

Contrary Opinion Phenomena in an Artificial Stock Market

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Abstract

This paper presents an artificial market model to clarify the definition of the contrary opinion phenomena. Our research target is to show the contrary opinion, which is based on market participants' experiences, statistically. At first, we constructed a more realistic artificial market model and simulated it. Second, we selected 'highly corresponded forecasts' among the fitted sample paths. Third, we classified them into three groups: the ones which on a uptrend with the following trend reversal, those which on a uptrend only and otherwise. Finally, we compared between the volume at all the observations and those both before and after at the observation in each group. This is based on a rule of thumb that both acceleration of price and increasing volume can be seen before the turning point in financial markets. The results indicate that the volume at the peak of the price, when a contrary opinion phenomenon occurs, is the largest. While those of other groups were not. This shows the rule of thumb was replicated in our model. Especially, because the contrary opinion phenomena were clarified statistically, these results could be noticeable.

Introduction

This paper presents results of our multi-agent simulation, i.e. artificial stock market. Our research target is to define the contrary opinion phenomena by a series of trading volume.

There have been several heuristics that tell us turning points in financial markets. But all of them are based on market participants' experiences, not on statistical analysis. At the same time, there are few researches about those heuristics. Even if there are something, their target is 'How to make profits', not 'How those heuristics appear'. So we investigated if the contrary opinion phenomena, one of the heuristics, are truly useful for judging the turning points using our artificial stock market model.

Among the heuristics, we selected the contrary opinion phenomena for the following reasons:

- Before turning points, both acceleration of price change and increasing volume can be seen in financial markets (Tvede 1999). Particularly we can easily analyze both of them.

- The definition of each technical analysis, Head and Shoulders for example, is not clear. So it is hard for us to distinguish turning points from chart analysis.
- There are books about contrary opinion phenomena as a trading strategy (Hadady & Hadady 2000), while there are few economic or financial thesis about that (neither about technical analysis).

In addition, the reasons we used a multi-agent approach are:

- If we interview to investors, the number is limited and they may forget the past events.
- Because the news, such as newspaper, newsletters or so, usually has hindsight bias, it is not useful to investigate the turning points from the news.
- In the multi-agent approach, we can easily replicate actual financial markets once we construct an appropriate computational market.

This paper is constructed as follows. The next section describes the market structure. The third explains the experimental results with the market simulations, which is followed by some conclusions in the last section.

Market Structure

Figure 1 shows the market structure. This model is an expansion of AGEDASI TOF (Izumi 1998). The differences are: (1) Existence of economist agents, (2) Introduction of several kinds of investors. By doing so, we can replicate the more realistic market structure.

Two kinds of agents exist in this market; 10 economists and 50 investors. Economist agents only predict the future price and do not trade. On the other hand, investor agents not only forecast the future price but also trade. First, the economists forecast the future price from inputs. Second, the investors determine their own trading strategies based on the economists' forecasts and on a part of the market data. Third, the supply and the demand in the market, or the market-clearing price, is determined. Finally, both kinds of agents improve their forecasts or trading strategies.

Input Data

Input data, which both the agents perceive, have four factors, and each of which factor has six branches. The factors are

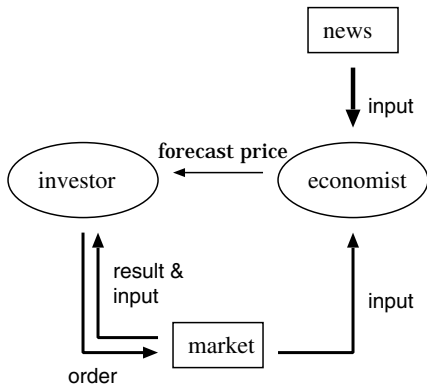


Figure 1: Market Structure

as follows:

- External Factor(From news in Figure 1)
Foreign Market, Currency, Macro Index, Politics, Company, Others
 - Market Factor(From market in Figure 1)
Price Change, Trading Volume, Excess of Demand or Supply, Consecutive Price-up/Price-down, Consecutive Volume-increase/Volume-decrease, Consecutive Demand-Excess/Supply-Excess
 - Technical Factor(From market in Figure 1)
Golden Cross and Death Cross, Granville's Rules, Rate of Change(ROC), Ratio of Price to Short Term Moving Average, Ratio of Price to Long Term Moving Average, Support Line and Resistant Line
 - Behavioral Factor(From market in Figure 1)
Japanese Individuals, Japanese Financial Institutions with Business Corporations, Foreigners, Hedgers, Security Companies, Governmental Traders
- Among the 24 input data, Macro Index, Politics, Company, and Others of External Factor have coded values, which range from -2 to $+2$ in a discrete manner. A plus value means good news for the stock price, while a minus does bad one. We use actual data for other branches of External Factor. We also use internal data for the other factors except Price and Consecutive Price-up/Price-down in the training period(see the next section).

Economist Agent

Economist agents forecast the price using their own judgment values and weights to the 24 input data. Each judgment value differs from each other according to the character of the datum. First, they determine the news impacts about all input data by their own judgment values. Then the news impact is multiplied by the corresponding weight together for each factor. Finally, the mean of the agent's forecast is the weighted average of the input data for this day, calculated as follows:

$$ep_i = \left\{ \sum_{j=1}^4 \left(\sum_{k=1}^6 (w_{j,k} \times n_{j,k}) \right) \times W_j \right\} \times scale \quad (1)$$

Table 1: Overview of the Shareownership

	Number	Stocks	Volume	Times
Individuals	10	10	10	5
Financial Inst.	26	10	20	30
Foreigners	4	10	20	30
Hedgers	2	0	20	20
Security Co.	6	0	20	5
Govt.	2	0	40	2

where ep_i means the economist agent i 's forecast price, $n_{j,k} \in \{-2, -1, 0, 1, 2\}$ is news impact, $w_{j,k} \in \{-2, -1, 0, 1, 2\}$ is weight for the data, and $W_j (\geq 0)$ means factor weight *s.t.*

$$\sum_{j=1}^4 W_j = 1 \quad (2)$$

Investor Agent

As Input Data shows, six kinds of investor agents exist in this market. Each kind of agent has its own character, and according to the character all agents assign their own trading volumes per day and trading times per month(every month has about 20 trading days). In addition, some investor agents have the following particular trading strategies(see Table 1). Those characters are based on (Tokyo-Stock-Exchange 1999) and on our past interviews to investors.

- Japanese Individuals
Their behaviors are based on their utility functions only.
- Japanese Financial Institutions with Business Corporations
Basically they also use their utility functions, but they adjust their behaviors so that their own actions are the same as the other Japanese Financial Institutions'. In addition, they follows the market trend. Unless there exists trend, they do not behave.
- Foreigners
After each agent's behavior is selected based on the maximized utility function, using the Foreign Market and the Currency of the External Factor the agent's behavior is readjusted.
- Hedgers
They sometimes try to accelerate the market trend independently from their utility function.
- Japanese Security Companies
Their trading behaviors have two ways. When the agents' positions are square, their behaviors are determined based on the utility function. Otherwise they try to order so that their positions become square. That is based on our past interviews to the traders. According to them, both taking positions and taking back to square in a day are their actual trading strategies. Therefore they can be regarded as Noise Traders.
- Governmental Traders

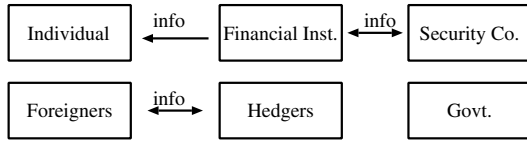


Figure 2: Relationships between the Shareownership

They only trade to support the price when the price lost much in the short time

All investor agents assign their judgment values and weights to the Market Factor, and they have weights to all the economist agents and to each of themselves.

By using them, they forecast the future price about Market Factor and determine their own trading strategies. At first, the investors calculates future price based on the Market Factor data the same as the economists do. Second, from all economists' forecast price and the each investor's forecast every agent's forecast price is determined.

$$mf_i = \sum_{k=1}^6 (w_k \times n_k) \times scale \quad (3)$$

$$ip_i = (mf_i \times w_{i,0} + \sum_{j=1}^{10} (ep_j \times w_{i,j})) \times scale \quad (4)$$

where mf_i means investor agent i 's forecast price about Market Factor, w_k is weight for the data, n_k is the news impact, ip_i is the investor i 's forecast price, and $w_{i,j} \in \{-2, -1, 0, 1, 2\}$ ($j = 0, \dots, 10$) is weight for the economists and investor i itself.

The variance of the every investor's forecasts is calculated as follows:

$$variance = \frac{1}{\sqrt{\{\sum c_+\}^2 - \{\sum c_-\}^2}} \quad (5)$$

where c_+ means product *s.t.* $weight \times price > 0$, and c_- does product *s.t.* $weight \times price < 0$.

The variance is inversely proportional to the coherence of forecast factors. Therefore, the larger the variance, the lower the confidence of the forecast.

Each agent has stock assets(i.e. Nikkei225 as a single asset) and Yen assets. On the basis of the agent's prediction, the trading strategy is determined. That is to maximize the utility function, $U(q)$, of the investor's position of stocks, q , as follows:

$$U(q) = mean \times q - \frac{1}{2} variance \times q^2 \quad (6)$$

The first term of above equation is the expected return and the second is the risk of the position. Therefore, each agent tries to increase returns and decrease risk.

If the investor's current position is smaller than the optimal assets, then a buy order for the agent is made so long as the probable price is smaller than the forecast price.

Price Determination

After all the investors determine their own trading strategies, the demand/supply curve is generated by aggregating the orders of all agents who want to trade. Then the demand and supply determines the equilibrium price, at which the volume of demand is equal to that of supply. That is the price for market-clearing.

The agents, who submit orders to buy at price above that determined price or to sell below that, can trade for the purpose of optimizing their assets. Stocks of other agents, who could not trade, remain the same as in the previous day.

Learning

In this model, different agents have different prediction methods. After the market clearing price was determined, all agents improve their own prediction methods by referring other agents' prediction. This model uses a GA to describe the learning interaction between the agents.

Using a GA, an individual is represented as a string of all judgment values or weights of one agent. In addition, the fitness value of the economist agent is the difference between the each forecast price and the market-clearing price, i.e.

$$fitness = -|(forecast\ price) - (market-clearing\ price)| \quad (7)$$

And the fitness of investor agents is given by the above equation in the training period(see the next section) and the profit rate in the trading period(see the next section) is given by the following the equation:

$$fitness = \frac{wealth\ after\ trade}{initial\ wealth} \quad (8)$$

where $wealth = Yen\ assets + price \times holdings$. Hence, the more precisely an agent forecasts or the more cash an investor has, the higher its fitness value is.

This model is based on the three genetic operators in the Simple GA(Mitchell 1996). Those are Selection, Crossover and Mutation.

After learning, this model proceeds the next day.

Simulation Results

This section describes the use of the artificial stock market model to extrapolate the actual stock price. The next subsection presents the simulations results. In the third subsection, we will show the condition for the contrary opinion phenomena take place, which is followed by some comparisons with actual data in the last section.

Simulation Methods

We repeated the following procedure in order to generate sample paths. Each simulation path consisted of an initialization, a training period and a trading period:

Initialization All agents' judgment values and weights were generated randomly.

Training Period We trained this model using the 24 real world input data. This period corresponds to January 1996 to December 1998. During the training period, the investor agents only forecast the future price and learn

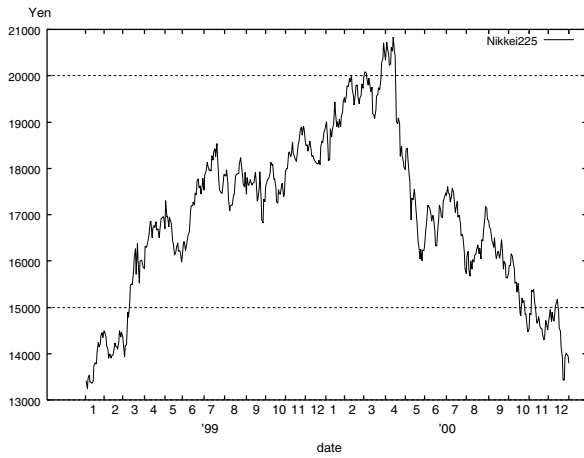


Figure 3: Nikkei225 Line Chart

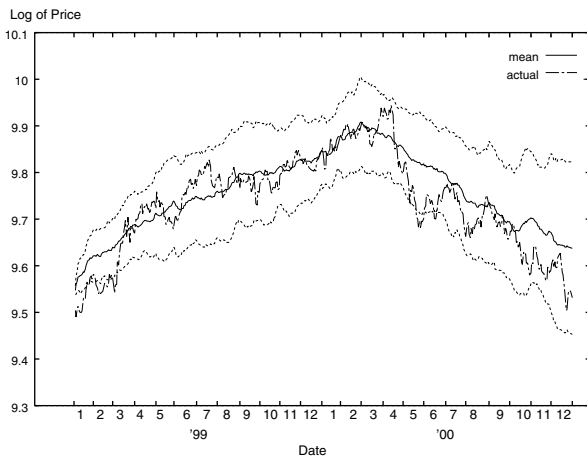


Figure 4: Mean of Sample Paths. The dotted lines denote the mean path \pm one standard deviation of simulation paths.

while they do not trade, so that the fitness function of the investor agents was the cumulative value of equation (7). Of all the input data, External Factor and Price and Consecutive Price-up/Price-down of Market Factor were external, while the others were internal.

Trading Period We constructed to extrapolate for the period covering January 1999 to December 2000(see Figure 3). In this period, the investor agents not only forecast and learn but also trade, their fitness function, therefore, is the profit rate(eq.(8)). Input data except External Factor, which were generated through trading, were used.

Among all sample paths, we selected especially fitted 23 paths and analyzed them. The paths are in Figure 4.

Definition of Contrary Opinion Phenomena

This part of the section shows the conditions for the contrary opinion phenomena take place.

As a whole, the characters of the contrary opinion phenomena are as follows:

Table 2: Overview of Each Group

	Group(a)	Group(b)	Group(c)
Number	14	98	383
Mean Log of Price Change	0.0169	0.0160	0.0166
Mean Volume	34.4	24.5	24.9

- When almost all market participants share a common view of the market, the trend is about to be over.
- Before turning points, both acceleration of price change and increasing volume can be seen in financial markets.

But the definition ‘almost all’ is not clear. So, we defined ‘highly corresponded forecast’ in this paper as follows:

When over 80% of both kinds of agents share a common view of the market. That is, more than 8 economists and more than 40 investors predict that the price will gain/lose.

Because the major phase transition occurred on April, 2000, this paper deals only ‘highly corresponded “price-up” forecasts’(Figure 3).

Among 23 sample paths, there were totally 495 observations satisfied with above conditions(Each sample path has 493 trading days). We classified them into three groups according to the following conditions(Table 2):

When a ‘highly corresponded forecast’ occurs and the following conditions are satisfied, that is in the bull market. That is, the price gained rapidly(acceleration). We used four moving averages to judge it: 5-day moving average(MA), 25-day MA, 13-week MA and 26-week MA.

1. The line chart and all the MAs are rising curve in the last ten trading days.
2. The line chart is the largest in this term. A shorter term MA is larger than the longer term MA(s) at the same time. That means:

$$\text{Line Chart} > 5\text{-day MA} > 25\text{-day MA} > 13\text{-week MA} > 26\text{-week MA} \quad (9)$$

These MAs, which are very popular(Nihonkeizaishinbunsha 1998), are based on the settings in the previous section. That is:

Short Term MA 5-day MA or 13-week MA

Long Term MA 25-day MA or 26-week MA

We classified the ‘highly corresponded forecasts’ which are not satisfied with above conditions into group(c).

And we categorized the others into two groups:

group(a) The price reached the maximum value after within two or three trading days since then, and lost to the extent that the line chart was under 5-/25-day MA afterward(see Figure 5).

group(b) The price kept gaining after the observation. Or even if the trend reversed, that observation was not the final, i.e. there were at least one other observations between at the turning point and at this observation.

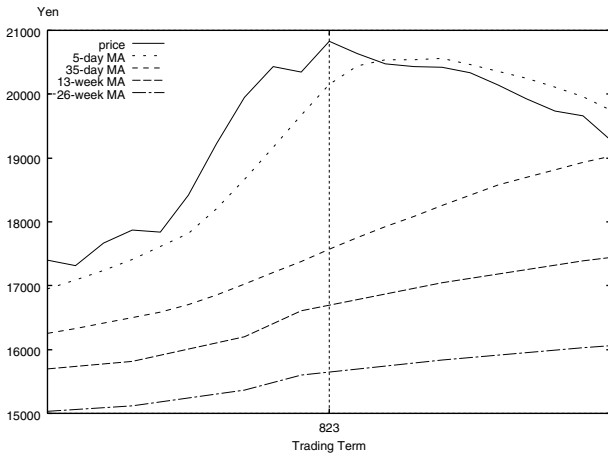


Figure 5: An Example of Group(a). There is a ‘highly corresponded forecast’ at 823.

Table 3: Distribution of the Peaks in Group(a). The third column denotes the number of having a tendency.

	p-value < 0.05	0.05 ≤ p < 0.1	else
before	11	0	3
after	11	1	2

Table 4: Distribution of the Observations in Group(b)

	p < 0.05	0.05 ≤ p < 0.1	else
before	35	5	58
after	40	6	52

Table 5: Distribution of the Observations in Group(c). The NA means the number which t-test could not be conducted.

	p < 0.05	0.05 ≤ p < 0.1	else	NA
before	156	12	213	2
after	165	18	199	1

Using those observations, we investigated the conditions for the ‘highly corresponded forecasts’ leads to the trend reversal.

First, we made a comparison between the volume(= $v(t)$) at the observation with that at ten trading days both before and after the observation respectively. That is, t-test was conducted under the following alternative hypothesis:

- Before the observation

$$v(t) > v(t-10), \dots, v(t-1) \quad (10)$$

- After the observation

$$v(t) > v(t+1), \dots, v(t+10) \quad (11)$$

The results are shown in Table 3, 4 and 5 respectively. Provided that the $v(t)$ in Group(a) is the time when the price is at the top, not at the observation.

The volume $v(t)$ at almost all peaks of the prices is significantly larger than those at both before and after the time in Group(a). This result supports the rule of thumb. While

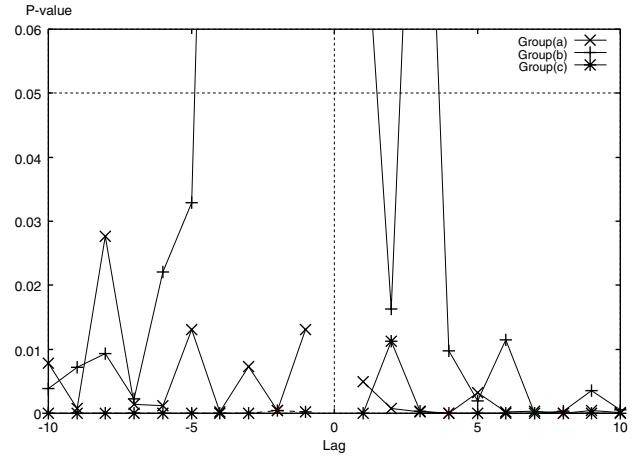


Figure 6: P-value of Each Lag

that at over the half of the observations in both Group(b) and Group(c) were not. The possible reasons are:

- Group(b)

Because the observation was in the middle of the uptrend, there might be some times with larger trading volume. Hence the eq.(10) and (11) were not satisfied.
- Group(c)

According to our past research, there was the positive correlation between the price change and the trading volume in our simulation model. However because the value was not so large, 0.243 for the most fitted sample path (Mean log of price change: -1.1×10^{-4} , Mean volume: 19.3) for example, the volume at each observation could not be overwhelming. That is why the eq.(10) and (11) were not satisfied.

From all those discussions, we concluded that a ‘highly corresponded forecast’ with the following turning point on a uptrend accompanies the large volume.

Second, we made a comparison between the set of the volume at the observation and that at lag k ($k = -10, \dots, -1, 1, \dots, 10$) in each group respectively. That is, we conducted t-test under the following alternative hypothesis:

$$v_1(t), \dots, v_n(t) > v_1(t-k), \dots, v_n(t-k) \quad (12)$$

The results are shown in Figure 6.

The volumes at all the peaks of the prices in Group(a) are significantly larger than those at all lags. This result also support the rule of thumb. Particularly, interesting is p-values after the peak of the prices are smaller than those before the peak. That is, both acceleration of price change and increasing volume could be seen before the turning point, not after.

On the other hand, those at the observations in Group(b) did not tend to be larger than those at around lag 0. On the contrary, there were lags at which volumes tend to be larger than that at observations. The reason is also that the time is in a bull market. Hence there are times when the volumes

Table 6: Distribution of Observations in Actual Data

	$p < 0.05$	$0.05 \leq p < 0.1$	else
before	6	0	14
after	6	0	14

are larger. The volumes at the observations in Group(c) is significantly larger than those at all lags as well as Group(a). That is the major difference from the previous analysis. The reason is we handled all observations about each lag, not each observation. That is, the volumes at the observations, as a whole, seem to be larger than those otherwise once the correlation value is positive.

By the way, all agents in this model can perceive the information about turnover and its trend. Hence, it's necessary to describe that these two inputs did not affect the results. Information all agents perceive about trading volume is the turnover in the previous day, while the latter is shown in eq.(13) and eq.(14). Therefore, because agents couldn't know if the volume was at the top/bottom apart from the price(i.e. Technical Factor), these settings did not affect the results.

- When the volume trend(= $x(t)$) is positive.

$$x(t+1) = \begin{cases} x(t) + 1, & \text{when } v(t+1) > v(t) \\ x(t), & \text{when } v(t+1) = v(t) \\ -1, & \text{otherwise} \end{cases} \quad (13)$$

- When the volume trend is negative.

$$x(t+1) = \begin{cases} x(t) - 1, & \text{when } v(t+1) < v(t) \\ x(t), & \text{when } v(t+1) = v(t) \\ 1, & \text{otherwise} \end{cases} \quad (14)$$

From all those discussions, if a 'highly corresponded forecast' in a bull market leads to the following turning point, there exists a heavy trading. We confirmed a contrary opinion phenomenon really occurs in our simulations.

Comparison with Actual Data

We are going to show the analytic results of actual data in order to make comparison with our simulation results.

Some actual market participants may say that the volume at the top of the price must be smaller. That is, our results did not reflect actual markets. So we investigated if our results applied to actual data.

Ten kinds of stock data, which are all traded at the New York Stock Exchange, were used for the analysis. Those data were as follows:

- Ticker Symbol
AHP, AVP, AXP, HLT, LLY, MMM, NAV, T, TRW, XRX
- Daily Price and Trading Volume(1991-2000)
- No Forecasts

20 observations, which were satisfied with the conditions of Group(a), were selected among those data, and were analyzed under the alternative hypotheses(eq.(10) and eq.(11)). The results are shown in Table 6.

It is true that the numbers in Table 6 are almost opposite from those in Table 3. But that does not mean our simulation results are non-realistic, because we could not know whether the 'highly corresponded forecast' existed at all observations. The following reasons are considered, but it's still an open question.

- If a crash occurs in actual markets, market participants desperately try to take back their positions to square. Therefore the volume at the peak of the price tends to be smaller than that during the crash. While, in our model, information agents perceive is only a part of it. Hence the news impact may weaken.
- Because of the introduction of investors' characters(Table 1), some investors could not do any order under the limit of their trading times. That might create smaller turnover after the peak of the price.

Conclusion

This paper presented an artificial market approach in order to clarify the definition of the contrary opinion phenomena. We confirmed the following points empirically: When a 'highly corresponded forecast' on a uptrend leads to the following trend reversal, there exists a heavy trading. Especially, when the price is at the top, the volume also tends to be the largest. That is the definition of the contrary opinion phenomena. On the other hand, when a 'highly corresponded forecast' in a bull market did not create the turnover, the contrary opinion does not take place. These results seems to be new because the contrary opinion, which is based on market participants' experiences, was defined statistically.

We are currently checking the contrary opinion phenomena on downtrend. At the same time, we are going to make more comparisons with actual data. We expect our research helps understand phase transitions in financial markets.

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