New Economic Windows

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Econophysics of Stock and other Markets

Proceedings of the Econophys-Kolkata II
Successful or not, we all (have to?) go to various markets and participate in their activities. Yet, so little is understood about their functionings. Efforts to model various markets are now substantial. Econophysicists have also come up recently with several innovative models and their analyses.

This book is a proceedings of the International Workshop on “Econophysics of Stock Markets and Minority Games”, held in Kolkata during February 14-17, 2006, under the auspices of the Centre for Applied Mathematics and Computational Science, Saha Institute of Nuclear Physics, Kolkata. This is the second event in the Econophys-Kolkata series of meetings; the Econophys-Kolkata I was held in March 2005 (Proceedings: Econophysics of Wealth Distributions, published in the same New Economic Windows series by Springer, Milan in 2005). We understand from the enthusiastic response of the participants that the one-day trip to the Sunderbans (Tiger Reserve; a world heritage point) along with the lecture-sessions on the vessel had been hugely enjoyable and successful. The concluding session had again very lively discussions on the workshop topics as well as on econophysics in general, initiated by J. Barkley Rosser, Matteo Marsili, Rosario Mantegna and Robin Stinchcombe (Chair). We plan to hold the next meeting in this series, on “Econophysics and Sociophysics: Debates on Complexity Issues in Economics and Sociology” early next year.

We are very happy that several leading economists and physicists engaged in these recent developments in the econophysics of markets, their analysis and modelling could come and participate. Although a few of them (Fabrizio Lillo, Thomas Lux and Rosario Mantegna) could not contribute to this proceedings volume due to shortage of time (we again try to get this proceedings published within six months from the workshop), we are indeed very happy that most of the invited participants could contribute in this book. The papers on market analysis and modellings are very original and their timely appearance here will render the book extremely useful for the researchers. The two historical notes and the Comments and Discussions section will give the readers two examples of personal perspectives regarding the new developments in econophysics, and
some ‘touch’ of the lively debates taking place in these Econophys-Kolkata series of workshops.

We are extremely grateful to Mauro Gallegati and Massimo Salzano of the editorial board of this New Economic Windows series of Springer for their encouragement and support, and to Marina Forlizzi for her efficient maintenance of publication schedule.

Kolkata, January 2006

Arnb Chatterjee

Bikas K. Chakrabarti
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Part I

Markets and their Analysis
On Stock-Price Fluctuations in the Periods of Booms and Stagnations

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1 Introduction

The statistical properties of the fluctuations of financial prices have been widely researched since Mandelbrot [1] and Fama [2] presented an evidence that return distributions can be well described by a symmetric Levy stable law with tail index close to 1.7. Many empirical studies have shown that the tails of the distributions of returns and volatility follow approximately a power law with estimates of the tail index falling in the range 2 to 4 for large value of returns and volatility. (See, for examples, de Vries [3]; Pagan [4]; Longin [5], Lux [6]; Guillaume et al. [7]; Muller et al. [8]; Gopikrishnan et al. [9], Gopikrishnan et al. [10], Plerou et al. [11], Liu et al. [12]). However, there is also evidence against power-law tails. For instance, Barndorff-Nielsen [13], and Eberlein et al. [14] have respectively fitted the distributions of returns using normal inverse Gaussian, and hyperbolic distribution. Laherrere and Sornette [15] have suggested to describe the distributions of returns by the stretched-exponential distribution. Dragulescu and Yakovenko [16] have shown that the distributions of returns have been approximated by exponential distributions. More recently, Malevergne, Pisarenko and Sornette [17] have suggested that the tails ultimately decay slower than any stretched exponential distribution but probably faster than power laws with reasonable exponents as a result from various statistical tests of returns.

Thus opinions vary among scientists as to the shape of the tail of the distribution of returns (and volatility). While there is fairly general agreement that the distribution of returns and volatility has fat tails for large values of returns and volatility, there is still room for a considerable measure of disagreement about universality of the power-law distributions. At the moment we can only say with fair certainty that (i) the power-law tail of the distribution of returns and volatility is not an universal law and (ii) the tails of the distribution of returns and volatility are heavier than a Gaussian, and are between exponential and power-law. There is one other thing that is important for understanding of price movements in financial markets. It is a fact
that the financial market has repeated booms (or bull market) and stagnations (or bear market). To ignore this fact is to miss the reason why price fluctuations are caused. However, in most empirical studies, which have been made on statistical properties of returns and volatility in financial markets, little attention has been given to the relationship between market situations and price fluctuations. Our previous work [18] investigates this subject using the historical data of the Nikkei 225 index. We find that the volatility in the inflationary period is approximated by an power-law distribution while the volatility distribution in the deflationary period is described by an exponential distribution. The purpose of this paper is to examine further the statistical properties of volatility distribution from this viewpoint. We use the daily data of the four stock price indices of the three major stock markets in the world: the Nikkei 225 index, the DJIA. SP500, and FT100, and compare the shape of the volatility distribution for each of the stock price indices in the periods of booms with that in the period of stagnations. We find that (i) the tails of the distribution of the absolute log-returns are approximated by a power-law function with the exponent close to 3 in the periods of booms while the distribution is described by an exponential function with the scale parameter close to unity in the periods of stagnations. These indicate that so far as the stock price indices we used are concerned, the same observation on the volatility distribution holds in all cases.

The rest of the paper is organized as follows: the next section analyzes the stock price indices and shows the empirical findings. Section 3 gives concluding remarks.

2 Empirical analysis

2.1 Stock price indices

We investigate quantitatively the four stock price indices of the three major stock markets in the world\(^1\), that is, (a) the Nikkei 225 index (Nikkei 225), which is the price-weighted average of the stock prices for 225 large companies listed in the Tokyo Stock Exchange, (b) the Dow Jones Industrial Average (DJIA), which is the price-weighted average of 30 significant stocks traded on the New York Stock Exchange and Nasdaq, (c) Standard and Poor’s 500 index (SP 500), which is a market-value weighted index of 500 stocks chosen for market size, liquidity, and industry group representation, and (d) FT 100, which is similar to SP 500, and a market-value weighted index of shares of the top 100 UK companies ranked by market capitalization. Figure 1(a)-(d) show the daily series of the four stock price indices: (a) the Nikkei 225 from January 4, 1975 to August 18, 2004, (b) DJIA from January 2, 1946 to August

\(^1\) The prices of the indices are close prices which are adjusted for dividends and splits.
18, 2004, (c) SP 500 from November 22, 1982 to August 18, 2004, and (d) FT 100 from April 2, 1984 to August 18, 2004.

After booms of a long period of time, the Nikkei 225 reached a high of almost 40,000 yen on the last trading day of the decade of the 1980s, and then from the beginning trading day of 1990 to mid-August 1992, the index had declined to 14,309, a drop of about 63 percent. A prolonged stagnation of the Japanese stock market started from the beginning of 1990. The time series of the DJIA and SP500 had the apparent positive trends until the beginning of 2000. Particularly these indices surged from the mid-1990s. There is no doubt that this stock market booms in history were propelled by the phenomenal growth of the Internet which has added a whole new stratum of industry to the American economy. However, the stock market booms in the US stock markets collapsed at the beginning of 2000, and the descent of the US markets started. The DJIA peaked at 11722.98 on January 14, 2000, and dropped to 7286.27 on October 9, 2002 by 38 percent. SP500 arrived at peak for 1527.46 on March 24, 2000 and hit the bottom for 776.76 on October 10, 2002. SP500 dropped by 50 percent. Similarly FT100 reached a high of 6930.2 on December 30, 2000 and the descent started from the time. FT100 dropped to 3287 on March 12, 2003 by 53 percent.

From these observations we divide the time series of these indices in the two periods on the day of the highest value. We define the period a period until it reaches the highest value as the period of booms and the period after that as stagnations, respectively. The periods of booms and stagnations for each index of the four indices are collected into Table 1.

<table>
<thead>
<tr>
<th>Name of Index</th>
<th>The Period of Booms</th>
<th>The Period of Stagnations</th>
</tr>
</thead>
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2.2 Comparisons of the distributions of absolute log returns

In this paper we investigate the shape of distributions of absolute log returns of the stock price indices. We concentrate to compare the shape of the distribution of volatility in the period of booms with that in the period of stagnations. We use absolute log return, which is a typical measure of volatility. The absolute log returns is defined as $|R(t)| = |lnS(t) - lnS(t - 1)|$, where $S(t)$ denotes the index at date $t$. We normalize the absolute log-return $|R(t)|$ using the standard deviation. The normalized absolute log return $V(t)$ is defined as
Fig. 1. The movements of the stock price indices: (a) Nikkei 225 (b) DJIA, (c) SP500, (d) FT100.
\[
V(t) = |R(t)|/\sigma \text{ where } \sigma \text{ denotes the standard deviation of } |R(t)|.
\]
The panels (a)-(h) of Figure 2 show the semi-log plots of the complementary cumulative distribution of the normalized absolute log-returns \(V\) for each of the four indices: Nikkei225, DJIA, SP500, and FT100 in the period of booms and that in the period of stagnations, respectively. In the all panels it follows that the tail of the volatility distribution of \(V\) is heavier in the period of booms than in the period of stagnations. The solid lines in all panels represent the fits of the exponential distribution,

\[
P(V > x) \propto \exp(-\frac{x}{\beta}) \tag{1}
\]

where the scale parameter \(\beta\) is estimated from the data using a least squared method. In all cases of the period of stagnations, which are panels (b), (d), (f) and (h), the exponential distribution (1) describes very well the distributions of \(V\) over a whole range of values of \(V^2\). The scale parameter \(\beta\) is estimated from the data except for these two extreme values using a least squared method is collected in Table 2. In all cases the estimated values \(\beta\) are very close to unity.

<table>
<thead>
<tr>
<th>Name of Index</th>
<th>The scale parameter (\beta)</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikkei225</td>
<td>1.02</td>
<td>0.995</td>
</tr>
<tr>
<td>DJIA</td>
<td>1.09</td>
<td>0.995</td>
</tr>
<tr>
<td>SP500</td>
<td>0.99</td>
<td>0.997</td>
</tr>
<tr>
<td>FT100</td>
<td>0.99</td>
<td>0.999</td>
</tr>
</tbody>
</table>

On the other hand, the panels (a), (c), (e), and (g) of Figure 2 show the complementary cumulative distribution of \(V\) in the period of booms for each of the four indices in the semi-log plots. The solid lines in all panels represent the fits of the exponential distribution estimated from the data of only the low values of \(V\) using a least squared method. In these cases the low values of \(V\) are only approximately well described by the exponential distribution (1), but completely fails in describing the large values of \(V\). Apparently, an exponential distribution underestimates large values in the complementary cumulative distribution of \(V\) in the period of booms.

Finally the panels (a) and (b) of Figure 3 show the complementary cumulative distributions of \(V\) for the four indices in the period of booms in a log-log

\footnote{Note that we exclude the tow extreme values of \(V\): (i) the extreme value in the Nikkei 225 on September 28, 1990, and (ii) the extreme value in the DJIA on September 10, 2001. The jump of Nikkei 225 perhaps was caused by investors speculation on the 1990 Gulf War. The extreme value of DJIA was caused by terror attack in New York on September 10, 2001.}
Fig. 2. The panels (a), (c), (e) and (g) indicate the complementary cumulative distribution of absolute log returns $V$ for each of the four stock price indices in the period of booms, and the panels (b), (d), (f) and (h) indicate that in the period of stagnations. These figures are shown in a semi-log scale. The solid lines represent fits of the exponential distribution.
scale, and those in the period of stagnations in a semi-log scale. The two figures confirm that the shape of the fourth volatility distributions in the periods of booms and of stagnations is almost the same, respectively. Furthermore, the complementary cumulative distribution of \( V \) in the period of booms for each of the four indices are approximately described by the power-law distribution in the large values of \( V \),

\[
P(V > x) \propto x^{-\alpha}
\]  

(2)

The power-law exponent \( \alpha \) is estimated from the data of the large values of \( V \) using the least squared method. The best fits succeed in describing approximately large values of \( V \). Table 3 collect the power-law exponent \( \alpha \), which is estimated. The estimated value \( \alpha \) are in the range from 2.83 to 3.69.

<table>
<thead>
<tr>
<th>Name of Index</th>
<th>The power-law parameter ( \alpha )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nikkei225</td>
<td>2.83</td>
<td>0.992</td>
</tr>
<tr>
<td>DJIA</td>
<td>3.69</td>
<td>0.995</td>
</tr>
<tr>
<td>SP500</td>
<td>3.26</td>
<td>0.986</td>
</tr>
<tr>
<td>FT100</td>
<td>3.16</td>
<td>0.986</td>
</tr>
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</table>

3 Concluding remarks

In this paper we focus on comparisons of shape of the distributions of absolute log returns in the period of booms with those in the period of stagnations for the four major stock price indices. We find that the complementary cumulative distribution in the period of booms is very well described by exponential distribution with the scale parameter close to unity while the complementary cumulative distribution of the absolute log returns is approximated by power-law distribution with the exponent in the range of 2.8 to 3.8. The latter is complete agreement with numerous evidences to show that the tail of the distribution of returns and volatility for large values of volatility follow approximately a power law with the estimates of the exponent falling in the range 2 to 4. We are now able to see that the statistical properties of volatility for stock price index are changed according to situations of the stock markets. Our findings make it clear that we must look more carefully into the relationship between regimes of markets and volatility in order to fully understand price fluctuations in financial markets. The question, which we must consider next, is the reasons why and how the differences are created. That traders herd behavior may help account for it would be accepted by most people. Recently we have proposed a stochastic model [19] that may offer the key
Fig. 3. The panels (a) and (b) show the complementary cumulative distributions of $V$ for the four indices in the period of booms in a log-log scale, and those in the period of stagnations in a semi-log scale.
to an understanding of the empirical findings we present here. The results of the numerical simulation of the model suggest the following: in the period of booms, the noise traders’ herd behavior strongly influences to the stock market and generate power-law tails of the volatility distribution while in the period of stagnations a large number of noise traders leave a stock market and interplay with the noise traders become weak, so that exponential tails of the volatility distribution is observed. However it remains an unsettled question what causes switching from boom to stagnation\(^3\). Our findings may provide a starting point to make a new tool of risk management of index fund in financial markets, but to apply the rule which we show here to risk management, we need to establish the framework of analysis and refine the statistical methods. We began with a simple observation on the stock price indices, and divided the price series into the two periods: booms and stagnations. However, there is room for further investigation on how to split the price series into periods according to the situations of markets.

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\(^3\) Yang, et.al. [20] also studies the log-return the dynamics of the log-return distribution of the Korean Composition Stock Price Index (KOSPI) from 1992 to 2004. As a result of the empirical study using intraday data of the index, they found that while the index during the late 1990s showed a power-law distribution, the distribution in the early 2000s was exponential. To explain this change in distribution shape, they propose a spin like model of financial markets. They show that changing the shape of the return distribution was caused by changing the transmission speeds of the information that flowed into the market.
An Outlook on Correlations in Stock Prices

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Summary. We present an outlook of the studies on correlations in the price time-series of stocks, discussing the construction and applications of "asset tree". The topic discussed here should illustrate how the complex economic system (financial market) enriches the list of existing dynamical systems that physicists have been studying for long.

“If stock market experts were so expert, they would be buying stock, not selling advice.”
– Norman Augustine, US aircraft businessman (1935 - )

1 Introduction

The word “correlation” is defined as “a relation existing between phenomena or things or between mathematical or statistical variables which tend to vary, be associated, or occur together in a way not expected on the basis of chance alone” (see http://www.m-w.com/dictionary/correlations). As soon as we talk about “chance”, the words “probability”, “random”, etc come to our mind. So, when we talk about correlations in stock prices, what we are really interested in are the nature of the time series of stock prices, the relation of stock prices with other variables like stock transaction volumes, the statistical distributions and laws which govern the price time series, in particular whether the time series is random or not. The first formal efforts in this direction were those of Louis Bachelier, more than a century ago [1]. Eversince, financial time series analysis is of prevalent interest to theoreticians for making inferences and predictions though it is primarily an empirical discipline. The uncertainty in the financial time series and its theory makes it specially interesting to statistical physicists, besides financial economists [2,3]. One of the most debatable issues in financial economics is whether the market is “efficient” or not. The “efficient” asset market is one in which the information contained in past prices is instantly, fully and continually reflected in
the asset’s current price. As a consequence, the more efficient the market is, the more random is the sequence of price changes generated by the market. Hence, the most efficient market is one in which the price changes are completely random and unpredictable. This leads to another relevant or pertinent question of financial econometrics: whether asset prices are predictable. Two simplest models of probability theory and financial econometrics that deal with predicting future price changes, the random walk theory and Martingale theory, assume that the future price changes are functions of only the past price changes. Now, in Economics the “logarithmic returns” is calculated using the formula
\[ r(t) = \ln P(t) - \ln P(t - 1), \]
where \( P(t) \) is the price (index) at time step \( t \). A main characteristic of the random walk and Martingale models is that the returns are uncorrelated.

In the past, several hypotheses have been proposed to model financial time series and studies have been conducted to explain their most characteristic features. The study of long-time correlations in the financial time series is a very interesting and widely studied problem, especially since they give a deep insight about the underlying processes that generate the time series [4]. The complex nature of financial time series (see Fig. 1) has especially forced the physicists to add this system to their existing list of dynamical systems that they study. Here, we will not try to review all the studies, but instead give a brief outlook of the studies done by the author and his collaborators, and the motivated readers are kindly asked to refer the original papers for further details.

2 Analyzing correlations in stock price time series

2.1 Financial correlation matrix and constructing asset trees

In our studies, we used two different sets of financial data for different purposes. The first set from the Standard & Poor’s 500 index (S&P500) of the New York Stock Exchange (NYSE) from July 2, 1962 to December 31, 1997 containing 8939 daily closing values, which we have already plotted in Fig. 1(d). In the second set, we study the split-adjusted daily closure prices for a total of \( N = 477 \) stocks traded at the New York Stock Exchange (NYSE) over the period of 20 years, from 02-Jan-1980 to 31-Dec-1999. This amounts a total of 5056 price quotes per stock, indexed by time variable \( \tau = 1, 2, \ldots, 5056 \).

For analysis and smoothing purposes, the data is divided time-wise into \( M \) windows \( t = 1, 2, \ldots, M \) of width \( T \), where \( T \) corresponds to the number of daily returns included in the window. Several consecutive windows overlap with each other, the extent of which is dictated by the window step length parameter \( \delta T \), which describes the displacement of the window and is also measured in trading days. The choice of window width is a trade-off between
too noisy and too smoothed data for small and large window widths, respectively. The results presented in this paper were calculated from monthly stepped four-year windows, i.e. $\delta T = 250/12 \approx 21$ days and $T = 1000$ days. We have explored a large scale of different values for both parameters, and the cited values were found optimal [5]. With these choices, the overall number of windows is $M = 195$.

In order to investigate correlations between stocks we first denote the closure price of stock $i$ at time $\tau$ by $P_i(\tau)$ (Note that $\tau$ refers to a date, not a time window). We focus our attention to the logarithmic return of stock $i$, given by $r_i(\tau) = \ln P_i(\tau) - \ln P_i(\tau-1)$ which for a sequence of consecutive trading days, i.e. those encompassing the given window $t$, form the return vector $r_i^t$. In order to characterize the synchronous time evolution of assets,

![Fig. 1. Comparison of several time series which are of interest to physicists and economists: (a) Random time series (3000 time steps) using random numbers from a Normal distribution with zero mean and unit standard deviation. (b) Multivariate spatio-temporal time series (3000 time steps) drawn from the class of diffusively coupled map lattices in one-dimension with sites $i = 1, 2, \ldots, n'$ of the form: $y_{i+1}^t = (1-\epsilon)f(y_i^t) + \frac{\epsilon}{2}(f(y_{i+1}) + f(y_{i-1}))$, where $f(y) = 1 - ay^2$ is the logistic map whose dynamics is controlled by the parameter $a$, and the parameter $\epsilon$ is a measure of coupling between nearest-neighbor lattice sites. We use parameters $a = 1.97$, $\epsilon = 0.4$ for the dynamics to be in the regime of spatio-temporal chaos. We choose $n = 500$ and iterate, starting from random initial conditions, for $p = 5 \times 10^7$ time steps, after discarding $10^5$ transient iterates. Also, we choose periodic boundary conditions, $x(n+1) = x(1)$. (c) Multiplicative stochastic process GARCH(1,1) for a random variable $x_t$ with zero mean and variance $\sigma_t^2$, characterized by a Gaussian conditional probability distribution function $f_i(x)$: $\sigma_t^2 = \alpha_0 + \alpha_1 x_{t-1}^2 + \beta_1 \sigma_{t-1}^2$, using parameters $\alpha_0 = 0.00023$, $\alpha_1 = 0.09$ and $\beta_1 = 0.01$ (3000 time steps). (d) Empirical Return time series of the S&P500 stock index (8938 time steps).]