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Multifractality and herding behavior in the Japanese stock market

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Abstract

In this paper we present evidence of multifractality and herding behavior for a large set of Japanese stocks traded in the Tokyo Stock Exchange. We find evidence that herding behavior occurs in periods of extreme market movements. Therefore, based on the intuition behind the tests to detect herding phenomenon developed, for instance, in Christie and Huang [Christie W, Huang R. Following the pied pier: do individual returns herd around the market? Financ Analysts J 1995;51:31–7] and Chang et al. [Chang EC, Cheng JW, Khorana A. Examination of herd behavior in equity markets: an international perspective. J Bank Finance 2000;24:1651–99], we suggest that herding behavior may be one of the causes of multifractality.

1. Introduction

The financial literature has witnessed a prolonged debate on whether stock markets are efficient or not in the past decades. This discussion is essential as most asset pricing models are based on the market efficient paradigm that excludes the possibility of predictability of stock returns. Therefore, empirical evidence of predictability of stock returns is often seen as a challenge of the market efficient paradigm.[1]

Many researchers have suggested that multifractality is a pervasive characteristic of stock prices [26,28,1,33]. Actually, multifractality may arise due to intrinsic properties of the dynamics of stock prices. In particular, it has been shown previously that long range correlations between past and present events and fat-tailed probability distributions of fluctuation may induce multifractality. Additionally, the presence of multifractality in financial time series excludes the possibility of efficient market.

If multifractality is present in stock returns then multifractal models such as the one presented in [12] may fit well the data and may be used for forecasting purposes. These models are competitors for traditional ARCH and GARCH models. Furthermore, traditional option pricing models are not valid, most asset pricing theories that assume Brownian motions for the dynamics of asset prices are misleading. Therefore, multifractality has many implications for portfolio and risk management.

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[1] See for example [16,7–11].

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The origins of multifractality in stock prices are not well understood yet. Understanding the origins of multifractality is an important research topic. In this paper, in agreement with the computational approaches due to Wang and Zhang [34] and Sornette and Zhou [32], we suggest that one of the causes of multifractality is the presence of herding behavior in the stock market. The relation between herding behavior and multifractality seems to be quite intuitive if one considers, for instance, the methodologies considered in [17] and [15] to test the presence of herding behavior. In these papers, the reasoning behind some of these methodologies is that individuals during periods of extreme market movements are suppressing their own beliefs in favor of the market consensus. If this reasoning is true then one may conclude that the phenomena behind small and large movements in financial time series are different which consequently causes multifractality.

This paper presents three main contributions to the financial literature. In the first place, the literature considering herding within specific industries is scant. In this paper we focus on industrial sectors for the Japanese economy, which is the largest stock market in Asia. Secondly, we use recent methods developed in the statistical physics to test for multifractality and show how it is related to the herding phenomenon that is found in the paper. Finally, we consider a very recent period, January 2000 to February 2006, in which the Japanese stock market has suffered extreme movements. In such periods it is more likely that herding phenomenon occurs due to increased uncertainty.

The paper is organized as follows: Section 2 provides a brief literature review. Section 3 describes the methodology associated with testing for multifractality and herding. Section 4 describes the data. Section 5 presents the results of applying the methodology. Finally, Section 6 offers a brief conclusion.

2. Brief literature review

The study of herding behavior, the phenomenon associated to the situation where people blindly follow the others' decisions, has generated a huge literature in economics. In general, considering the presence of externalities in the structure of the market, the microeconomic theory says that herding behavior is rational if the predecessor's decisions affects one's (1) payoff structure such that imitation implies in a higher payoff (this is called payoff externality); (2) probability of assessment the state of the world such that this behavior is more informative than the private signal. Details of these ideas may be found in [6] and [14].

It is interesting to stress that in spite of being rational, the herding phenomenon is in disagreement with the efficient market hypothesis. Investors that follow the crowd and imitate others may destabilize markets as prices are driven away from fundamentals creating excess volatility [18,27].

In this context, one important recent line of research has been to propose methodologies to detect the presence of herding behavior in the market. These methodologies were introduced, for example, in [27], [17], [15] and [23] and used to detect the presence of herding behavior in a variety of markets by, for instance, Gleason et al. [21,22], Bowe and Domuta [5] and Demirer and Kutan [19]. Furthermore, this empirical literature has documented that herding behavior is more likely to occur when markets suffer large fluctuations, specially in bear markets [23]. Therefore, we should expect that large and small fluctuations of stock prices to present different dynamics, the former with the presence of herding and the later without it. Thus, as it was already stressed, since the dynamics of large and small fluctuations are different due herding behavior, this might be one of the sources of multifractality in stock returns.

Finally, some computational approaches have risen some interesting issues about the consequences of the presence of herding behavior in financial markets. In particular, Wang and Zhang [34] develop a microscopic model of financial markets based on belief propagation in order to simulate the dynamics of the stock market. The beliefs of market leaders spread in their model resulting in the herd behavior of trade. Within this framework the authors are able to reproduce stylized aspects of financial markets such as multifractal property. Sornette and Zhou [32] build a computational model of financial price dynamics that incorporates imitation. They are able to reproduce stylized facts of financial markets only when agents are overconfident and mis-attribute the success of news to predict returns to herding effects. Furthermore, their model exhibits a rich multifractal structure. These references seem to be the start point of this paper. However, while these references are based on computational microscopic markets, our paper presents an empirical approach for studying real markets.

3. The estimation of multifractality and herding behavior

3.1. Multifractality

The concept of multifractality for time series (and other self-affine fractals) was introduced in Barabási and Vicsek [3]. Since this work, some ways to detect multifractality were introduced. Barabási et al. [4] proposed to identify the multifractal phenomenon using the so-called high–high correlation functions. Recently, these parameters used to characterize multifractality in [4] have been called Global Hurst Exponents [20]. On the other hand, Bacry et al. [2] suggested the use of wavelets to detect multifractality.

In this paper, we follow a different approach and employ the MF-DFA (MultiFractal-Detrended Fluctuation Analysis) developed by Silva and Moreira [30] and investigated recently by Kantelhardt et al. [25]. This method is an extension of the DFA developed independently by Moreira et al. [29] and Peng et al. [31] and used to determine the Hurst exponent of self-affine monofractals.

In order to introduce the MF-DFA, let $Y(t)$ be the integrated time series of logarithm returns, i.e., $Y(t) = \log(X(t))$, where $X(t)$ is the price of the asset. So, one considers the τ-neighborhood around each point $Y(t)$ of the time series. The local trend in each τ-size box is approximated by a polynomial[2] of order m, namely $Z(t)$).

Then, one may evaluate the q-order fluctuation function, namely

$$w_q(Y,\tau) = \left\{ \frac{1}{\tau} \sum_{t\in\tau} [(Y(t) - Z(t))^2]^{q/2} \right\}^{1/q}, \tag{1}$$

where q can take any real value different from zero.[3]

It is easy to show [13,25] that

$$\langle w_q(\tau)\rangle \sim \tau^{H(q)}. \tag{2}$$

According to Kantelhardt et al. [25], two different sources of multifratality in time series can be found. Both of them require a multitude of scaling exponents for small and large fluctuations: (i) Multifractality due to a broad probability density function for the values of the time series such as the case of time series described by power laws; (ii) Multifractality due to different long range correlations for small and large fluctuations. Considering the extreme case, for instance, it is known that the dynamics behind large price fluctuations such as crashes is usually different from the one presented in a market normal phase (for details, see [24]).

Richer multifractality correspond to higher variability of $H(q)$. Therefore, we will compute Generalized Hurst exponents for different qs.

3.2. Herding behavior

Christie and Huang [17] and Chang et al. [15] have introduced an interesting technique to detect the presence of herding behavior in financial markets. Their main idea is that in the presence of herd behavior, security returns tend to not deviate far from overall market returns. In this case, individuals make investment decisions based on collective actions of the market, instead of trading based on their individual beliefs.

In order to test for herding behavior we follow particularly Chang et al. [15] and use the cross-sectional absolute deviation (CSAD) as a dependent variable. This measure can be interpreted as a proxy for securities dispersion around the market average.

We assume an index market model given by:

$$E_t(R_i) = \gamma_0 + \beta_i E_t[R_m - \gamma_0], \tag{3}$$

for $i = 1,\ldots,n$, where R_i and R_m are, respectively, the ith asset and market returns and γ_0 is the return of the zero return portfolio. Let β_m be the systematic risk of the market portfolio. Then

$$\beta_m = 1/n \sum_{i=1}^{n} \beta_i. \tag{4}$$

The absolute value of deviation (AVD) of security i's expected return in period t from the tth period portfolio expected return can be expressed as

$$\mathrm{AVD}_{i,t} = |\beta_i - \beta_m| E_t R_m. \tag{5}$$

[2] This polynomial of order m is usually a first order polynomial, i.e., a straight line where the parameters are determined by a least square fitting.

[3] The value of $H(0)$, which corresponds to the limit $H(q)$ for $q \to 0$, cannot be determined directly using Eq. (1) presented above. One may calculate it using the logarithm average procedure $w_0(Y,\tau) = \left[\frac{1}{\tau}\sum_{t\in\tau} ln[(Y(t) - Z(t))^2]\right] \sim \tau^{H(0)}$.

Therefore, we can define the expected cross-sectional absolute deviation (ECSAD) of stock returns in period t as follows:

$$\mathrm{ECSAD}_t = 1/n \sum_{i=1}^{n} \mathrm{AVD}_{i,t} E_t R_m. \tag{6}$$

We use the cross-sectional absolute deviation of returns (CSAD) and $R_{m,t}$ to proxy, respectively, for the unobservable ECSAD_t and $E_t(R_{m,t})$.

Our regression specification[4] is as follows:

$$\mathrm{CSAD}_t = \alpha + \beta_d D_{d,t} + \beta_{u,t} D_{u,t} + \epsilon_t, \tag{7}$$

where $D_{d,t} = 1$, if the return on the market portfolio on day t below a threshold level (1% or 5%) and zero otherwise, and $D_{u,\ t} = 1$, if the return on the market portfolio on day t above a threshold level (99% or 95%) and zero otherwise.

These dummies are used to capture differences in return dispersions during periods of extreme market movements. Testing for herding behavior implies that the coefficients β_d and $\beta_{u,t}$ are statistically significant and negative.

The regression specification (7) is specially interesting for this work. With this specification, it is possible to separate the behavior of large positive events from small positive events and large negative events from small negative events in order to approach explicitly the relation between herding behavior and multifractality.

The hypothesis behind Eq. (7) is that in the case of herding in extreme events (upper or lower tails of the return distribution) the cross-sectional standard deviation of stock returns reduces as investors tend to imitate other investors and follow market consensus. For details, see [15].

4. Data

This study uses daily closing prices Japanese individual stocks that comprise the Nikkei Index. The Nikkei 225 is the most widely followed and most frequently quoted Japanese stock index, is calculated to accurately reflect the Japanese stock market. The Nikkei is a price-weighted index. This index is comprised of 225 top-rated, blue-chip Japanese companies listed in the First Section of the Tokyo Stock Exchange.

Our focus is on different sectors as they are more likely to show herding behavior patterns from investors. Therefore, we study individual stocks that belong to the Nikkei index (as of December 2005). However, we are not able to use all 225 stocks because some of these stocks do not have a long time history available. Therefore, we use stocks that have a time series history from 4 January, 2000 to 9 February, 2006. Only 202 stocks have a complete price history and they were selected to comprise our sample.

Fig. 1 presents the Nikkei 225 index. The stock market has plunged −91.54% in the period from January 4, 2000 to April 28, 2003 (bottom of the bear period). After that, it has increased 74.15% until February 9, 2006. We have selected this period to include a period of extreme movements in the Japanese stock market, with both a bear and bull markets to study herding behavior and multifractality in different stock market sectors.

We have classified all stocks in one of the following sectors: basic materials (25 stocks), communication (6 stocks), consumer cyclical (45 stocks), consumer non-cyclical (28 stocks), energy (3 stocks), financial (17 stocks), industrial (66 stocks), technology (7 stocks) and utilities (5 stocks). All data was collected from the Bloomberg database.

5. Empirical results

We employ the cross-sectional absolute standard deviation (CSAD_t) of returns as a measure of dispersion to detect the existence of herding in the Japanese stock market. The main idea behind our testing strategy is that we should expect that stock returns dispersion decreases in periods of extreme market movements, which is an indication of herding behavior.

Table 1 presents results for the regression:

$$\mathrm{CSAD}_t = \alpha + \beta_d D_{d,t} + \beta_{u,t} D_{u,t} + \epsilon_t. \tag{8}$$

[4] This specification is only one of the specifications presented in [15].

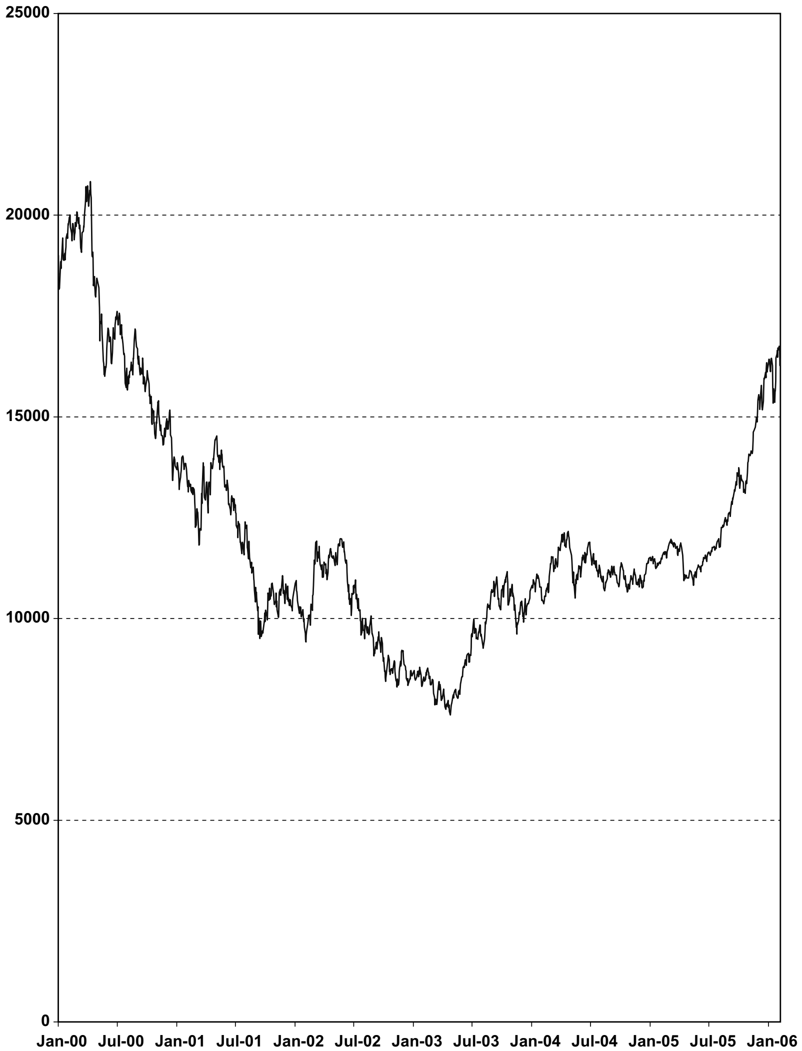

Fig. 1. Nikkey Stock Index.

The estimations were done using the Newey-West heteroskedasticity and autocorrelation consistent standard errors. Panels A and B present results for two sets of dummy variables. In the former, we restrict the variables $D_{d,t}$ and $D_{u,t}$ to the 1% lower and upper tails, respectively. While, in the latter we employ the 5% criteria.

All estimated coefficients are significant. However, only for down markets the coefficients are negative, suggesting that the presence of herding behavior only for bear markets. This result is robust to using the lower (upper) 1% and 5% percentile of the return distribution. Therefore, in bear markets traders are more likely to heard than in bull markets.

One possible explanation for herding in bear markets is that performance evaluation of traders is done on a comparative basis. Therefore, in periods of increasing uncertainty people tend to follow the crowd, and minimize the probability of achieving results that are worse than average.

To confirm the validity of our approach, Table 2 presents results for the multifractality tests using the MF-DFA methodology. As we can see generalized Hurst exponents $H(q)$ depend on the q, which suggests the presence of multifractality.

Our empirical results suggests that herding behavior may be the cause of multifractality, which is a novel finding in the financial literature.

Table 1
This table presents regressions coefficients for $CSAD_t = \alpha + \beta_d D_{d,t} + \beta_u D_{u,t} + \epsilon_t$

	β_d		β_u	
Panel A: Market return in the extreme 1%				
Basic materials	−0.005076***	(0.000282)	0.004611***	(0.000274)
Communication	−0.019441***	(0.001082)	0.017658***	(0.001048)
Consumer, cyclical	−0.005351***	(0.000298)	0.00486***	(0.000288)
Consumer, non-cyclical	−0.013198***	(0.000734)	0.011988***	(0.000711)
Energy	−0.014596***	(0.000812)	0.013257***	(0.000786)
Financial	−0.014141***	(0.000787)	0.012844******	(0.000762)
Industrial	−0.010755***	(0.000598)	0.009769***	(0.00058)
Technology	−0.01499***	(0.000834)	0.013615***	(0.000808)
Utilities	−0.033331***	(0.001854)	0.030274***	(0.001796)
All sectors	−0.012064***	(0.000671)	0.010957***	(0.00065)
Panel B: Market return in the extreme 5%				
Basic materials	−0.003452***	(0.000129)	0.003282***	(0.000113)
Communication	−0.013219***	(0.000496)	0.012569***	(0.000433)
Consumer, cyclical	−0.003638***	(0.000136)	0.003459***	(0.000119)
Consumer, non-cyclical	−0.008974***	(0.000336)	0.008533***	(0.000294)
Energy	−0.009924***	(0.000372)	0.009436***	(0.000325)
Financial	−0.009615***	(0.00036)	0.009142***	(0.000315)
Industrial	−0.007313***	(0.000274)	0.006953***	(0.00024)
Technology	−0.010192***	(0.000382)	0.009691***	(0.000334)
Utilities	−0.022663***	(0.00085)	0.021549***	(0.000743)
All sectors	−0.008203***	(0.000307)	0.007799***	(0.000269)

The symbols *** stand for statistical significance at the 1% level. Newey-West heteroskedasticity and autocorrelation corrected standard errors are presented in parentheses.

Table 2
This table presents MF-DFA Hurst exponents $H(q)$ for stock market sector indices for different q

	q			Δ_q
	1	5	10	
Panel A: MF-DFA raw data				
Basic materials	0.485	0.420	0.366	0.311
Communication	0.484	0.424	0.378	0.247
Consumer, cyclical	0.486	0.414	0.364	0.312
Consumer, non-cyclical	0.454	0.360	0.297	0.467
Energy	0.462	0.368	0.286	0.485
Financial	0.471	0.419	0.381	0.212
Industrial	0.482	0.409	0.359	0.339
Technology	0.476	0.423	0.381	0.227
Utilities	0.451	0.387	0.358	0.235
Panel B: MF-DFA shuffled data				
Basic materials	0.516	0.471	0.428	0.197
Communication	0.528	0.500	0.466	0.127
Consumer, cyclical	0.517	0.463	0.414	0.233
Consumer, non-cyclical	0.524	0.462	0.403	0.286
Energy	0.507	0.469	0.425	0.182
Financial	0.516	0.490	0.459	0.125
Industrial	0.516	0.466	0.416	0.233
Technology	0.500	0.469	0.449	0.113
Utilities	0.511	0.466	0.429	0.175

The last column presents the degree of multifractality measured as $\Delta_q = \ln(H_{max}) - \ln(H_{min})$.

6. Conclusions

This paper, using real data from the Japanese stock market, has suggested that the presence of multifractality in stock returns may be a consequence of the presence of herding behavior.

The procedure performed here is dependent from the choice of the specification of the regression analysis proposed in [15] where one can separate the behavior of large fluctuations from small fluctuations justifying the presence of multifractality from its definition. Furthermore, we also have presented the results of the multifractality tests confirming our expected results.

The main contribution of the paper is that we have shown that multifractality may be due to herding in stock markets. Further research could study the relationship between multifractality in asset prices and market microstructure.

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