# Herd Behaviors in the Futures Exchange Markets

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ABSTRACT

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The herd behavior of returns is investigated in Korean futures exchange market. It is obtained that the probability distribution of returns for three types of herding parameter scales as a power law $R^{-\beta}$ with the exponents $\beta$=3.6 (KTB203) and 2.9 (KTB209) in two kinds of Korean treasury bond. For our case since the active state of transaction exists to decrease lesser than the herding parameter $h$=2.33, the crash regime appears to increase in the probability with high returns values. Especially, we find that it shows a crossover toward a Gaussian probability function near the time step $\Delta t$=360 from the distribution of normalized returns. Our result will be also compared with other well-known results.

*Keywords*: Herd behavior; Returns; Bond futures; Futures exchange market

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# 1. Introduction

In financial markets, there has recently been attracted the considerable interests for the microscopic models in natural and social sciences [1-3]. It is in particular well-known that the major models of interest in self-organized phenomena are the herding multiagent model [4,5] and the related percolation models [6,7], the democracy and dictatorship model [8], self-organized dynamical model [9], the cut and paste model, the fragmentation and coagulation model [10]. One of challenging microscopic models is the herding model [11,12] that means some degree of coordination and crowd effect between a group of agents sharing the same information or the same rumor and making a common decision. It has recently been introduced that the probability distribution of returns scales a power law and that it exists the financial crashes in the probability with low herding parameters and high return values [5]. Moreover, the distribution of normalized returns has the form of the fat-tailed distributions [13] of price return, and a crossover toward the Gaussian distribution can be shown in financial markets.

The theoretical and numerical arguments for the volume of bond futures traded at Korean futures exchange market were presented in the previous work [14]. We mainly considered the number of transactions for two different delivery dates and found the decay functions for survival probabilities [15,16] in our bond futures model. We also have studied the tick dynamical behavior of the bond futures price using the range over standard deviation or the R/S analysis in Korean Futures Exchange market [17]. The Norwegian and US stock markets presented in recent work [18] have been led to the notable persistence caused by long-memory in the time series. The multifractal Hurst exponents and the height-height correlation function have mainly been discussed numerically with long-run memory effects. It is particularly shown that the form of the probability distribution of the prices leads to the Lorentz distribution rather than the Gaussian distribution [17].

The purpose of this paper is to study the dynamical herding behavior of the bond futures price for two kinds of Korean treasury bond in Korean futures exchange market. In this paper, we only consider two different delivery dates: October KTB203 and April KTB209. The tick data for KTB203 were taken from October 2002 to March 2002 while we used the tick data of March KTB209 transacted for six months from April 2002. In section 2 we mainly find the financial crashes and the distribution of normalized returns from the distribution of returns. We end with some results and conclusions in the final section.

## 2. Financial crashes and simulations

In our model, we introduce bond futures prices for two sets of data (KTB203 and KTB209) in Korean futures exchange market. In Fig.1, we show the time series of bond futures price $P(t)$ that is found in the case of bond futures of KTB203 traded for six months at Korean futures exchange market. We can also obtain numerically the returns $R(t_i) = \ln P(t_i) / P(t_i - 1)$, as plotted in Fig.2, when the activity of transactions takes place at the time step $i$. We use two sets of tick data (KTB203 and KTB209) composed of bond futures prices, and the average time between ticks for these is about one minute.

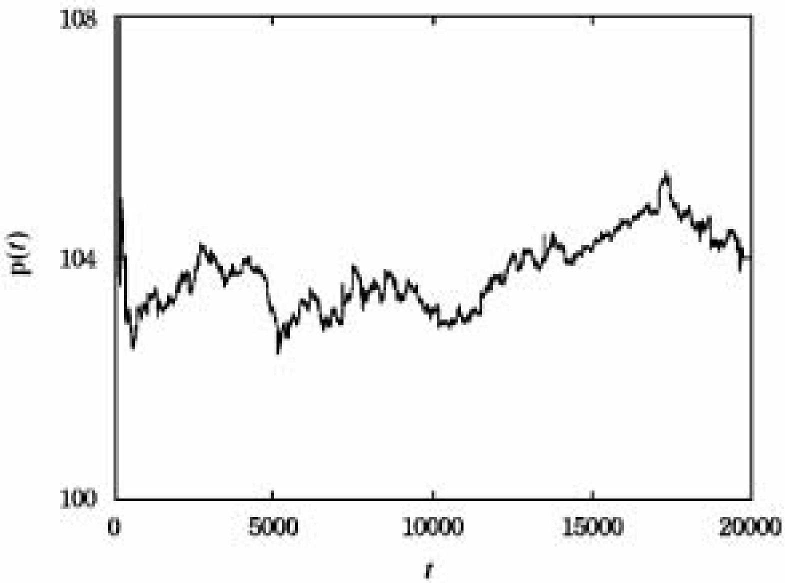



**Fig. 1** Time series of bond futures price $P(t)$ for KTB203.

From now on, let's consider three return states composed by $N$ agents, i.e., the continuous tick data of bond futures price. We assume that the states of agent $l$ can be constituted into $\varphi_l$ = {-1, 0, 1}, where the state of clusters is given by $s(t_i) = \sum_{i=1}^{N} \varphi_l$ . Thus the waiting state that occurs no transactions or gets no return corresponds to $\varphi_l$ = 0, and the selling and buying states, i.e., the active states of transaction, are $\varphi_l$ =1 and $\varphi_l$ = -1, respectively. The active states of the transaction are represented by vertices in a network having links of time series, and we assume that it belongs to the same cluster between a group of agents sharing the same information and making a common decision. Since the distribution of returns is really related to the distribution of cluster, we can obtain the averaged distribution of cluster in our model. Fig.3 presents the log-log plot of the averaged distribution of cluster as a function of the size of the transacted states, and these scale with the scaling exponent $\alpha$ =1.75.

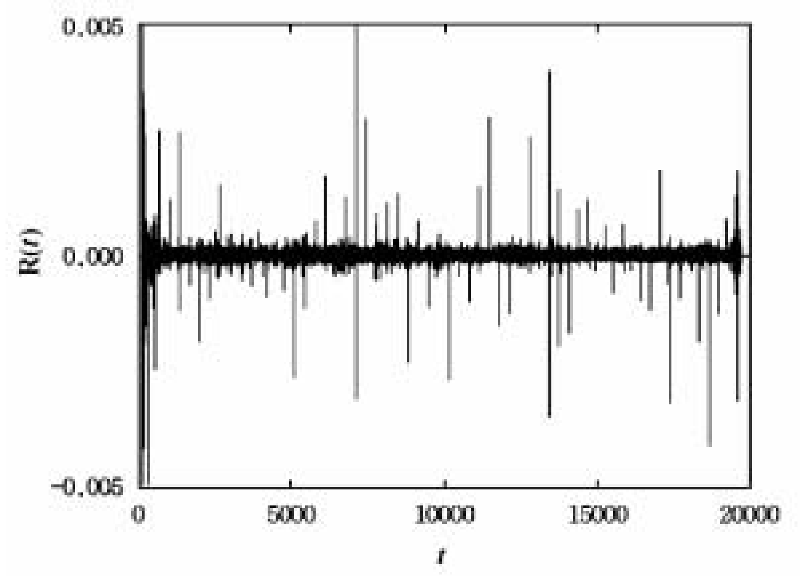



**Fig. 2** Plot of the price return $R(t_i) = \ln P(t_i)/P(t_i - 1)$ for KTB203.

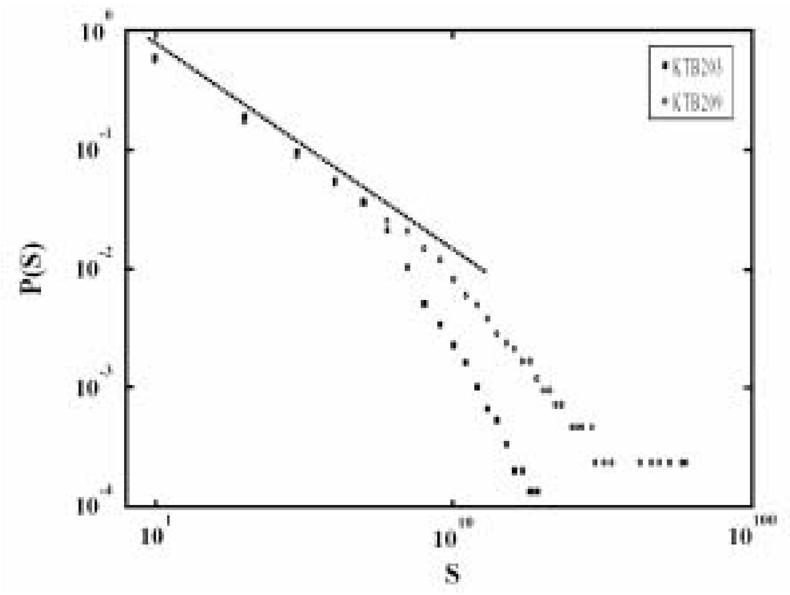
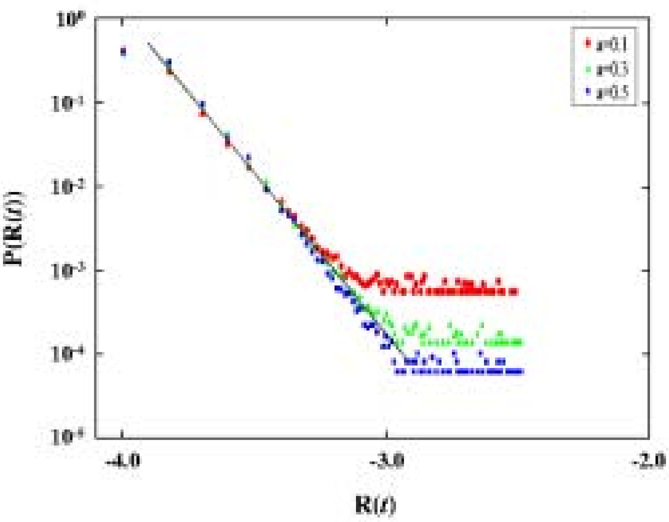
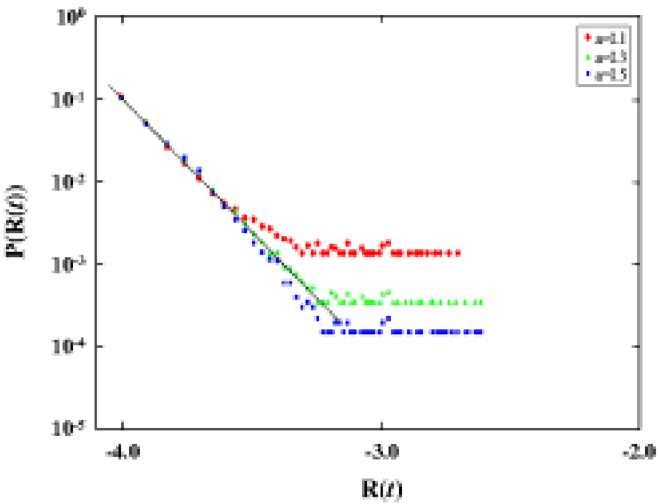



**Fig. 3** Plot of the averaged probability distribution of cluster sizes *s* for the herding probability *a*=0.5 (*h*=1), where the averaged probability distributions for KTB203 and KTB209 scales as a power law $S^{-\alpha}$ with the exponent $\alpha$ = 1.75 (the dot line).




(a)

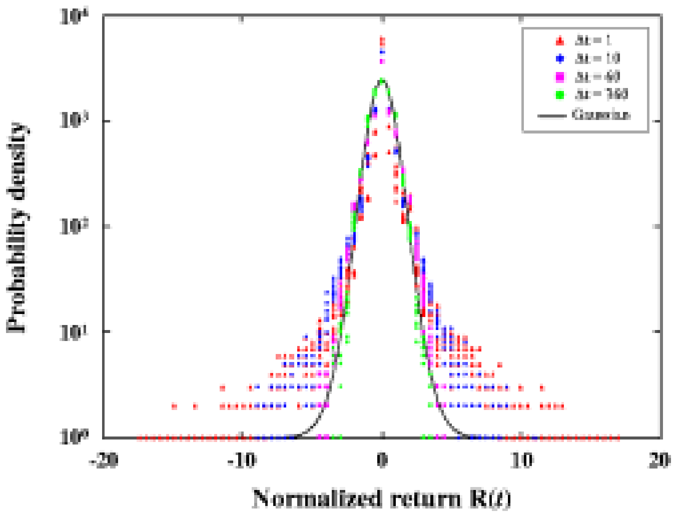



(b)

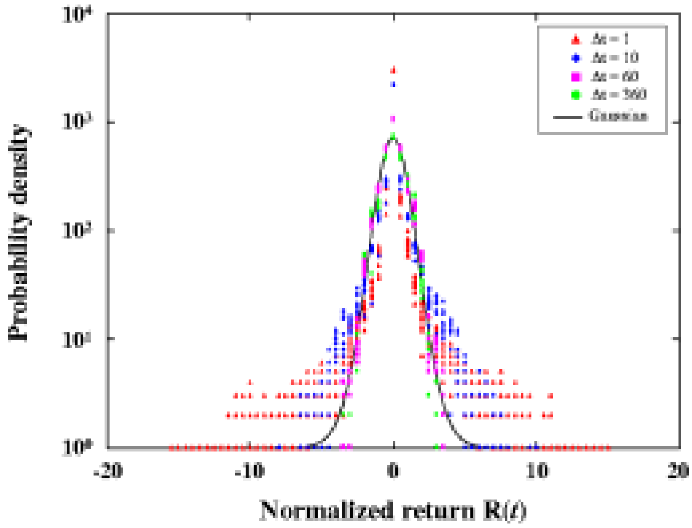
**Fig. 4** Log-log plot of the probability distribution of returns for three types of herding probabilities a=0.1, 0.3, 0.5 (h=9, 2.33, 1), where the dot line scales as a power law $R^{-\beta}$ with the exponents (a) $\beta$=3.6 (KTB203) and (b) 2.9 (KTB209).

In order to find the distribution of the price return $R$ for different herding probabilities, the network of links for $R$ can be selected at random value $a = a_+ + a_-$, where $a_+$ and $a_-$ is, respectively, probability of the selling and buying herds. As the herding parameter is defined by $h = (1-a)/a$, the probability distribution of returns for three types of herding parameter scales as a power law $R^{-\beta}$ with the exponents $\beta$=3.6 (KTB203) and 2.9 (KTB209), as shown in Fig.4(a) and (b). Here we would suggest that $h^* = 2.33$ ($a$=0.3) is the so-called critical herding parameter from our data. It is obtained that the financial crashes occur at $a$<0.3 ($h$>2.33). Thus the crash regime appears to increase in the probability with high returns values, since the state of transaction exists to decrease lesser.

Particularly, we can calculate the distribution of normalized returns for the bond futures price since the normalized return is given by $(R - \langle R \rangle)/\sigma$, where $\langle R \rangle$ is the value of returns averaged over the time series and the volatility $\sigma = (\langle R^2 \rangle - \langle R \rangle^2)^{1/2}$. In Fig.5(a) and (b), we show, respectively, the semi-log plot of the probability distribution of the normalized returns in one case of herding probability $a$=0.1 ($h$=9), where the time steps $\Delta t$ = 1, 10, 60, and 360 for two kinds of Korean treasury bond. Here the herd behavior for $\Delta t$ = 1, 10, and 60 is obtained to take the form of fat-tailed distribution of price returns. On the other hand, the distribution of normalized returns really reduces to a Gaussian probability function for the time step $\Delta t$ = 360.




(a)




(b)

**Fig. 5** Semi-log plot of the probability distribution of the normalized returns ($(R-<R>)/\sigma$) for herding probability a=0.1 (h=9), where the dot line is the form of Gaussian function with (a) $\sigma=1$ for KTB203 and with (b) $\sigma=1$ for KTB209**.**

## 3. Summary

In conclusion, we have investigated the dynamical herding behavior of the bond futures price for two kinds of Korean treasury bond (KTB203 and KTB209) in Korean Futures Exchange market. Specially, the distribution of the price return for our bond futures scales as a power law $R^{-\beta}$ with the exponents $\beta$ = 3.6 (KTB203) and 2.9 (KTB209). However, our distributions of the returns are not in good agreement with those of Eguiluz and Zimmermann [5]. It is in practice found that our scaling exponents $\beta$ are larger than theirs, because our price returns are real values for KTB203 and KTB209. It would be noted that the existence of financial crashes has extremely high probability for the active herding states making the same decision as the herding parameter takes the larger value. We would also suggest that the critical value of herding parameter is $h^*$ = 2.33 ($a$=0.3), and it shows a crossover toward a Gaussian probability function for the distribution of normalized returns.

In future, our results may be expected to be satisfactorily studied extensions of foreign financial analysis for the won-yen and won-dollar exchange rates in Korean foreign exchange market. We hope that it will apply our model of herd behavior to the other tick data in Korean financial markets and in detail compare our results with bond futures transacted in other nations.

## ACKNOWLEDGMENT

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