On possible origins of trends in financial market price changes

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Abstract

We investigate possible origins of trends using a deterministic threshold model, where we refer to long-term variabilities of price changes (price movements) in financial markets as trends. From the investigation we find two phenomena. One is that the trend of monotonic increase and decrease can be generated by dealers’ minuscule change in mood, which corresponds to the possible fundamentals. The other is that the emergence of trends is all but inevitable in the realistic situation because of the fact that dealers cannot always obtain accurate information about deals, even if there is no influence from fundamentals and technical analyses.

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1. Introduction

Many phenomena in human society are composed of human choices. Buying and selling is one of them, and we regard financial markets as the aggregation of dealers’ choices and their interactions. A major indicator in financial markets is price change (price movement). Price change in financial...
markets fluctuates irregularly, as shown in Fig. 1. However, the mechanism of the fluctuations has not been elucidated yet, and the question is still venerable and challenging. There are two major approaches to tackle the question. One is to investigate features or natures of the data from the viewpoint of statistics and dynamical systems [1, 2, 3], and the other is to construct an artificial market using a model and investigate events in the market [4, 5, 6, 7, 8, 9, 10, 11]. The merit of the former approach is that it provides us with various knowledge and insights for the understandings of the phenomena of price changes. However, this approach is restrictive, because it does not always lead us to the understanding of the mechanism of price changes produced by the interaction between dealers’ choices and market price properties [10]. In contrast, the latter approach significantly contributes to clarifying the mechanism. As the purpose of this paper is to find possible origins of trends (see below) in financial market prices, we follow the latter approach.

Some models have been proposed and the models are called dealer models [4]. The dealer model, which is an agent-based model, constructs an artificial market. The first dealer model was introduced by Takayasu et al. in 1992 [4]. They considered that a market is composed of many dealers and buying and selling are interactions among them with discontinuous (nonlinear) and irreversible processes. To implement this mechanism they introduced a numerical model of financial market prices using threshold dynamics [4]. In the model a deterministic dynamics is assumed for an assembly of agents describing mutual trades by threshold dynamics including discontinuous irreversible interactions. After this pioneering work, numerous studies have been done (for example, see Refs. [5, 6, 7, 8, 9, 10, 11]). These models have been improved and refined to be able to reproduce basic empirical laws such as the power-low distributions of price changes, slow decay of autocorrelation of volatility and so on. For the details see [11].

In this paper, we observe afresh the behaviours of financial market data carefully. As mentioned above, to put it briefly, price changes in financial markets show irregular fluctuations (see Fig. 1). The irregular fluctuations can be divided into two main features, short-term variabilities and long-term variabilities. The long-term variabilities are usually called trends.

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1When there is a long-term slower and larger variation relative to the magnitude (amplitude) of short-term variabilities, we call the behaviour or the movement “trend.”
behaviours exhibiting these two fluctuations are extremely natural for price changes in financial markets. Hence, models must be built or improved so as to reproduce these two fluctuations. A possible origin for the short-term variabilities has already been indicated by Takayasu et al. [4]. Despite that there are numerous works after the work, curious to say, discussions on the origins of trends seem not to be lively, although many market participants should observe the trends rather than details of the short-term variabilities to know the overall movement of markets.

One of the major underlying reasons seems to be that the existence of
the trends is taken to be granted, since it can be seen in any financial data to a varying degree. Also, the two factors, fundamentals (for example, the gross domestic product (GDP) that change according to policy interest rate, remarks by senior administration officials or central bankers, and so on) and technical analyses are vaguely considered to be the main origins of these fluctuations. The major trends in the medium and long term are believed to be generated by fundamentals. On the other hand, it is well known that the trends can also be observed without remarkable news and important economic index to be released. Under these circumstances, dealers have too small clues to predict the movement of price changes. In this case, dealers make their deals based on technical analyses. As a result, minor trends of the moment are generated or accentuated by these actions. Hence, it seems to be commonly accepted that fundamentals generates relatively-long period trends and technical analyses accelerates the movement of the moment rather than generating trends. From these two factors we obtain the following conventional idea: prices rise when the momentum of buyers exceed that of sellers and prices fall when the momentum of sellers exceed that of buyers. This idea seems to make sense. However, it brings up the following simple question on the origin of trends nonetheless: if it were not for these factors, do trends make no appearance at all? We focus our attention mainly on this point.

It should be noted here that, although we understand that it is important to reproduce basic empirical characteristics of the data, we do not aspire for the reproduction in this paper. We simply focus on the origins of trends.

In this paper, two investigations are shown. One is to make an attempt to generate monotonic increase and decrease at our disposal in the framework of the dealer model to verify the common belief that the medium and long term trends are under the influence of fundamentals. The other is to show that the trends are spontaneously generated even if fundamentals and technical

\[\text{\footnotesize 2} \text{ By the progress of computer technology we can obtain high frequency financial data with high resolution time. The data are generally called tick data. Tick is the minimum movement in the price of financial instruments and the term \textquote{tick} refers to the minute change in the price from deal to deal. Various analyses have been done using tick data. However, we note that all deals are not recorded in the tick data. Tick data we can obtain are data measured at certain time intervals. There are not many discussions about discrepancy of statistical nature between intermittent data and data with all deals. In a subsequent paper we shall make the investigative study.}\]
analyses have no influence on financial markets, which suggests a possible unknown mechanism of generating trends.

This paper is organized as follows. We use a deterministic dealer model with threshold elements which has been previously proposed. In Section 2, we briefly review the model, show the behaviours of the data generated by the dealer model, and have some observations. In Section 3 we make attempts to generate given types of trends under some well-defined situations. Section 4 is for the discussions and summary.

2. Current technologies: deterministic threshold dealer model

To generate trends reflecting fundamentals and find possible (or unknown) origins of trends, we use a previously proposed deterministic dealer model with threshold elements. As the model is proposed in 1992 by Takayasu et al. [4], we refer to the model as “dealer model 92.” As the dealer model 92 is deterministic including no probabilistic factor, we expect that we have a better sense of the behaviours generated by the model. As the model treats price of all deals, the price data generated by the model should be compared to tick data. For simplicity the deal in the model is assumed to be one brand in one market. Also, we assume that all dealers participate deals with the same rule.

After the dealer model 92 was proposed, some modifications have been made [5, 10, 11]. However, we consider that the modifications are considered to be artificial, since all deals are done by only two dealers, that is, one buyer and one seller. In the actual deals there are usually one or more than one seller, which we consider one of the vital aspects of deals. As the dealer model 92 treats such a situation, we use the dealer model 92.

In this section we briefly review the dealer model 92 and clarify the mechanism of the price change.

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3The dealer model 92 was modified by Sato and Takayasu in 1998 [5]. We call the modified model the dealer model 98. The dealer model 98 has the opposite assumption to the dealer model 92. The dealer model 98 assumes that all dealers have a small amount of properties and basically change their attitudes (that is, a buyer becomes a seller and a seller becomes a buyer in the next deal) when the deals are done. Unlike the dealer model 92, the dealer model 98 is tractable and can generate irregular fluctuations over long periods like Fig. 1. This seems to be one of the supposed reasons that the subsequent market price analyses are developed based on the dealer model 98 [10, 11]. In a subsequent paper we will show that we can generate similar phenomena using the dealer model 98.
2.1. Dealer model 92

A deal, composed of consecutive selling and buying, is a typical discontinuous and irreversible process. A deal is done, if a buying condition and a selling condition meet, while it is undone, if not. This is the origin of the discontinuity. The buyer and the seller of the last deal would never deal again under the identical condition at least for a while. This is the origin of the irreversibility. The dealer model 92 is introduced to reflect these aspects of dealing [4].

The market is composed of \( N \) dealers. Let the \( i \)th dealer’s buying price and selling price be \( B_i \) and \( S_i \), respectively. The selling price \( S_i \) is larger than the buying price \( B_i \), and the difference \( L_i = S_i - B_i \) is always positive. For simplicity we use a constant value \( L \) for \( L_i \). This simplification gives \( L = S_i - B_i \) for all \( i \). A deal is done between pairs of \( i \) and \( j \) where \( B_i \geq S_j \). In this model a deal is done when the following condition is satisfied:

\[
\max \{B_i\} - \min \{B_i\} \geq L, \tag{1}
\]

where \( \max \{B_i\} \) and \( \min \{B_i\} \) indicate the maximum and minimum values. In the dealer model 92 there is one buyer and one or more than one seller. A dealer can be the buyer when the dealer gives the highest buying price. The buyer \( i \) can buy at the price from other dealers \( j \) who satisfy the following condition

\[
\max \{B_i\} - \{B_j\} \geq L.
\]

This price \( P(t) \) of the deal is defined by the \( \max \{B_i\} \). If Eq. (1) is not satisfied, the deal is not done and the market price does not change as follows:

\[
P(t) = \begin{cases} 
\max \{B_i\} & \text{(when a deal is done)}, \\
P(t-1) & \text{(when a deal is not done)}.
\end{cases} \tag{2}
\]

When a deal is done, there are the buyer and sellers who could make the deal and other dealers who cannot participate in the deal. However, other dealers do not look wistfully and enviously at the deal with doing nothing. As all dealers are potentially willing to participate in the deals, all dealers re-establish their prices for the next deal. To reflect the eagerness, the \( i \)th

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\footnote{Buying price \( B_i \) and selling price \( S_i \) are called Ask and Bid in financial markets, respectively.}

\footnote{Eq. (1) has the same meaning of \( \max \{B_i\} - \min \{S_i\} \geq 0 \) because \( S_i = B_i + L \).}
dealer’s expectation \( a_i \) is introduced. The term is a character of the \( i \)th dealer. If \( a_i > 0 \), the dealer rises the price setting, and if \( a_i < 0 \), the dealer lowers the price setting. In this model we consider that each dealer has each expectation. Hence, the values of \( a_i \) are given by uniform random numbers in a range and the mean of \( \{a_i\} \) is normalized to be zero. By this operation dealers’ expectation for buying and selling is kept in equilibrium. As dealers becomes buyers and sellers depending on their conditions or circumstances in the actual financial markets, inside details of the deals are very complicated. For a simple situation, this model assumes that all dealers have infinitely large amount of property and the dealers do not change their attitudes even if deals are done (that is, a buyer is always a buyer and a seller is always a seller). Also, this model is assumed in an invariant state (steady state). Hence, the values of \( a_i \) do not change.

An unique aspect of this model is that it takes into account an acquisitive nature of the buyer and sellers for the next deal. It is assumed that the buyer and sellers who could participate a deal expect that they can participate again in the next deal with a cheaper price for the buyer and a higher price for the sellers. The other dealers who could not participate in the previous deal do not have such a psychological tendency. To reflect such a tendency, the term \( \Delta_i \) reflecting the acquisitive nature is introduced:

\[
\Delta_i = \begin{cases} 
-\delta & \text{(for buyer)} \\
\delta/n & \text{(for sellers)} \\
0 & \text{(for nonparticipants of the deal)}
\end{cases}
\]  

(3)

where \( 0 < \delta < L \) and \( n \) is the number of the sellers of the deal. That is, the next buying price of the buyer falls by the amount of \( \delta \) from the current buying price and the next selling prices of the sellers rises by the amount of \( \delta/n \) from the current selling prices. The buyer and sellers who cannot participate in the next deal have no anticipation. Also, when Eq. (3) is not satisfied (that is, a deal is not done), \( \Delta_i = 0 \) for all \( i \). Note that the summation of all dealers’ acquisitive nature becomes zero.

\[6\] Broadly speaking, there are three economic expectations: (i) myopic expectation, (ii) adaptive expectation and (iii) rational expectation. In the actual financial markets a dealer’s expectation \( a_i \) should be given based on some reasons. However, we do not wish to overinterpret it in this paper.
Figure 2: (Colour online) Schematic diagram of $\Delta$ from time $t$ to $t+1$ when Eq. (1) is satisfied. The length of each vertical bar is the constant $L$. The top and bottom of each bar correspond to the upper and lower threshold price of each dealer, respectively. The $\Delta$ of the buyer is $-\delta$ and that of the sellers is $\delta/n$, where $0 < \delta < L$ and $n$ is the number of the sellers. The value of $\delta$ is constant defined by Eq. (3). In this figure the buyer is $i = 2$, the sellers are $i = 1$ and $3$ ($n = 2$), and the dealer $i = 4$ does not participate the deal.

Based on these ideas the dealer model 92 is given by

$$B_i(t + 1) = B_i(t) + \Delta_i(t) + a_i + c_i\{P(t) - P(t_{\text{prev}})\}; \quad (4)$$

where the term $c_i$ characterizes the $i$th dealer’s response to the change of market price and $t_{\text{prev}}$ indicates the time when the last deal is done [4]. However, we note that the dealer model 92 is extremely unstable and uncontrollable when $c_i \neq 0$ [4, 12]. Hence, the behaviour of the model have been scrutinized with changing values of $c_i$ and $a_i$ and the number of dealers. For details see [12]. Hence, we use the model with $c_i = 0$ as the dealer model 92 for our work, which becomes

$$B_i(t + 1) = B_i(t) + \Delta_i(t) + a_i. \quad (5)$$

### 2.2. Typical behaviours in the dealer model 92

We show typical behaviours in the dealer model 92. To generate the data we take the number of dealers $N = 100$ and $\delta = 0.4$. The initial value
Figure 3: Typical behaviours of simulated price data $P(t)$ of the dealer model 92 of Eq. (5).

For the model $N = 100$, $L = 1$, $\alpha = 0.01$ and $\delta = 0.4$ are used. The value of $a_i$ and the initial condition of $B_i(t)$ are taken from uniform random numbers in the ranges $(-\alpha, \alpha)$ and $(-L, L)$, respectively.

The value of $a_i$ and the initial condition of $B_i(t)$ are taken from uniform random numbers in the ranges $(-\alpha, \alpha)$ and $(-L, L)$, respectively.

The behaviours are stable over long periods and $P(t)$ fluctuates around the mean value showing short-term variabilities but does not have trends.

2.3. Some observations and possible reasons for lacking of trends

As the mean of dealer’s expectation $\{a_i\}$ is zero, the summation of the dealer’s expectation is obviously zero. However, the number of dealers with $a_i > 0$ is not always a half of the total (that is, the number of the buyers is not always a half). The numbers of the buyers for Fig. 3 is 38 where the numbers of the total dealers is 100, as mentioned above.

From the observations we consider that trends do not appear when dealers’ expectation

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7 This normalization for $\{a_i\}$ is not mentioned in [4] and is mentioned very casually in [12]. However, we note that this operation is indispensable. Without this operation, the data generated by the dealer model 92 are monotonic increase or decrease in almost all cases, even if we use Eq. (5) (that is, Eq. (4) with $c_i = 0$).

8 The number of the buyers is slightly extreme examples. As $\{a_i\}$ is uniformly distributed between $-\alpha$ and $\alpha$ with $\alpha > 0$, the number with $a_i > 0$ is usually around half of the total.
for buying and selling equals out. In other words, breaking the balance of dealers’ expectation of buying and selling might be useful for generating trends. Based on this idea, we make attempts to generate trends under some well-defined situations in the next section.

3. Exploration of origins for trends

In this section we make attempts to generate two types of trends. One is the trends with surmise. We consider that it corresponds to the trends reflecting fundamentals. The other is the trends with no surmise. We consider that it corresponds to trends generated almost spontaneously. After generating both trends, we unite both ideas into one model and generate data using it.

3.1. Trends with surmise: trends reflecting fundamentals

We show here that we are able to generate monotonic increase or decrease trends at our disposal. It is widely believed that the major trends in the medium and long term are generated by fundamentals. However, the correspondence between the types of fundamentals and the types of trends is basically unknown. We therefore avoid the overinterpretation of this relationship and do not touch on the problem. We simply focus on the problem of how we can generate monotonic increase and decrease trends at our disposal.

As Eqs. (3) and (5) show, when a deal is done, the buyer brings down the asking price for the next deal, expecting that it might be possible to buy at a cheaper price. Similarly, when a deal is done, the sellers bring up their selling prices for the next deal, expecting that it might be possible to sell at a higher price.

How does the acquisitiveness change in the existence of trends in a market? When a monotonic increase (or decrease) trend is expected in a market, which corresponds to self-fulfilling expectation, it seems to be plausible that a dealer, whether the dealer is either a buyer or a seller, considers that the dealer is not likely to take the same attitude in the next deal if the dealer offers a higher (or cheaper) price. Based on the idea Eq. (3) is redefined

\[ a_i \]
using the small values $\varepsilon_b$ and $\varepsilon_s$ as follows:

$$\Delta_i = \begin{cases} 
-\delta \times (1.0 + \varepsilon_b) & \text{(for buyer)} \\
(\delta \times \varepsilon_s)/n & \text{(for sellers)} \\
0 & \text{(for nonparticipants of the deal)} 
\end{cases} \quad (6)$$

where $0 < \delta < L$ and $n$ is the number of the sellers of the deal as taken in Eq. (3). For newly introduced parameters, $\varepsilon_b$ and $\varepsilon_s$, $-1 \leq \varepsilon_b \leq 0$ and $\varepsilon_s \geq 0$ when a monotonic increase trend is expected, and $0 \leq \varepsilon_b \leq 1$ and $\varepsilon_s \leq 0$ when a monotonic decrease trend is expected.

Figure 4 is the data generated by the dealer model 92 with $\varepsilon_b = \pm 0.002$ and $\varepsilon_s = 0$, which exhibits a monotonic increase trend for $\varepsilon_b = -0.002$ and a monotonic decrease trend for $\varepsilon_b = 0.002$. We have also confirmed that the dealer model 92 with $(\varepsilon_b, \varepsilon_s) = (0, 0.002)$ show similar behaviours. Although the values of the parameters are small, this tiny little ulterior motive generates major trends. The results indicate that, even if the amount of a change in the psychological tendency of a dealer caused by fundamentals is very small, it can bring a major influence on the market forces.

When we use larger values of $\varepsilon_b$ or $\varepsilon_s$ or when we use the pair of $\varepsilon_b$ and $\varepsilon_s$ together, we have confirmed steeper trends.
3.2. Trends with no surmise: unpremeditated trends

In this section we consider possible (or unknown) underlying origins of the trends without the influence of fundamentals and technical analyses on financial markets.

Let us carefully examine an important feature of the dealer model 92. Generally speaking, all dealers in the actual financial markets cannot know the number of sellers in the deal in advance, when a deal is done. However, the number of sellers $n$ is included in Eq. (3) to reflect the acquisitive nature of the dealers. That is, the dealer model 92 contains a parameter which is impossible to know in advance in actual deals. The number of sellers $n$ plays a crucial role in the dealer model 92. As Eq. (3) shows, the buyer’s price falls $\delta$ and each of $n$ sellers’ prices rises $\delta/n$ from those when the deal is done. In other words, the total amount of the rises of the sellers’ prices $n \times \delta/n$ exactly compensates for the decline of the buyer’s price $\delta$. Because of this exact compensation effect, we consider that the data generated by the dealer model 92 have only short-term variabilities and do not have trends.

It is unlikely and unnatural for sellers to know the precise number of sellers in a deal in advance (any dealer cannot actually know it). However, it is possible to know it in the past deals. Hence, we investigate the behaviours of the number of sellers of the data shown in Fig. 3. Figure 5 shows that the number of sellers varies greatly at each deal, where the minimum is 1 and the maximum is 14. It does not seem to be easy to predict the next number of sellers using the past data. In such cases each seller would have each idea for the price rise. As a result, the expectation for buying and selling would not always equal out. As the simple situation, we use the average sellers number $\mu_n(t)$ instead of the precise sellers number $n$ in Eq. (3), where $\mu_n(t)$ is calculated using all of the sellers number prior to time $t$ (that is, from 1 to $t - 1$). We note that this idea is not so irrelevant. When the prediction does not seem to be easy, one of the common approaches is to use the mean value of the data: the average number of sellers who participated deals in

\footnote{We apply the small-shuffle surrogate (SSS) method to the data\cite{13}. The result indicates that the data are independently distributed random variables or time-varying random variables. Hence, we consider that we cannot predict the data using the data.}
the past. Based on these considerations, Eq. (3) is renewed as follows:

\[ \Delta_i = \begin{cases} 
-\delta & \text{(for buyer)} \\
\delta/\mu_n(t) & \text{(for sellers)} \\
0 & \text{(for nonparticipants of the deal),}
\end{cases} \] (7)

where \( 0 < \delta < L \).

Figure 6 shows the behaviours of the dealer models using the average sellers number. Figure 6(a) shows that the simulated price data \( P(t) \) have short-term variabilities and exhibit the appearance of medium and long-term rising and falling behaviours of trends. The difference in the behaviour from the one for the original dealer model shown in Fig. 3 is striking. The overall behaviour seems to be similar to the real data shown in Fig. 1. Figure 6(b) shows that the average number of sellers converges very quickly. In contrast, from Fig. 6(c) that shows the number of sellers at each deal, the number fluctuates wildly at each deal between 1 and 13. The behaviour is similar to Fig. 5(a). We emphasize that the emergence of the monotonic increase and decrease trends by this model is rarely reported. In Fig. 6 we calculate \( \mu_n(t) \) using all of the sellers number data, although taking the average over all sellers number is not essential. Averaging over the data in certain interval, that is to say, the last 100 sellers number data from \( t-1 \) to \( t-100 \), is equally permissible for generating trends.

3.3. Mingled trends with surmise and no surmise: trends reflecting fundamentals and unpremeditated trends

In the Subsection 3.1 we discussed an idea to generate monotonic increase and decrease trends reflecting fundamentals. In the Subsection 3.2, we discussed that the emergence of trends is generated due to the imbalance between the momentum of buying and selling, which is inevitable in financial markets even without the influence of fundamentals and technical analyses.

The essentiality of this operation is to make an imbalance between the sellers’ price rise and the buyer’s price decline. Although the buyer’s price decline \(-\delta\) is a constant value in Eq. (7), the buyer should change the value depending on situations and it is indeed possible to use a time dependent or time varying value (that is, \(-\delta(t)\)). However, we use \(-\delta\) for simplification.

We apply the SSS method to the number of sellers (not average number). As it is for the previous application of the SSS method, the result indicates again that the data are independently distributed random variables or time-varying random variables.
Although we discussed these two cases separately to make the course of arguments clear, it is true that they are strongly interconnected and mingled with each other in real markets. In this Subsection, we treat these two cases on the same footing.

Incorporating both ideas described in Subsection 3.1 and Subsection 3.2, we use the following improved expression for $\Delta_i$:

$$
\Delta_i = \begin{cases} 
-\delta \times (1.0 + \varepsilon_b) & \text{(for the buyer)} \\
\delta / \mu_n(t) & \text{(for the sellers)} \\
0 & \text{(for nonparticipants of the deal)},
\end{cases}
$$

(8)
Figure 6: Typical behaviours of the dealer models 92 using the average number of sellers in the past. (a) simulated price data $P(t)$, (b) the average number of sellers, and (c) the number of sellers at each deal. All other conditions are the same in Fig. 3.

where the notations of $\delta$ and $n$ are the same as described in Eq. (3) and the notations of $\varepsilon_b$ and $\mu_n(t)$ as the same as described in Eqs. (6) and (7).

Figure 7 shows the data generated by the dealer model 92 defined by Eq. (8) using different values of $\varepsilon_b$. We also show the plots for the data corresponding to unpremeditated trends defined by $\varepsilon_b = 0$ for comparison.
By replacing the number of sellers \( n \) with the average value \( \mu_n(t) \), the profiles of the trends becomes significantly susceptible to the actual values of \( \varepsilon_b \).

Without the replacement of \( n \) with \( \mu_n(t) \), a negative \( \varepsilon_b \) generates a monotonically increasing trend, and a positive \( \varepsilon_b \) generates a monotonically decreasing trend as shown in Fig. 4. Figure 7(a) shows similar results for \( \varepsilon_b = \pm 0.031 \). However, the sign of \( \varepsilon_b \) does not have a simple relationship with increasing or decreasing nature of trends in this case. For Fig. 7(b), we use a much smaller absolute value for \( |\varepsilon_b| = 0.0021 \) than that used in Fig. 7(a), \( |\varepsilon_b| = 0.031 \). In this plot, a trend produced by the positive value, \( \varepsilon_b = 0.0021 \), shows much more prominent increase than that produced by the negative value, \( \varepsilon_b = -0.0021 \). Only by taking a slightly smaller absolute value, \( |\varepsilon_b| = 0.002 \), we see that a negative value, \( \varepsilon_b = -0.002 \), generates a decreasing trend and a positive value, \( \varepsilon_b = 0.002 \), generates an increasing trend as shown in Figure 7(c). Note that these values, \( |\varepsilon_b| = 0.002 \), are the same as those used in Fig. 4.

4. Discussion and Summary

We have investigated possible origins of trends in financial market price using deterministic threshold models from the viewpoint of dealers’ expectation for the price, where we consider financial markets as a game field of commercial activity composed of human choices and their interactions. We observed that monotonic increase and decrease trends can be generated by dealers’ minuscule changes in mood, where the phenomena corresponds to trends with surmise. We also indicated that irregular fluctuations with short-term variabilities and long-term variabilities (trends) emerge spontaneously by a natural approach under the very normal situation that we cannot obtain precise information about deals, where the phenomena corresponds to trends with no surmise. The interesting point is that the result indicates a possibility that the emergence of trends is all but inevitable in the realistic situation, even if there is no influence on fundamentals and technical analyses in financial markets. When we use both the ideas to generate trends with surmise and no surmise at the same time, we observed two distinctive aspects. One is that dealers’ minuscule changes in mood make a large difference in the behaviours. The other is that there are cases where the behaviours of price changes are different from, even opposite to, dealers’ expectation of the price changes. Both of the aspects indicates that the data always cannot tell us the underlying dealers’ expectation. In other words, the behaviours do not
Figure 7: (Colour online) Mingled trends generated by the improved dealer model 92 defined by Eq. (8). (a) $\varepsilon_b = -0.031$ for plot $\omega$ and $\varepsilon_b = 0.031$ for plot $\lambda$. (b) $\varepsilon_b = -0.0021$ for plot $\omega$ and $\varepsilon_b = 0.0021$ for plot $\lambda$. (c) $\varepsilon_b = -0.002$ for plot $\omega$ and $\varepsilon_b = 0.002$ for plot $\lambda$. Plots labelled by $\gamma$ in (a), (b), and (c) are the data generated by $\varepsilon_b = 0$. Note that plot of $\omega$ originally corresponds to a monotonic increase trend, that of $\lambda$ to a monotonic decrease trend, and that of $\gamma$ to unpremeditated trends. All other conditions are the same in Fig. 3.
always accord with dealers’ expectation for a long term. We consider that this is very intriguing result. From the behaviours or movements of a price change, each dealer infers his/her specious justification of the cause of the change and offer future prospects to others in the next deal. Once the price in the market moves against their expectaions, however, dealers doubt their justifications and may take a counter reaction to their original expectation. Such counter reactions of the dealers may cause excess volatility.

We understand that there should be other origins to generate trends other than the ones described in this paper. The point is, however, that dealing tactics between buyers and sellers in the actual financial markets should be more ingenious than that in the dealer model. We consider therefore that the knowledge gained from the ideas pursued in this paper contains an essential ingredient and is universal. As no dealer has access to complete information about deals in the actual financial markets, dealers would have their own expectation. As the expectation is brought by the incomplete information, it would be rough and flimsy. The results obtained in this paper indicate that such an expectation causes the emergence of trends. In the real world we always cannot obtain complete information and it is difficult to predict behaviours. The fact and the results imply that the emergence of trends is all but inevitable in financial markets. Hence, we consider that the results are insightful and the knowledge is suitable for many situations.

In the actual markets we often find that there are price changes with very similar behaviours, although the brands are different. Our results indicate that some trends might be unpremeditated. Although the trends emerge spontaneously, why the behaviours are similar? What kinds of interactions are there between the brands? Those will be very interesting questions.

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