index at t (amplifying the logarithmic yield result for easy observation).

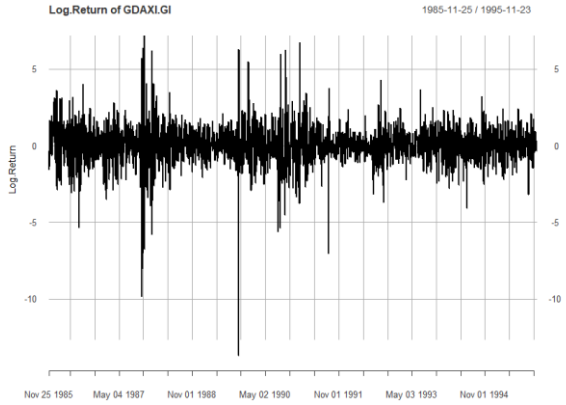
Table 1: Characteristics of sample data

Stock index futures	Stock index	Listing date	Sample interval
S&P 500 Futures	SPX.GI	1982.04.21	1977.04.21-1987.04.21
DAX Index Futures	GDAXI.GI	1990.11.23	1985.11.25-1995.11.23
Hang Seng Index Futures	HSI.HI	1986.05.06	1981.05.06-1991.05.06
CSI 300 stock index futures	CSI300	2010.04.16	2005.04.18-2015.04.16

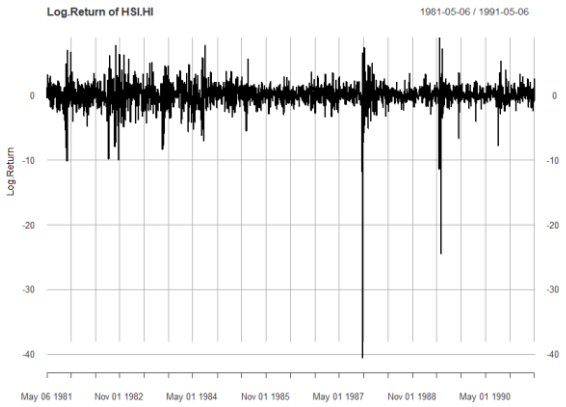
Figures 1-4 below correspond to the time series time series plots of the daily closing prices of the four stock indexes selected, respectively. As can be preliminarily judged by the graph, the time series line chart corresponding to each stock index seems to show a large number of continuous calm and volatility alternating, that is, there is a significant volatility cluster. It is also implied that the sample data we selected may match the characteristics of volatility clustering in terms of conditional variance, autocorrelation, and distribution characteristics, which will be verified in the empirical process.



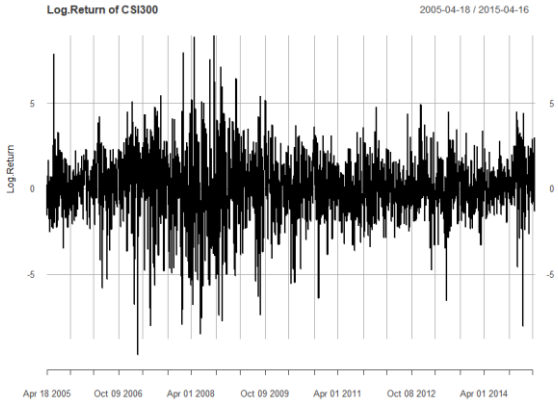
Figures 1: SPX.GI time series plot



Figures 2: GDAXI.GI time series plot



Figures 3: HSI.HI time series plot



Figures 4: CSI300 time series plot

3.2. Modelling

The autoregressive condition heteroscedasticity model (time series model) can more accurately characterize the time-varying volatility and fluctuation aggregation exhibited by the time series. The general linear regression model for arch family models is:

$$y_t = X_t\overline{\psi} + \varepsilon_t \tag{2}$$

Where X_t is a vector of explanatory variables of $1\times(k+1)$ dimension; $\overline{\psi}$ is a coefficient of $1\times(k+1)$ dimensions; and ε_t is a random perturbation term. Let $\varepsilon_t = \sigma_t Z_t$, $Z_t \sim iidN(0,1)$, whose conditional variance is $\sigma_t^2 = Var(\varepsilon_t \mid \sigma_{t-1},\cdots\cdots)$, assume that σ_t^2 depends on the squared of the previous period perturbation term:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots\cdots + \alpha_q\varepsilon_{t-q}^2 \tag{3}$$

Where $\alpha_0 > 0$, $\alpha_i \geq 0$, i>0.

Equation (2) is the basic function expression of the ARCH(q) model. However, the ARCH(q) model has some disadvantages, such as in order to get more information so that the result description is accurate, usually q will be very large, which will lose the sample size, that is, reduce the degree of freedom. Thus, the GARCH model (Generalized Autoregressive Condition

Heteroscedasticity Model) came into being. The GARCH model assumes that the error variance on the basis of the ARCH model uses an autoregressive moving average model (ARMA model), that is, σ_t^2 is not only related to $\left\{\varepsilon_{t-1}^2 \cdots\cdots \varepsilon_{t-q}^2\right\}$, but also a function of $\left\{\sigma_{t-1}^2 \cdots\cdots \sigma_{t-q}^2\right\}$.

The widest range of GARCH(1,1) models:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

Where ε_t is the random error term and the others are the parameters to be estimated. In particular, σ_t^2 is a period forward prediction variance based on historical information, called conditional variance. To ensure that the condition variance is positive, $\omega > 0, \alpha_1 \geq 0, \beta_1 \geq 0$ is required.

The conditional variance equation for the TGARCH(1,1) model (threshold self-regression conditional heteroscedasticity model) is:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\ \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5}$$

Where ε_{t-1} is the stochastic error term of the previous period, σ_{t-1}^2 is the conditional variance of the previous period's return, ω, α, β is the parameter to be estimated, and γ is the asymmetric parameter. Define the variable I_{t-1} as:

$$I_{t-1} = \begin{cases} 1, \varepsilon_{t-1} < 0 \\ 0, \varepsilon_{t-1} \geq 0 \end{cases} \tag{6}$$

The information in the current period is good news, that is, when $\varepsilon_{t-1} \geq 0$, the impact coefficient is α; the current period of information is negative news, that is, $\varepsilon_{t-1} < 0$, the impact coefficient is $\alpha + \gamma$. When $\gamma = 0$, the response of the conditional variance to the impact is symmetrical, that is, the GARCH (1.1) model; when $\gamma \neq 0$, the response of the conditional variance to the impact is asymmetrical, and if γ is positive and significant, the existence of the leverage effect is proved. When using this model to predict, it is assumed that the distribution of residuals is basically symmetrical, so that I_{t-1} is 1 in half the time and 0 in the other half of the time. However, it is not known when it will be 1 and when it will be 0, so it can be assumed that I_{t-1} is 0.5 in the forecast.

4. Empirical Results

In the fitted results of the 5 years before the launch of stock index futures, 4 stock indexes (SPX.GI,GDAXI.GI,HSI.HI, and CSI300) met the condition of $\gamma \neq 0$, indicating that the conditional variance of the stock index returns reacted asymmetrically to external shocks. Moreover, the asymmetric parameter (γ) of the DAX index and the Hong Kong Hang Seng Index is positive, indicating that there is a leverage effect, but the estimates of γ of the S&P 500 index and the CSI 300 index are not significant, so the leverage effect of the S&P 500 index and the CSI 300 index can be ignored. When the yield increases ($\varepsilon \geq 0$), the impact of ε of the 4 stock indexes on the conditional variance is 0.023299, 0.040761, 0.034801 and 0.066332 times; when the yield decreases ($\varepsilon < 0$), due to the neglect of the leverage effect of the S&P 500 index and the CSI 300 index, that is, the impact of the same degree of bearish news and good news on the stock market is equated, so the impact of ε of the 4 stock indexes on the conditional variance is 0.023299, 0.155811,

0.143915 and 0.066332 times, which shows that the bearish news has a greater impact on the DAX index and the Hong Kong Hang Seng Index than the good news. In the face of positive news, investors will make more reasonable investment decisions, resulting in less volatility in the stock market, while in the face of bearish news, investors will further strengthen the volatility of the stock market.

Similarly, in the fitted results of 5 years after the launch of stock index futures, 4 stock indexes still meet the condition of $\gamma \neq 0$, and the conditional variance of stock index returns reacts asymmetrically to external shocks. The estimates of γ of the S&P 500, DAX and CSI 300 are not significant, and the p-value of the estimate of γ of the S&P 500 is larger and not significantly enhanced, so the leverage effect of the S&P 500, DAX and CSI 300 can be ignored. On the contrary, when testing the estimate of γ of the Hang Seng Index in Hong Kong, $p = 0$ can judge that the estimate is significant at a confidence level of 99%, indicating that the Hong Kong Hang Seng Index still has a significant leverage effect after the launch of stock index futures. Meanwhile, the estimate of γ in Hong Kong's Hang Seng Index increased by 0.347626, indicating further strengthening of the leverage effect. When the yield increases ($\varepsilon \geq 0$), the impact of ε on conditional variance in the four stock indexes is 0.023102, 0.030951, 0.061732, and 0.027283 times, compared with the stock index futures before the launch, the impact of ε on conditional variance has decreased to a certain extent in the S&P 500 index, DAX index and CSI 300 index market, especially in the CSI 300 index; conversely, the impact of the ε on conditional variance has been significantly enhanced in the Hong Kong Hang Seng Index market. When the yield decreases ($\varepsilon < 0$), the impact of ε on conditional variance of the 4 stock indexes is 0.023102, 0.030951, 0.518472, and 0.027283 times, indicating that the bearish news is more important than the impact of the good news on the Hang Seng Index of Hong Kong, and compared with the introduction of stock index futures, the impact of ε on conditional variance is still reduced to a certain extent in the S&P 500, DAX and CSI 300 index markets. At this time, the decrease in the DAX index and the CSI 300 index is more obvious, and the impact of ε on the conditional variance is also significantly enhanced in the Hong Kong Hang Seng index market. In general, after the launch of stock index futures, the leverage effect of the DAX index is no longer significant, and like the S&P 500 index and the CSI 300 index, their stock market volatility has decreased. However, Hong Kong's Hang Seng Index has the opposite performance, with its leverage effect and stock market volatility further enhanced.

Finally, in the fitted results of the overall sample range (10 years), there is leverage in the DAX index and the Hong Kong Hang Seng Index, ignoring the leverage effect of the S&P 500 Index and the CSI 300 Index. When the yield increases ($\varepsilon \geq 0$), the impact of ε of the four stock indexes on the conditional variance is 0.027672, 0.038830, 0.081604 and 0.043601 times, and when the yield decreases ($\varepsilon < 0$), the impact of ε of the four stock indexes on the conditional variance is 0.027672, 0.119151, 0.319858 and 0.043601 times, respectively, which still indicates that the bearish news hit the DAX index and the Hang Seng index in Hong Kong more than the good news.

5. Conclusions

In the empirical test of the impact of stock index futures on volatility, the volatility changes of the S&P 500 Index, DAX Index, Hong Kong Hang Seng Index, and CSI 300 Index in the 5 years before and after the launch of stock index futures can be observed. In the period before and after the launch of the corresponding stock index futures, the conditional variance of the returns of the four stock indexes reacts to external shocks asymmetrically, and the S&P 500 index and the CSI 300 index have almost no leverage effect. The DAX index and the Hong Kong Hang Seng Index have

obvious leverage effects before the launch of the corresponding stock index futures, and the bearish news will have a greater impact on the stock market than the good news. However, the leverage effect of the DAX index is almost non-existent after the launch of the corresponding stock index futures, and the leverage effect of the Hong Kong Hang Seng Index is further enhanced after the launch of the corresponding stock index futures. In addition, after the launch of the corresponding stock index futures, the volatility of the S&P 500 Index, DAX Index, and CSI 300 Index has decreased to a certain extent, especially in the DAX Index and the CSI 300 Index, while the volatility of the Hong Kong Hang Seng Index has further increased. All in all, the conditional variance of stock index returns reacts asymmetrically to external shocks; in leveraged markets, bearish news will have a greater impact on the market than good news; at the same time, the introduction of stock index futures has a promoting or restraining effect on stock market volatility, and according to the samples currently studied, it is not clear that stock index futures have a role in mature markets and emerging markets.

References

[1] Schwert, G.W. (1989) Why does stock market volatility change over time?. The journal of finance, 44(5), 1115-1153.

[2] Chang, E.C., Cheng, J.W. and Pinegar, J.M. (1999) Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets. Journal of Banking & Finance, 23(5), 727-753.

[3] Yang, J., Yang, Z. and Zhou, Y. (2012) Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. Journal of Futures Markets, 32(2), 99-121.

[4] Harris, L. (1989) S&P 500 cash stock price volatilities. The Journal of Finance, 44(5), 1155-1175.

[5] Gulen, H. and Mayhew, S. (2000) Stock index futures trading and volatility in international equity markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products, 20(7), 661-685.

[6] Xie, S. and Mo, T. (2014) Index futures trading and stock market volatility in China: a difference‐in‐difference approach. Journal of Futures Markets, 34(3), 282-297.

[7] Fan, X. and Du, D. (2017) The spillover effect between CSI 500 index futures market and the spot market: Evidence from high-frequency data in 2015. China Finance Review International.

[8] Darrat, A.F. and Rahman, S. (1995. Has futures trading activity caused stock price volatility?. Journal of futures markets, 15(5), 537-557.

[9] Jochum, C. and Kodres, L. (1998) Does the introduction of futures on emerging market currencies destabilize the underlying currencies? Staff Papers, 45(3), 486-521.

[10] Dennis, S.A. and Sim, A B. (1999) Share price volatility with the introduction of individual share futures on the Sydney Futures Exchange. International Review of Financial Analysis, 8(2), 153-163.

[11] Chen, X. and Zhang, N. (2015) An Empirical Study of China's Financial Stock Index Futures Effect on Stock Spot Market Based on CSI 300. International Journal of Multimedia and Ubiquitous Engineering, 10(11), 407-416.