Research on the Measurement Effect of Futures Market Sentiment on the Extreme Risk of the Stock Market

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Abstract: As a kind of financial derivative with price discovery function, stock index future has a wide range of applications in risk management. However, the high leverage and short selling mechanism of stock index futures also greatly increased the trading risk. This paper takes CSI 300, SSE 50, and CSI 500 stock index futures and their corresponding indexes as the research objects. Using the relevant data of the past five years, this paper first constructs VAR model, analyzes the impact of futures market sentiment on stock index volatility by impulse response, and then constructs XGBoost model (a machine learning algorithm), uses futures market sentiment for series fitting and prediction. The research finds that: First, futures market sentiment has several periods of impact on the stock index volatility, and the length of different research targets varies; Second, the sentiment many periods before can still provide important information, which cannot be ignored when fitting the volatility of the sequence; Third, the fitted sequence generally underestimates the extreme risk of the real stock market, mainly due to the over-reaction of stock market investors to the transmission of sentiment in the futures market. Finally, based on the research findings, the paper puts forward relevant recommendations.

1. Introduction

As a kind of financial derivative, stock index futures have the function of price discovery and are widely used in risk management. However, with the continuous development of the financial market, the profit seeking nature of capital has spawned a large number of short-term investors or even speculators, intensifying the risk of volatility. In the short term, the stock market is affected by the futures market. Investors' short or long positions in stock index futures will, to some extent, convey their sentiment, which will lead to a considerable number of investors' psychological expectations in the stock market, resulting in the rise or fall of the stock market. Therefore, it is of practical significance to study the impact of trading sentiment on stock market volatility and risk.

Relevant research on stock index futures has been carried out by foreign scholars. Bessembinder and Seguin (1993) studied the relationship between the trading volume, position and market volatility of futures contracts, and found that both the trading volume and position had an impact on the market volatility; Chan, Christie and Schultz (1995) found that the increase in volatility of the S & P 500 stock index led to the increase in the corresponding futures contract positions. The research directions are mostly around the relationship between the spot and futures market, which have reference significance for promoting the development of domestic related fields.

Later, domestic scholars have successfully expanded the research direction and broadened the previous ideas in recent years.

Firstly, they further developed the research on the relationship between the futures market and the spot market by focusing on them at the same time. Li Fei and Huang Feng (2019) took China Securities 500 stock index futures as the research object, and found that the price discovery function of stock index futures was stronger than stock index itself.

Secondly, based on the theory of behavioral finance, they have deepened the understanding of trading volume and position. Li Jiajia and Wang Cong (2019) took the trading volume of active contracts of zinc futures as the representative of futures market sentiment, and found that market sentiment had significant mean value spillover effect on zinc spot and futures prices.

In addition, with the continuous development of the financial market, the attention to risk

management has gradually increased. Two of the main concerns are the prediction of volatility and the measurement of extreme risk. GARCH family models have also been widely used. Lin Wenhao, etc. (2019) used relevant models to fit the stock market volatility series, and used VaR method to forecast extreme risks, so as to analyze the stock market risk warning ability.

Finally, with the continuous development of big data technology and deep learning theory, some algorithms have also been applied to financial problems to study the sequence trend and risk measurement. Zhou Yuping and Chen Guanyu (2019) studied the personal credit evaluation based on machine learning method, and put forward relevant suggestions to improve the accuracy of investors' credit risk assessment.

In summary, in recent years, the domestic research on the stock index futures market and the spot market is deepening, especially in the above aspects. However, the above directions are basically separately studied, and fewer joint researches are involved. In fact, due to the linkage of index futures market and stock market, the trading of the stock index futures will transmit emotional signals, affect the behavior of the investors in the stock market, and thus influence the volatility of the stock price. The high correlation of the above research directions indicates the importance of comprehensive research self-evident. Therefore, the innovation of this article is a comprehensive analysis of the above areas.

2. Model Description

(1) VAR model & Pulse response analysis

The VAR model regards all variables as a system and is a function of the current value of all variables and their lag value. Through the construction of VAR model and pulse response analysis, we can determine the impact of future market sentiment variables on stock index fluctuations, and then select appropriate fitting and forecast variables for the next stage.

(2) XGBoost model

The machine learning model XGBoost trains the first weak learner based on the original data set, calculates the residual between the predicted value and the real value, and regards it as the learning object of the next weak learner. Each weak learner aims to reduce the difference between the real value and the predicted value. The final output of the model can be expressed as a combination of several weak learners, and the multiple learning process can significantly improve the fitting accuracy and efficiency.

Applying the results from the pulse response analysis to the construction of the feature set, and through the steps of feature scaling, set training, parameter optimization, test set prediction, etc., the simulated stock index volatility series fitted by the emotional variables of the futures market can be established.

(3) TGACH model & VaR

TGARCH model can better fit the asymmetric effect of market response to positive and negative news. The conditional variance predicted by the TGARCH model can be used to predict the VaR value and thus measures the extreme risk. In addition, historical simulation method and Monte Carlo simulation method can also be used to calculate VaR.

$$\sigma_t^2 = a_0 + a_1\mu^2_{t-1} + v\mu^2_{t-1}d_{t-1} + b_1\sigma^2_{t-1}$$

$$d_t = \begin{cases} 0(\mu_t \geq 0) \\ 1(\mu_t < 0) \end{cases}$$

The TGARCH model is applied to both the predicted series and the original series. The results are used to calculate the value at risk. By comparing the VaR of the two series, the extreme risk measurement effect of the predicted volatility series can be examined, thus relevant conclusions can be drawn.

3. Empirical Study

(1) Data Source and Variable Selection

The data used in this paper comes from iFinD financial terminal. The time span selected is 5 years (2015.7-2020.6). The stock index futures position (variable named h) and trading volume (variable named t) represent the sentiment of the futures market, and the fluctuation of the stock index is measured by the rise and fall of the closing price of the stock index (variable named i).

(2) Feature Set Construction

The feature set for fitting is established based on the results of impulse response analysis. The VAR model of variables i, dh and dt is established, where dh represents the change of position and dt represents the change of trading volume. Results of AR root test identified the stationarity of it.

The impulse response of the three models is analyzed, and the impulse response diagram of dh and dt to i is drawn in Figure 1. Based on this, we can determine the variables that should be included in the fitting feature set. For example, the fitting feature set of i (CSI 300) includes 12 variables, which are the change of position (dh) and trading volume(dt) of CSI 300 in the past six periods. The relevant information is summarized in Table 1.
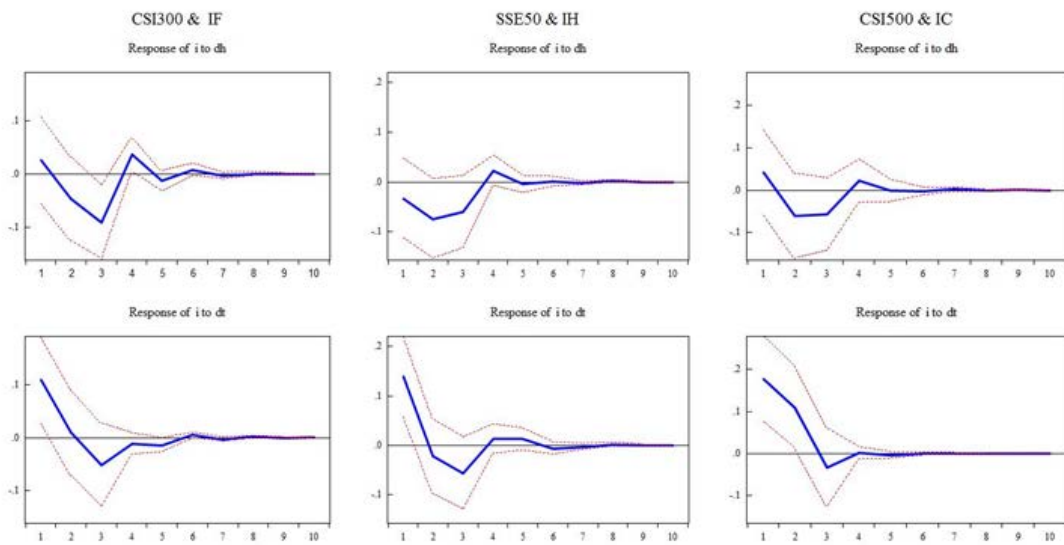

Figure 1 Response of i to dh/dt

Table 1 Feature Set for Series Fitting

Target	Number of Periods Affected by dh/dt	Feature Set	Number of Features
i (CSI300)	6	dh(-1)- dh(-6); dt(-1)-dt(-6)	12
i (SSE50)	5	dh(-1)- dh(-5); dt(-1)-dt(-5)	10
i (CSI500)	4	dh(-1)- dh(-4); dt(-1)-dt(-4)	8

(3) Series Fitting Based on Emotional Feature Set

Use XGBoost model to fit the rise and fall series (i). Firstly, the sample interval is divided into training set, cross validation set and test set, accounting for 65%, 10% and 25%, respectively. Secondly, the default parameter set is used to train and cross verify the model, and the importance of the output features is sorted in Figure 2, for the three markets, the position and trading volume of many periods ago can still reflect important information, which plays an important role in fitting the volatility series. Thirdly, based on the principle of minimum MAPE, the optimal parameters of the model are determined. Finally, the model of optimal parameters is used to fit the test set data, and the fitted sequence on the test set interval can be obtained.
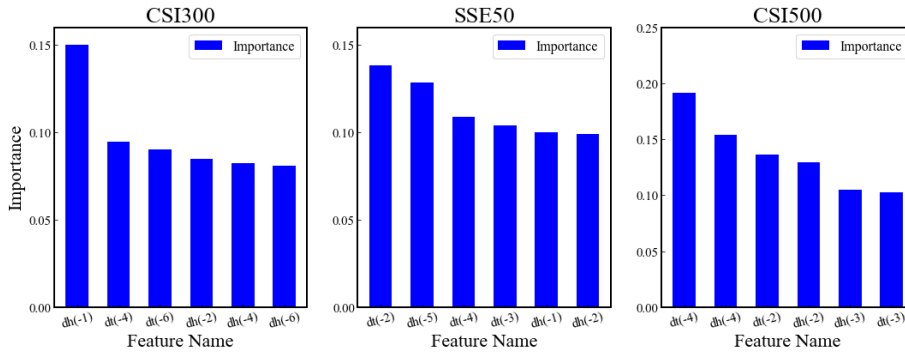
Figure 2 Feature Importance

(4) Test of Extreme Risk Measurement Effect

Based on the theoretical analysis, the test results of CSI 300, SSE 50 and CSI 500 in the test set interval are shown in Table 2. The data shows that both the fitted series and the original series of CSI 300 have ARCH effect, so the VaR value can be calculated based on the volatility predicted by TGARCH model. However, the fitted sequence of SSE 50 and the actual series of CSI 500 has no ARCH effect. In order to unify the measurement standard, VaR values of both the fitted and the original series of SSE 50 and CSI 500 are calculated based on the historical simulation method.

Table 2 Results of Tests

series	CSI300 fitted	CSI300 actual	SSE50 fitted	SSE50 actual	CSI500 fitted	CSI500 actual
normality	fail	fail	fail	fail	fail	fail
stationarity	pass	pass	pass	pass	pass	pass
ARCH	yes	yes	no	yes	yes	no

The calculation results are visualized in Figure 3-4. It can be concluded that the fitted stock index fluctuation based on the sentiment feature set of futures market underestimates the extreme risk and degree of left deviation of the real stock market. This phenomenon has been verified in all the listed markets.
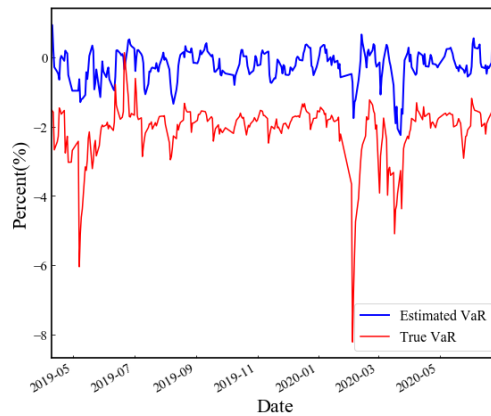

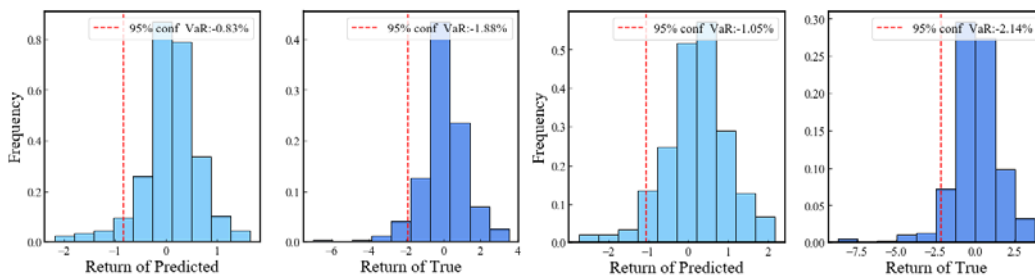Figure 3 VaR Predicted by TGARCH Model (CSI 300)

Figure 4 VaR Predicted by Historical Simulation Method (SSE 50 & SCI 500)

(4) Results Analysis

The reason accounts for this phenomenon is that, the transmission of this sentiment seems to have a magnifying effect on the stock market. In other words, stock market investors tend to overreact to futures market sentiment. Due to the price discovery function of futures market, the changes of speculators' positions and trading volume indicate the rise and fall of the stock market to some extent. This paper exactly measures the value of this prediction effect. However, due to the irrational factors in stock market trading, the psychology of stock market investors will further amplify this effect, resulting in a greater volatility in the stock price, thus increases the extreme risk in the real stock market. The left-skewed, fat tail distribution of the volatility series, as well as the overreaction of stock market investors, all indicate that the efficient market hypothesis is not valid in China's stock market at present.

4. Conclusions and Recommendations

By using various empirical approaches, this paper takes CSI 300, SSE 50 and CSI 500 stock index futures and their corresponding indexes as the research objects, to analyze the impact of futures market sentiment on the volatility of stock index, and use futures market sentiment for series fitting and prediction based on machine learning algorithms. The research finds that: Firstly, futures market sentiment has several periods of impact on the stock index volatility, the sentiment many periods before can still provide important information, which cannot be ignored when fitting the volatility of the sequence; Secondly, the fitted sequence generally underestimates the extreme risk of the real stock market, mainly due to the over-reaction of stock market investors to the transmission of sentiment in the futures market.

Since the advent of CSI300 stock index futures, China's stock index futures market has experienced rapid development for more than 10 years, and its position in China's capital market is irreplaceable. However, the high leverage and short selling mechanism of stock index futures also greatly increase the transaction risk. If there is no rational guidance for futures market investors, it may have a huge impact on the capital market. On the one hand, it is of great significance for investors to establish the concept of rational investment, value investment and risk prevention. On the other hand, the relevant authorities should improve the early warning mechanism of sudden risks and promote the development of stock index futures market by stock market, since the latter exists much longer, which makes its adaptive mechanism more mature and stable.

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