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Weekend Effect and Herding Behavior: A Case Study of Chinese Stock Market

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Abstract— **The abnormality of Chinese stock markets has attracted attention from many researchers and is not easy to explain by the traditional analysis based on average returns. This paper tries to analyze the Chinese stock market behavior in a different way. Instead of observing the daily returns, we study the presence of the "weekend effects" and "herding behavior" by the daily integrated stock volatility. The SSE Constituent Index and the Financials Index are used during the period of January 2008 and August 2009. We construct the confidence intrerval of the daily integrated volatility by using bootstrap method.The result shows that the highest volatility and the lowest volatility are observed on Wednesday and Monday respectively, and the difference of the volatility between Friday and Wednesday is not obvious. While the "weekend effect" is not significant, the result does suggest the existence of a partial "herding behavior", which we name it as the "cautious herding behavior".**

Key words: Realized volatility, high frequency data, weekend effects, herding behavior.

I. Introduction

The volatility is a key ingredient for the pricing of the financial markets since it directly measures the risks for the investors. As Engle [9] has pointed out, investors who dislike risk may adjust their portfolios by reducing their investments in those assets whose volatility is expected to increase. Thus the modeling of the volatility is of great importance in many finance research area, for example, the risk management, the selection strategy of the portfolio, the pricing of the financial derivatives and so on.

There is an abundant literature of modeling the volatility. Starting from the constant assumption of the volatility by Black and Scholes [2], it has been thoroughly studied and many new models were established, see Engle [5]´s ARCH model, Bollerslev [4]´s generalized ARCH, Nelson [6]´s exponential ARCH, and Poon and Granger [11]´s stochastic volatility models. Recently, high frequency data analysis becomes more popular due to the huge improvement of the computing speed, and a new technique of modeling the volatility, the realized volatility, has been developed. ABDL [12] and ABDE [13] have initially pointed out the realized volatility as a consistent estimator of integrated volatility. BNGJS [14] have developed an asymptotic theory for measures of variation such as realized volatility. Recently Gonçalves and Meddahi [15] have developed the bootstrap method for constructing the confidence interval of the integrated volatility.

The weekend effect and herding behavior are also documented extensively since 1970's. Cross [1] and French [3] pointed out that the average return on Monday is significantly less than the average return over the other days of the week. Bikhchandani, Hirshleifer and Welch [7], and Scharfstein and Stein [8] had developed the theoretical model for herding behavior, Wermers [10] empirically studied the herding behavior in mutual fund, and recently Tan, Chiang, Masonb, and Nelling (2008) did examinations of herding behavior in Chinese stock markets of A and B shares. While most of the weekend effect studies focus on the average returns, the pattern analysis of the daily volatility was seldom seen in the literature. It is the same in the herding behavior studies, though Tan, Chiang, Masonb, and Nelling [16] had mentioned that herding in Chinese market tends to occur during the period of the high volatility.

Though Chinese stock market is an emerging market, recently its abnormal behavior, like the high trading volume in the middle of the week and abrupt price increase or decrease, can not be easily explained by the traditional analysis based on average daily returns and the GARCH models of the volatility. Instead of using the traditional methods, this paper focus on the daily volatility behavior of the Chinese stock market. We pick up two stock indexes, the SSE Constituent Index and the Financials Index, and apply the bootstrap framework to get the confidence interval of the daily integrated volatility. By comparisons of the volatility confidence intervals, we find the weekend effect is not obvious in the perspective of the daily volatility. While the herding behavior does seem to occur, it needs a kind of warm period and we name this phenomena as the "cautious herding behavior". The paper is organized as following, next section we talk about the data collection and manipulations. Section three will discuss the bootstrap framework to get the confidence intervals and display the empirical results. The last section will draw the conclusion of the data analysis.

II. Data Description

The data collected is daily tick by tick data for the SSE Constituent Index and the Financials Index. The time interval is from January 2008 to August 2009. The SSE Constituent Index was constructed in June 2002 by Shanghai Stock Exchange to promote the long-term infrastructure construction and the standardization process of the security market. Its objective is to select constituents that best represent Shanghai market and establish a benchmark index that will serve as a performance benchmark and a basis for financial innovation. The Financials Index is of the similar position in Shenzhen Stock markets. In order to apply the bootstrap framework to the data, we need to convert the daily tick by tick data into daily evenly spaced time data. For the given time t in a day, we simply pick up the price which has the closest transaction time to t.

III. Setup and the Confidence Interval

We consider the setup for the realized volatility by following Gonçalves and Meddahi [15]. Let $\{S_t\}$ be the price of the stock at time t, and we assume the log-price generated by the following diffusion:

$$d\log S_t = \mu_t dt + \sigma_t dW_t,$$

where μ_t is a drift term, σ_t is a volatility term which is random and time dependent and W_t is a standard Brownian motion. We are now interested in the integrated volatility over a fixed time interval [0, 1], which is denoted by $\bar{\sigma}^2 \equiv \int_0^1 \sigma_u^2 du$. The realized volatility is a consistent estimator of $\bar{\sigma}^2$ and is defined by $R_2 = \sum_{i=1}^{1/h} r_i^2$, where $r_i = \log S_{ih} - \log S_{(i-1)h}$ denotes the high frequency return measured over the period $[(i-1)h, ih]$, for $i = 1, ..., 1/h$.

Let $R_4 = h^{-1} \sum_{i=1}^{1/h} r_i^4$, and denote $\hat{V} = \frac{2}{3} R_4$. BNGJS [14] showed that under very general conditions:

$$T_h \equiv \frac{\sqrt{h^{-1}}(R_2 - \bar{\sigma}^2)}{\sqrt{\hat{V}}} \xrightarrow{\text{d}} N(0, 1).$$

Though we can get the confidence interval directly from this asymptotic normality of the integrated volatility $\bar{\sigma}^2$, Gonçalves and Meddahi [15] suggested to use bootstrap for getting a better interval estimator. In this paper we apply the bootstrap method to construct the confidence interval for the one day's integrated volatility of the stocks.

By following Gonçalves and Meddahi [15], We denote the bootstrap intraday h-period returns as r_i^*, which is i.i.d. from $\{r_i : i = 1, ..., 1/h\}$. Then we have the bootstrap analogue of T_h:

$$T_h^* \equiv \frac{\sqrt{h^{-1}}(R_2^* - R_2)}{\sqrt{\hat{V}^*}},$$

where $R_2^* = \sum_{i=1}^{1/h} r_i^{*2}$, $\hat{V}^* \equiv R_4^* - R_2^*$ and $R_4^* = h^{-1} \sum_{i=1}^{1/h} r_i^{*4}$. By running 1000 bootstrap replications, we can therefore get the confidence interval. In our stock data, we use $1/h = 48$, corresponding to 5 minute returns in a day. In each week from January 2008 to August 2009, the data of Monday, Wednesday, and Friday was chosen to get the confidence intervals. The week was omitted if it did not have the data for all these three days.

Figure 1 plots the mid point, and the length of the 95 % confidence interval of the daily integrated volatility of the SSE Constituent Index. The top is the plot of the mid point, the middle one is the plot of the length and the bottom plot is the maximum daily volatility from all the bootstrap samples. The x axis means the different weeks.

By comparing the three days in the same week, we count the frequency of maximum appearance. For the mid point of the confidence interval, we find:

TABLE I

The SSE Constituent Index

Frequency of the maximum of mid points		
Monday	*Wednesday*	*Friday*
19	23	21

and for the length of the confidence interval we have the following result.

TABLE II

The SSE Constituent Index

Frequency of the maximum of interval length		
Monday	*Wednesday*	*Friday*
17	25	21

For the Financials Index, results are very similar to the SSE Constituent Index case and we simply provide the comparison tables as follows:

TABLE III

The Financials Index

Frequency of the maximum of mid points		
Monday	*Wednesday*	*Friday*
13	26	25

and the table of confidence interval length:

TABLE IV

The Financials Index

Frequency of the maximum of interval length		
Monday	*Wednesday*	*Friday*
12	25	27

From the above tables, we can see for both indexes Wednesday's volatility is obviously higher than Monday's. A paired T test between the volatilities of Monday and Wednesday shows statistical significance with p value 0.029 for the SSE Constituent Index and 0.018 for the Financials Index. The difference between the Wednesday's volatility and the Friday's is not obvious, and the paired T test also show non statistical significance. While considering the length of confidence interval, the Monday's also seem to be smaller than the Wednesday's. The paired T test shows weak statistical significance for the SSE Constituent Index with p value 0.051, and shows the statistical significance for the Financials Index with p value 0.030. Therefore we can say that in the view of the daily integrated volatility, Monday's is obviously smaller than those for Wednesday's and Friday's. The difference between Wednesday's and Friday's is not significant. This result is not compatible with the usual weekend effects of stock market, since the weekend effect will suggest higher volatility on Monday and Friday and lower volatility in the other trading days.

IV. Conclusion and Remarks

From the analysis of the two stock Indexes in Chinese stock markets, we find that in the perspective of the volatility, the "weekend effect" is not obvious since the Wednesday's volatility was shown to be higher than the Monday's and was similar to Friday's. However this might explain the "herding behavior" in the stock market. Since investors are not sure whether the stock will behave well in the week, they would like to watch the market rather than jump into the market right away. Thus it causes the low volatility on Monday. After watching two days, the "herding behavior" occurs and people would like to buy what others buy the most, and it gives rise to the high volatility on Wednesday and keeps it high till Friday. It fits the data well and the existence of the watching periods makes it different from the typical herding behavior. We therefore would like to name it as the "cautious herding behavior". Notice that our result is partially congruent to the findings in Tan, Chiang, Masonb, and Nelling [16], which says that herding in Chinese market tends to occur during the period of the high volatility. The problem of how to quantify the "cautiousness" still remains open and needs the further investigation.

References

[1] F. Cross, "The behavior of stock prices on fridays and mondays," Financial Analysts Journal, vol. 29, pp. 67-69, 1973.
[2] F. Black and M. Scholes, "The pricing of options and corporate liabilities," Journal of Political Economy, vol. 81, pp. 637-654, 1973.
[3] K.R. French, "Stock returns and the weekend effect," Journal of Financial Economics, vol. 8, pp. 55-69, 1980.
[4] T. Bollerslev, "Generalized auotregressive conditional heteroskedasticity," Journal of Econometrics, vol. 31, pp. 307-328, 1986.
[5] R. F. Engle, "Autoregressive conditional heterosickedasticity with estimates of the variance of united kingdom inflation," Econometrica, vol. 50, pp. 987-1008, 1982.
[6] D. B. Nelson, "Conditional heteroskedasticity in asset returns: a new approach," Econometrica, vol. 59, pp. 347-370, 1991.
[7] S. Bikhchandani, D. Hirshleifer, I. Welch, "A theory of fads, fashion, custom, and cultural change as informational cascades," Journal of Political Economy, vol. 100, pp. 992-1026, 1992.
[8] D.S. Scharfstein, J.C. Stein, "Herd behavior and investment," American Economic Review, vol. 80, pp. 465-479, 1990.
[9] R. Engle, "Statistical models for financial volatility," Financial Analysts Journal, vol. 49, pp. 72-78, 1993.
[10] R. Wermers, "Mutual Fund Herding and the Impact on Stock Prices," Journal of Finance, vol. 54, pp. 581-622, 1999.
[11] S.H. Poon and C. W. J. Granger, "Forecasting volatility in financial markets: a review," Journal of Economic Literature, vol. 41, pp. 478-539, 2003.
[12] T. G. Andersen , T. Bollerslev, F. X. Diebold , and P. Labys, "The distribution of realized exchange rate volatility," Journal of the American Statistical Association, vol. 96, pp. 42-55, 2001.
[13] T. G. Andersen , T. Bollerslev. F. X. Diebold , and H. Ebens, "The distribution of realized stock return volatility," Journal of Financial Economics, vol. 61, pp. 43-76, 2001.
[14] O. Barndorff-Nielsen, S. E. Graversen, J. Jacod, and N. Shephard, "Limit theorems for bipower variation in financial econometrics," Econometric Theory, vol. 22, pp. 677-719, 2006.
[15] S. Gonçalves and N. Meddahi, "Bootstrapping realized volatility," Econometrica, vol. 77, pp. 283-306, 2009.
[16] L. Tan, T. C. Chiang, J. R. Mason, and E. Nelling, "Herding behavior in chinese stock markets: an examination of a and b shares," Pacific-Basin Finance Journal, vol. 16, pp. 61-77, 2008.

V. Appendix

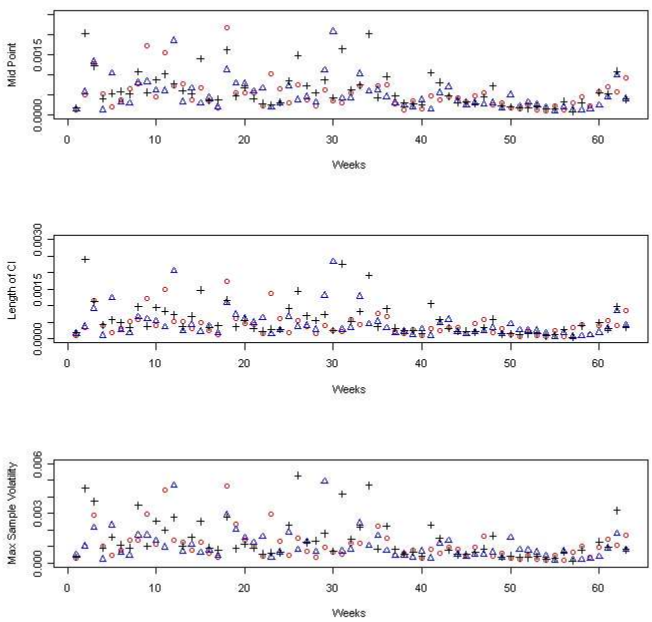

Fig. 1. Mid point, length of the 95% confidence interval and the max point in simulation, Blue triangle: Monday; Black plus : Wednesday; Red circle : Friday.