

## Stock market dynamics derived from a cognitive bias

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**Abstract:** Econophysics and behavioral economics give two new directions to economics. In econophysics, Non-Gaussianity of a distribution on stock market returns and generating mechanisms of that have been researched. Behavioral economics gives some approaches to human economic behaviors derived from cognitive biases. In these two approaches, we can find contrastive views on markets: i.e. “collective and individual”. Connecting the two approaches, we can see a new aspect on market dynamics. In this study, we present a cognitive experiment which simulates human prediction of stock market returns, which follow an intermediate distribution between a Gaussian and a Cauchy’s. Stock market dynamics may be based on not only self-organization of collective traders but also cognitive processes of individuals. Each of individuals can generate non-Gaussian distributions on the predicted prices. As the result of a cognitive experiment, we obtained distributions which are similar to the ones of stock market returns.

**Keywords:** Abductive reasoning, Overgeneralization, Distribution feature.

### 1 INTRODUCTION

Econophysics and behavioral economics give two new directions to economics. Non-Gaussianity of a distribution on stock market returns and generating mechanisms of that have been researched in econophysics, which had been presented by Mantegna and Stanley [1]. Some important ideas in econophysics are inspired by statistical mechanics and complex systems science: i.e. phase transitions of a market system and self-organization of market traders [2-4]. On the other hand, behavioral economics, which evolved from prospect theory presented by Kahneman and Tversky [5], gives some approaches to human economic behaviors derived from cognitive biases.

In these two approaches, we can find contrastive views on markets: i.e. “macroscopic and microscopic” or “collective and individual”. Econophysics describes market dynamics as collective phenomena. It focuses on interaction structures of traders and on statistical features such as a sort of distributions of stock market returns. Behavioral economics researches human reactions to some stock trading situation: i.e. its research object is an individual and one’s behaviors. Connecting the two approaches, we can see a new aspect on market dynamics.

In our previous researches [6-7], we studied relations between abduction (or abductive reasoning, which is a sort of heuristic reasoning) and parameter estimation with overgeneralization. The estimates based on the “simulated abduction” follow non-Gaussian distributions, which have features as intermediate distributions between a Gaussian and a Cauchy’s. The intermediate feature is also in a distribution of stock market returns.

The above facts suggest that non-Gaussianity of stock market returns is derived from overgeneralization on time series of stock dynamics. A cognitive bias generating the overgeneralization is a subject of behavioral economics, and non-Gaussianity of stock market returns is a subject of econophysics. The two subjects have to be discussed in the view to connect them.

In this study, we present a cognitive experiment which simulates human prediction of stock market returns, which follow an intermediate distribution between a Gaussian and a Cauchy’s. Stock market dynamics may be based on not only self-organization of collective traders but also cognitive processes of individuals. This study focuses on the latter: i.e. the ability of individuals generating non-Gaussian distributions. The experiments were done by 142 volunteers, using Windows PCs and application programs for the cognitive experiments. Each subject watches one’s monitor displayed a graph of random walk time series, operates one’s mouse and input a predicting value on the graph. In the result, we obtained distributions which are similar to the ones of stock market returns.

### 2 ABDUCTIVE REASONING AND ITS MATHEMATICAL MODEL

Conventional formal logic, which is equal to deduction, is based on transitivity of entailment. The simplest model is a syllogism: i.e.  $A \rightarrow B$  and  $B \rightarrow C$  imply  $A \rightarrow C$ . On the other hand, whole of human reasoning includes not only deduction which is secure reasoning but also abduction which is insecure and creative reasoning [8-10]. Abduction

is a type of reasoning which has the following form: i.e.  $A \rightarrow C$  and  $B \rightarrow C$  imply  $A \rightarrow B$ . Three types of reasoning, deduction, induction and abduction, are coordinated by C.S.Peirce [8]. The three types can be represented by Sawa-Gunji diagrams [6,7,10].

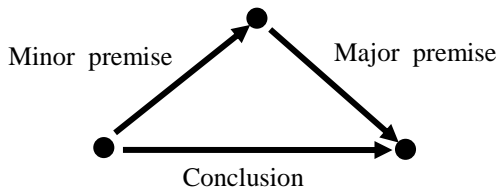


Fig. 1. Sawa-Gunji diagram

A Sawa-Gunji diagram (Fig.1) is a triangle with three arrows which correspond to a minor premise, a major premise and conclusion. Each of the three types of reasoning is represented by an operation in which one arrow induced from the other two arrows.

In our previous works [6-7], we show a correspondence between abduction based on a Sawa-Gunji diagram and generalized parameter estimation on a numerical function: i.e. when transitivity of a syllogism is equated with that of a system  $y = f(x; a)$ , abduction in which a minor premise is induced from a major premise and a conclusion is translated into estimation of a parameter  $a$ . It is not constrained by some conditions for conventional parameter estimation. The generalized parameter estimation, which has multi-aspect according to constraints, can be “simulated abduction” on a numerical system.

An example of simulated abduction is incomplete  $AR(p)$  parameter estimation based on the small number of data  $N$ . Under  $N \rightarrow \infty$ , the incomplete estimation results in conventional estimation, and the estimated parameters follow a Gaussian distribution. The Gaussianity disappears under  $N \rightarrow p+1$ , and the distribution approaches asymptotically to Cauchy distribution. Under  $p+1 < N \ll \infty$ , we obtain intermediate distribution between a Cauchy’s and a Gaussian.

Conventional parameter estimation on a system  $y=f(x;a)$  is a kind of mathematically appropriate generalization for given data  $x$  and  $y$ . On the other hand, incomplete parameter estimation like the above can be summed up as a kind of overgeneralization for given data. Avoiding overgeneralization and pursuing “appropriate” generalization are based on mathematical and technological requirements. Human beings would have ability of

overgeneralization, although some apparent irrationality is in it as well as in abduction.

In the present study, we have a conjecture: i.e. non-Gaussianity of stock market returns would be induced from overgeneralization for market data series. In the following sections, we check non-Gaussianity of real market data (Nikkei 225), and we present a cognitive experiment to study causes of the non-Gaussianity.

### 3 NON-GAUSSIANITY ON STOCK DYNAMICS

A blue line of Fig.1 is a histogram of returns  $\Delta x_t := x_t - x_{t-1}$  of Nikkei225 closing price  $x_t$ . The histogram consists of 7006 daily data from 4/January/1984 until 3/July/2012.

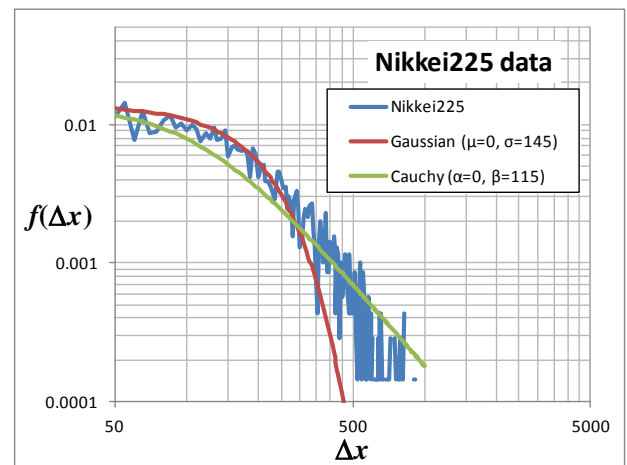


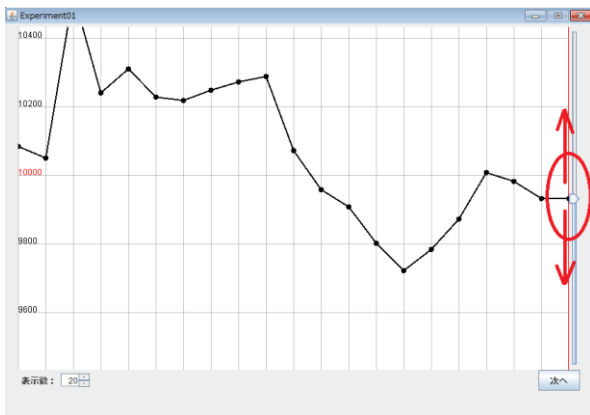
Fig. 2. Distributions of returns of Nikkei225 closing price, a Gaussian and a Cauchy’s.

Note that Fig.2 is double logarithmic. A red line and a green line of Fig.1 are a Gaussian distribution ( $\mu=0, \sigma=145$ ) and a Cauchy distribution ( $\alpha=0, \beta=155$ ). The peaks of that are fitted to the peak of the Nikkei225 histogram, which is characterized as intermediate distributions between a Gaussian and a Cauchy’s. This fact induces motivation of a cognitive experiment described in the next section: i.e. does prediction of an individual generate the intermediate distribution?

### 4 COGNITIVE EXPERIMENT

Patzelt, et al. [11] show that distances between a moving target and a mouse-driven cursor on a PC monitor follow a power law distribution by a cognitive experiment. In the present study, we propose a cognitive experiment, which is inspired by the Patzelt’s experiment, simulates a process of pseudo stock price predicting. In the experiment, each

subject uses application software with the following GUI on a PC (Fig.3).

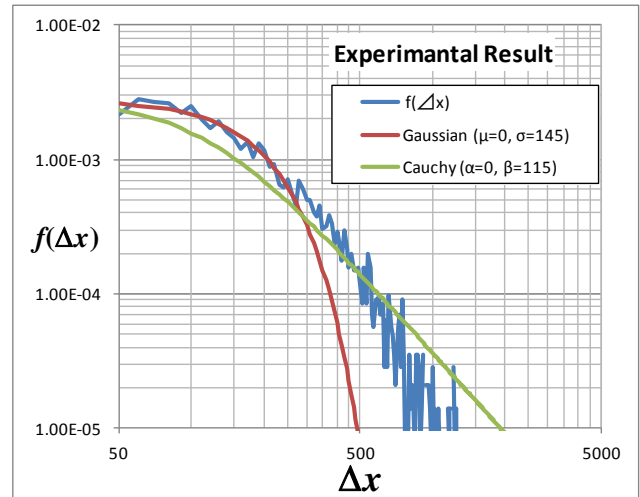


**Fig. 3.** The GUI of application software for the experiment on stock price predicting

The application indicates just random work time series  $p_{t+1} = p_t + \varepsilon_t$  where  $\varepsilon_t$  follows a Gaussian distribution with the S.D. =145 and the initial price is  $p_{-25} = 9839$ . For the subject, we explain the time series as a daily chart on an artificial stock market, and we instruct them to input a predicting price of the next day via the slider of the application. A subject can see 20 days data of the time series on the application window. (S)He iterates through 100 times (i.e. 100 days) to move the slider, to decide the prediction price and to push a “next” button to go to the next day. The predicted prices  $\{x_t | 0 \leq t \leq 100\}$  do not influence the indicated time series.

## 5 EXPERIMENTAL RESULT

A total of 142 men and women in their twenties participated in the cognitive experiment. Each person iterated 100 predictions in the experiment therefore we obtained 14200 data on the predicted prices  $x_t$  and the difference  $\Delta x_t := x_t - p_{t-1}$ , where  $1 \leq t \leq 100$  and  $p_{t-1}$  is an indicated price as a value on the random walk time series. A blue line in Fig.4 shows a histogram of the difference  $\Delta x_t := x_t - p_{t-1}$ . A red line and a green line are a Gaussian distribution and a Cauchy distribution which are the same in Fig.2. The histogram of the difference in Fig.4 is also characterized as an intermediate distribution between them.



**Fig. 4.** The distribution of the differences between the predicted prices and the indicated prices.

## 6 CONCLUSION

Econophysics and behavioral economics give two new directions to economics. In these two approaches, we can find contrastive views on markets: i.e. “macroscopic and microscopic” or “collective and individual”. Connecting the two approaches, we can see a new aspect on market dynamics. In this study, we presented a cognitive experiment which simulates human prediction of stock market returns, which followed an intermediate distribution between a Gaussian and a Cauchy’s. Stock market dynamics may be based on not only self-organization of collective traders but also cognitive processes of individuals. This study focuses on the latter: i.e. each of individuals can generate non-Gaussian distributions on the predicted prices. As the result of a cognitive experiment, we obtained distributions which are similar to the ones of stock market returns.

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