Analyse the complexity of the financial time series using artificial market

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1 Introduction

In financial time series, as you know, the distribution of the difference of time series do not obey normal distribution. Financial time series have hi-peak fat-tail distribution, and fat-tail has brought unstability to markets. In spite of appearance of hi-peak fat-tail distribution, we have treated financial time series as stochastic processes or deterministic chaos on the assumption of "Central Limit Theorem" and "Efficiency Market Hypothesis." The models which were made on these assumption cannot grasp the characteristics of the real markets. Therefore we must find the seeds of the hi-peak fat-tail distributions.

The purpose of this paper is to reveal the characteristics of real financial time series by using wavelet analysis. And through the analysing of the difference of existing time series models and artificial market analysis, we will show that artificial market analysis is useful to analyse real financial time series.

Finally, we propose that "Rugged Market" which is a state of lack of continuity can be one of the cause to make non-Gaussian distribution.

2 Analysis Methods

2.1 Wavelet Multiresolution Analysis (MRA)

Wavelet analysis is one of frequency analysis. Figure 2.1 shows the result of MRA of J30 stock index. The top of time series is J30 stock index as original time series, and from D1 to D7 and S7 are time series divided by MRA. Upper side of time sereis are the component of low frequency and lower side of time series are the component of high frequency. Contrary, sum of the component of each resolution corresponds to the original time series.

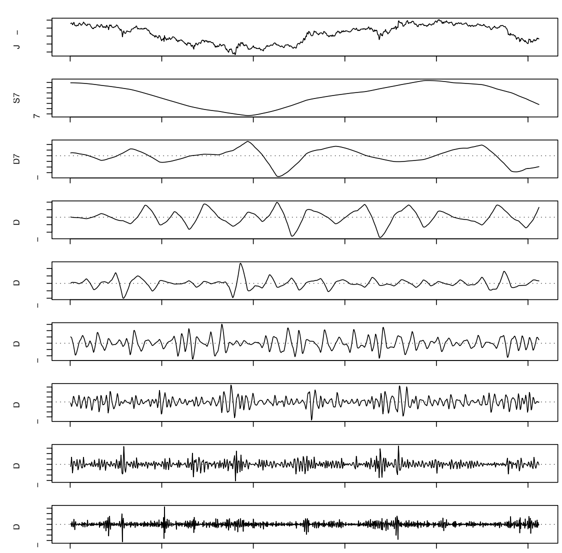

Figure 2.1: J30 MRA (Daubechie8)

2.2 Kurtosis distribution

To compare the characteristics of time series divided by MRA, we made a kurtosis distribution. That is made as follows.
First, kurtosis of each level is calculated. Second, you plot the kurtosis of eachlevel on Level-Kurtosis surface. Finally, you make box plots on Level-Kurtosis surface.

3 Behavior of time series

This experiments adopted the wavelet analysis to observe the behavior of the time series. First of all, time series were divided into each frequency bands by using wavelet multiresolution analysys. And then, we calculated the kurtosis of each level time series. The x-axis denotes frequency level. D1 is the highest frequency band, and S7 is the lowest frequency band. The y-axis denotes the kurtosis level. If kurtosis is equal to three, that means the distribution is normal distribusion. If kurtosis is higher than three, that means the distribution has fat-tails.

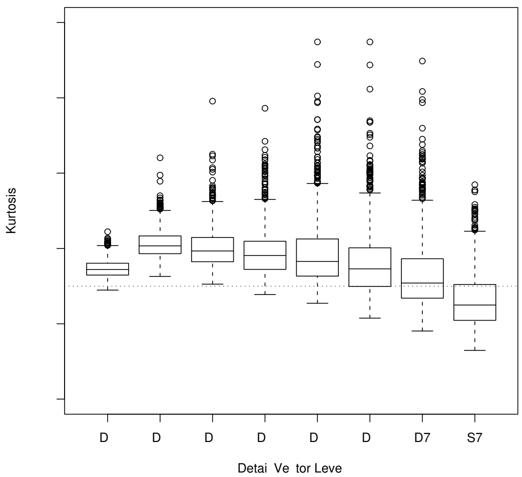

Figure 3-1: Random walk

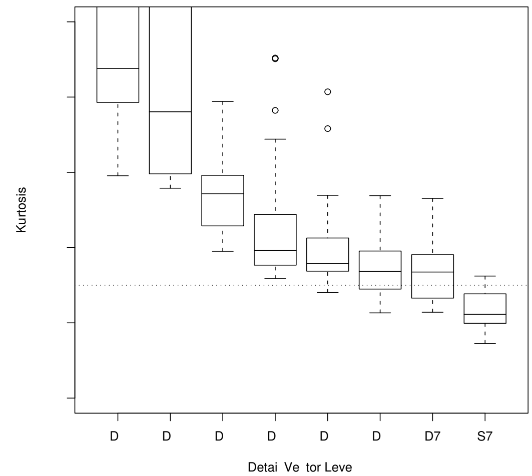

Figure 3-2: J30 (day)

In the Figure 3-1, the kurtosis distribution of random walk are shown. One of the characteristics of this type is that the kurtosis distribution in high-frequency area(D1) is in low level. This random walk type includes geometric linear stochastic process, GARCH model and so on.

But, the real financial time series have increasing high-frequency area. That is shown in Figure 3-2. This is the kurtosis distribution of J30 which is one of the stock index in Japan.

Other sample models of the real markets are shown in Figure 3-3 and 3-4. NIKKEI225 and NIKKEI225 Futures are shown respectively.

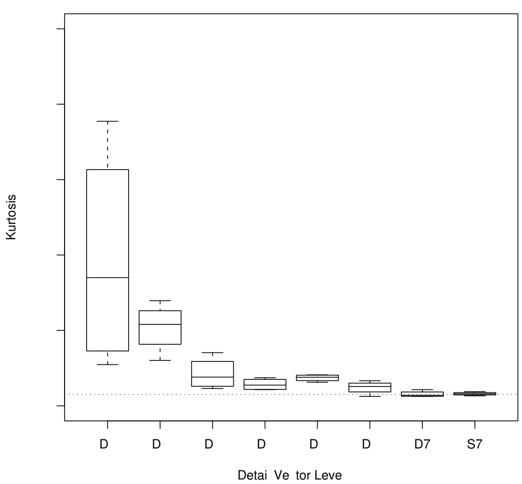

Figure 3-3: NIKKEI225 (minutes)

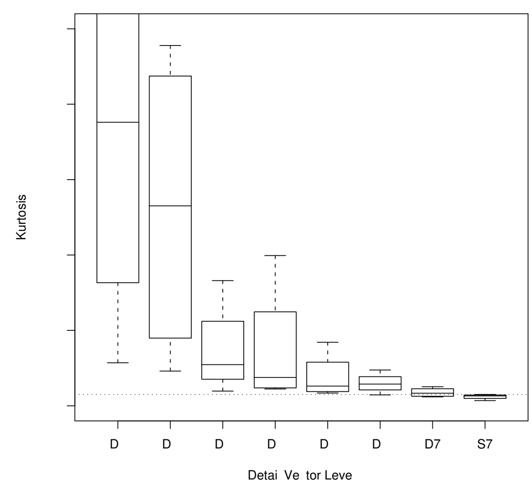

Figure 3-4: NIKKEI225 Futures (minutes)

The high-frequency area of the kurtosis distribution of NIKKEI225 is higher than J30's. Furthermore, the kurtosis distribution of NIKKEI225 Futures is higher than NIKKEI225's. It seems that more complecated trade makes more higher level. There are no financial models including this characteristics.

4 Analysis using the artificial futures market, U-Mart

U-Mart is an artificial market which is used in this experiment. That is a system which has spot prices as an input, the construction of trade agents as inner states, and futures prices and agents' behavior as outputs. We used random walk time series as an input to minimize the effect of the characteristics of the input. The market settings are 128 days and 8 boards a day.

In the Figure 4-1, the result of the experiment that ten random trade agents traded randomly around spot prices in this market. Although the input sequences are random walk, the kurtosis distribution of the high-frequency area is high by trading of random agents.

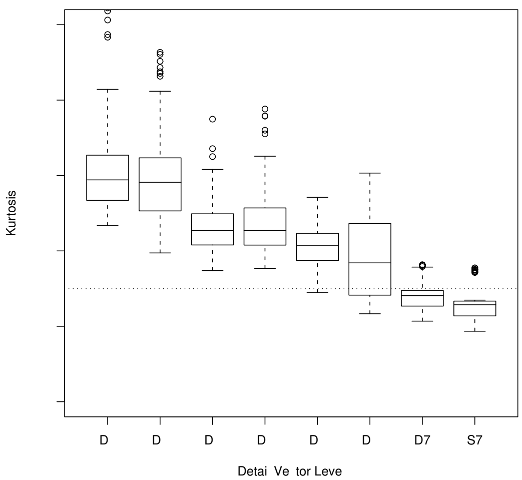

Figure 4-1: Random Agents (around spot) x10

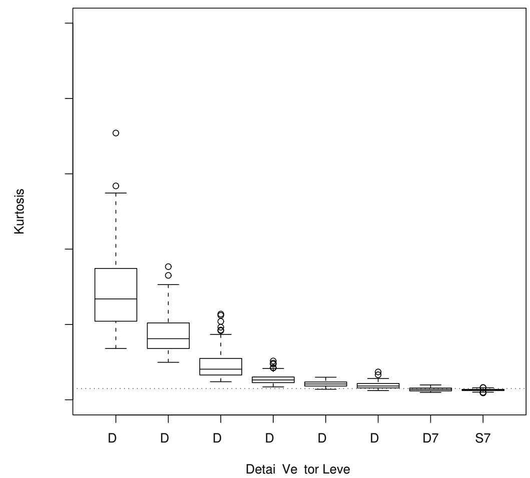

Figure 4-2: Random Agents (around spot) x5 and Random Agents (around futures) x5

Then we exchanged the half of the trade agents, the construction of the agents is five random trade agents which trade randomly around futures prices and five random trade agents which trade randomly around spot prices. Although every trader trads only randomly, the difference of the random center makes the complexity of the market. This means that there are agents who have less knowledge of the market to trade. The result of tha experiment is shown in Figure 4-2. Apparently, trades of the agents raise the kurtosis distribution in high-frequency area.

At the next experience, we exchange the Random Agents for the Trend Agents which trade with a trend strategy. Those ware shown in Figure 4-3. and 4-4.

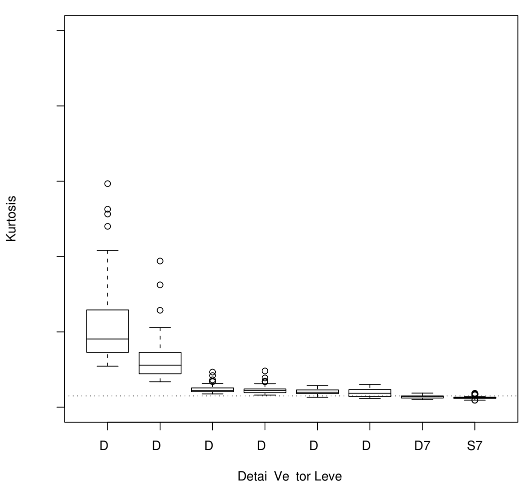

Figure 4-3: Random Agents x5 (around spot) and Trend Agents x5

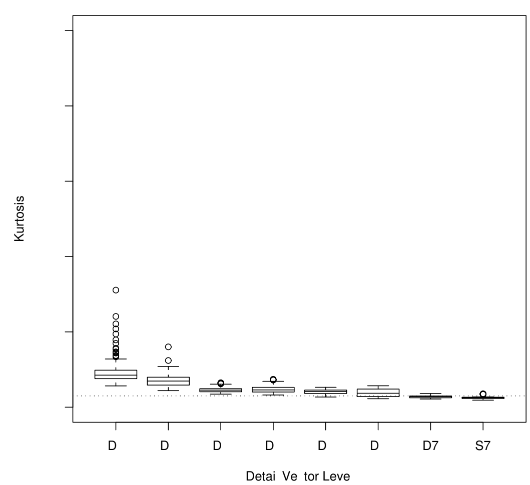

Figure 4-4: Random Agents x8 (around spot) and Trend Agents x2

In the case of Trend Agents, the kurtosis distribution has a same digree complexity. And the kurtosis distribusion of less Trend Agents has a less digree complexity.

Figure 4-5 and 4-6 shows in the case of Anti-Trend Agents.

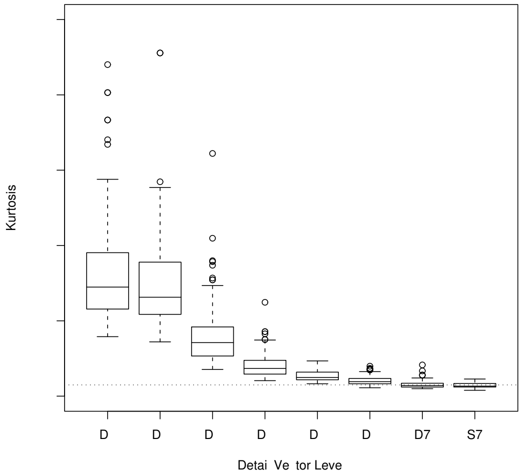

Figure 4-5: Random Agents x5 (around spot) and Anti-Trend Agents x5

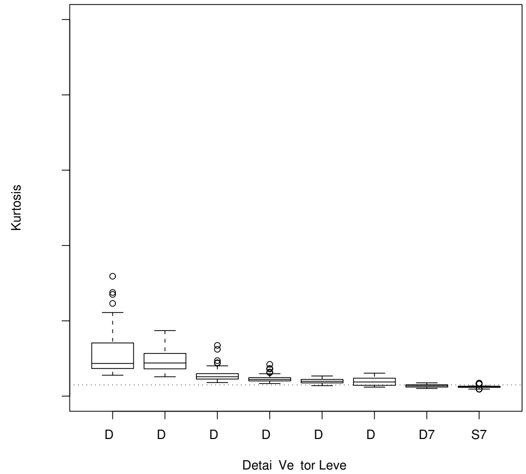

Figure 4-6: Random Agents x8 (around spot) and Anti-Trend Agents x2

And then, How is the behavior in the high-frequency area in the case of six Random Agents, two Trend Agents and two Anti-Trend Agents. The figure of the result is shown in Figure 4-7.

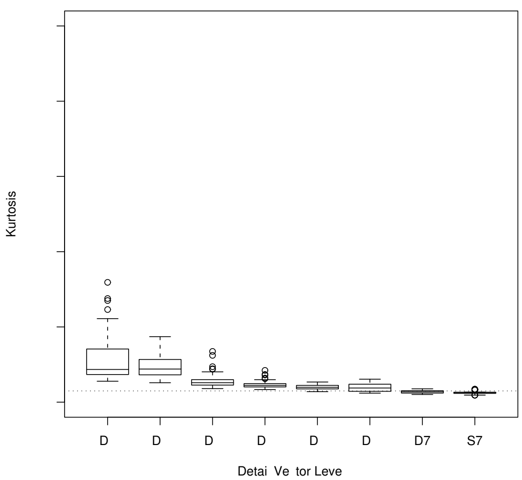

Figure 4-7: Random Agents x6 (around spot), Trend Agents x2 and Anti-Trend Agents x2

That figure has apparently higher level distribution than the case of only Random Agents. But, that has less level distribution than the case of four Trend Agents or four Anti-Trend Agents. This means the market gains stability by the variety of agents.

5 Conclusion

We showed that there are differences between financial models and real financial time series in the behavior of the high-frequency ingredient, and artificial market approachs have enough validity to examine financial time series.

Why does the construction of agents makes high level distribution in high-frequency area? Because the real and artificial market may be “Rugged Market.” The real market is made from various orders,and these orders are NOT continuous. Then supply-demand curve is lack of smoothness. Therefore, the slight difference of orders affects the difference of the market prices.

We cannot analyse the characterisity of high level distribution in high-frequency area by using existing financial theory. We propose to use an artificial market to analyse rugged market.

6 References

Donald B. Percival, Andrew T. Walden (2000), “Wavelet Methods for Time Series Analysis”, Cambridge University Press.