日本の株式市場における
投資家の株価予測形成メカニズムの実証分析

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Extended abstract：

ファンダメンタルズを反映しない株価の乱高下は、株式市場のみならず、企業の経済活動や金融機関行動にまで大きな影響を与える。金融政策当局がそのような金融市場の不安定性の原因を解明し、市場整備を行うことは非常に重要である。90 年代以降、金融市場の自由化に伴い投資家の期待が金融資産価格に反映されるようになったことを考えると、価格の乱高下の原因を解明する鍵は投資家の期待形成メカニズムを理解することにあるはずである。

本研究では QUICK による投資家への株価予測月次調査の個票データを利用し、日本の株式市場における投資家の期待形成メカニズムをエージェントベース理論をもとに明らかにする。市場構造分析の経済理論として注目を集めるエージェントベース理論モデルでは株価が大きく変動する理由として、投資家の予測がいくつもの投資戦略を組み合わせる形で形成され、投資家がその組み合わせの比重を時間を通じて調整していることに注目する。標準的なモデル（例えば Brock and Hommes(1998)）によると、投資家はテクニカル戦略（T 戦略）とファンダメンタル戦略（F 戦略）を組み合わせて期待を形成する。ここで、T 戦略とは過去の価格情報をもとに期待を形成する戦略であり、F 戦略とは、企業の純利益や配当金などの代理変数で測られる企業の根源的価値の周りを株価は推移すると予測する戦略である。両戦略の組み合わせの比重は時間を通じて変化し、予測が主に過去の価格のトレンドに沿って形成する時期と、F 戦略に大きく依存する時期があるとする。期待が主に価格のトレンドに沿って形成される場合は、株価は短期的にはバブルなどに見られる不安定な動きをし、F 戦略に大きく影響を受ける場合は、株価は安定的に推移する。多くのエージェントベース理論モデルでは、この「戦略の切替え」が市場不安定の主たる要因と考える。

本研究では、この戦略の切替えが実証的に見て市場の不安定性を引き起こした要因であるか否かを、日本の株式市場に関して検証する。先行研究では、いくつかの室内実験や為替市場でこの「戦略の切替え」について実証がなされているが、特に日本の株式市場に関しての実証研究は未だ見られないことを考えると、本研究の学術的貢献は大きい。具体的に本研究では、Pfajfar and Santoro (2010)に倣って毎期ごとに予測値による並び替えを行い、予測値の統計百分位数ごとの「戦略の切替え」を分析する。先行研究では予測の平均値の決定要因を分析したものが殆どである。しかし予測値の分布は非対称であるかもしれないし、分布は時間に応じて変わるかもしれず、予測の平均値のみを扱う研究では平均値より離れて予測する投資家の期待形成プロセスを無視してしまうことになる。本研究では予測値を毎期、百分位数に分け、百分位数ごとの期待形成プロセスを研究する。この分析から楽観的・悲観的双方の予想プロセスが明らかになる。すなわち、バブル期には過去の価格トレンドに沿って予測する楽観派が増え、暴落期にはトレンドに沿って予想をする悲観派が増え暴落を助長する、というような市場不安定化メカニズムを解明できる。

1. Introduction

Unstable stock price movements have a significant impact on economic activities of firms and financial institutions. It is important that monetary policymakers clarify the cause of the instability and provide stable environments for financial market participants. Since the 1990s, the number of financial asset traders has been increasing dramatically due to the liberalization of global financial markets, and thus, investors' expectations are more likely to be incorporated in the asset prices. Therefore, it has become crucial for policymakers to understand the mechanism of investors' expectation formation for conducting better policy managements in financial markets. This paper provide evidences on the expectation formation process of professionals in Japanese stock market by using a monthly forecast survey dataset on the TOPIX distributed by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group.

We demonstrate that the expectation formation mechanism in Japanese stock market is consistent with an important prediction of several agent-based models as follows. Recent agent-based theoretical models successfully explains the causes of stock market instability that is still not explained enough with traditional asset pricing models with efficient market and rational expectation hypotheses.[1] Many agent-based theoretical models assume that agents form their expectations by combining several investment strategies. The stock market instability is explained in an environment where agents switch the weights on the strategies over time. Standard agent-based models, popularly a model of Brock and Hommes (1998), assume that agents combine the technical trading strategy with fundamental strategy in their forecasting. The technical trading strategy is constructed by the past price information, while the fundamental strategy suggests that the stock price moves around its fundamental price, which is often measured with firms' earnings or dividends.[2] The weights on the two strategies change over time, and their predictions follow the past trend for some periods while they depend on the fundamental strategy for some periods. When most agents select the technical strategy, the stock market tends to be unstable which explains such as bubble and crash. The fundamental strategy stabilizes the trend, which moves the market price back to the fundamental price. As a result, the market becomes informationally efficient. Standard agent-based theoretical models demonstrate that this "strategy switching" is a major factor for explaining the unstable price movements of financial assets. Our paper provides empirical evidence on the strategy switching in Japanese stock markets and we demonstrate that the strategy switching explains well the stock price dynamics.

Some laboratory experiments with human subjects support this important observation in theoretical agent-based stock markets, such as Hommes, Sonnemans, Tunstra, and van de Velden (2008) and Heemeijer, Hommes, Sonnemans, and Tuinstra (2009). Some survey studies in foreign exchange markets, such as Frankel and Froot (1990) and Ito (1990), provide evidence on strategy switching on foreign exchange market professionals. Although we have seen theoretical and laboratory works, the direct evidence on expectation formation in stock markets is still needed to empirically support the theoretical and laboratory findings in agent-based stock markets. We achieve this goal by using survey data in Japanese stock market.

Following the approach taken by Pfajfar and Santoro (2010), we sort forecasters' expectations in each period in an ascending order in values, and construct time series of percentiles from the empirical distribution. We argue the strategy switching of each percentile and figures out how the agents from different percentiles of expectations change their behavior over time.[3] Previous studies on expectation formations in stock markets characterize the expectation formation process by

[1] Agent-based models also replicate volatility clustering, fat tails of return distribution, non-zero volume, autocorrelations of volume, and positive contemporary cross-correlations between the volume and the squared returns. See, for example, Hommes (2006) and LeBaron (2006).

[2] Forecasters with the fundamental strategy construct their predictions based on the difference between the current price and the fundamental or intrinsic value of the asset. They predict downward (upward) price movements when the current price is above (below) the fundamental price. Technical trading strategy suggests that the expectation is positively related to the recent price movements if agents are momentum traders, while they are contrarians when the relation is negative.

[3] Pfajfar and Santoro (2010) take this approach to investigate the strategy switching in inflation expectations.

using the averaged series of forecasts across forecasters.[4] But the distribution of the forecasts may not be symmetric and the distribution may vary over time. If we use the mean forecast series, we cannot characterize the expectation formation of professionals forecasting far from the mean. Since this paper examines the expectation formation of the percentiles, we can illustrate the expectation formations by optimistic and pessimistic professionals. As a result, we can explain possible sources destabilizing the market. We document that when the market becomes unstable, i.e., periods of relatively large price increases and decreases, more professionals put larger weights on the trend-following strategy, destabilizing the market further. In particular, during the periods of large price increases (decreases), pessimists (optimists) rapidly switch their strategies to follow the market trend, which intensify the stock price movements.

Boswijk, Hommes, and Manzan (2007) provide evidence on the strategy switching in stock markets. They estimate Brock and Hommes's type of an agent-based model (Brock and Hommes (1998)) where agents switch their strategies between fundamental and trend-following regimes based on the recent past performance. They use yearly S&P500 and its earning data from 1871-2003 and show that trend-following behavior explains the persistence of the deviation of stock prices from their fundamental value, which is estimated based on the Gordon growth model by using earnings data, and fundamental strategy tends to revert the prices back to its historical mean.

Our paper differs from Boswijk, Hommes, and Manzan (2007) as follows. First, we characterize expectation formations of the percentiles, i.e., expectations across different types of professionals. Thus, we demonstrate how different types of professionals, e.g., optimists and pessimists, switch their strategies. Second, Boswijk, Hommes, and Manzan (2007) estimate a Brock and Hommes (1998)'s agent-based model so that they assume the model itself for estimating the strategy switching. In particular, they estimate strategy switching under a condition where the market is in equilibrium on average. As we see in the following section, we follow the approach of Boswijk, Hommes, and Manzan (2007) to derive a fundamental price and construct a fundamental strategy. But our estimation equation is not an equilibrium pricing equation, but rather uses forecast survey data of stock market professionals to investigate the strategy switching. Thus, compared to Boswijk, Hommes, and Manzan (2007), we impose less assumption for validating the strategy switching.

Our results indicate that professional forecasters combine the technical and fundamental strategies, meaning that they refer to the past price information for predicting future prices. It suggests that the forecasts are anchored toward some observable priors, contradicting the prediction of the efficient market hypothesis. The efficient market hypothesis suggests that a market is informationally efficient when the market price already reflects all known information at any point in time. Beliefs of all investors on the future prices are fully incorporated into the current price. So, the market price is an unbiased estimate of the true asset value in a sense that past price information cannot be used to predict future prices. While Shiller (1999) discusses that past price information helps explain current prices in stock markets, several studies examine this hypothesis by using survey data on professional forecasters, but have shown systematic evidence that forecasters in reality refer to the past price information for making their forecasts.[5] The empirical results on the systematic prediction biases and the anchoring toward some observable priors are consistent with the findings in laboratory studies by Kahneman and Tversky (1973). Thus, our results help improving the robustness of the findings in laboratory studies by Kahneman and Tversky (1973) by using the survey data of Japanese stock markets.

The rest of the paper is structured as follows: Section 2 first introduces our dataset of professional forecasts on the TOPIX and then presents our empirical models. Section 3 explains how we address our research questions and provides possible results.

[4] For example, see Lux (2009, 2010).

[5] Among many, for example, see Nordhaus (1987), Campbell and Sharpe (2009), and Kaustia, Alho, and Puttonen (2008).

2. Data and model

Our analyses rely on a monthly survey dataset distributed by QUICK Corporation. We use the dataset covering 117 months from June 2000 to February 2010, and 1,143 professionals in total provide one-, three-, and six-month ahead expectations on the TOPIX. The average number of respondents in each month is 187.1 and the minimum number of respondents in a month is 156, while each forecaster replied 20.8 times on average. The survey is usually conducted during three consecutive days at the beginning of each month where the last day is the first Thursday of the month, and the survey report is released on the following Monday. The published report only includes summarized survey results such as mean, standard deviation, median, minimum, maximum of the forecasts, and so on. However, our dataset contains survey response from each professional and also includes respondents' information, such as the individual code and company code, so that we can track the forecast record of a particular individual and firm over time, although not all of the professionals replied to the survey for the full time.

We construct time series of percentiles by sorting forecasters' expectations in each period in an ascending order. Each percentile is represented with *i* and we call percentile *i* as type *i* professional. We denote that ${}_tF_{t+k,i}$ is the forecast made by type *i* at *t* for a future price at *t+k*. Since the survey is released around the beginning of each month, ${}_tF_{t+k,i}$ indicates that forecasters form their expectation at the beginning of month *t*, given the price information from the preceding months. Defining P_t as a monthly stock price recorded at the end of each month, ${}_tF_{t+k} - P_t$ presents unconditional expected changes from the most preceding stock price.

We estimate the following model to validate the strategy switching.

(1) $$\left(\frac{{}_tF_{t+k} - P_t}{P_t}\right) = \left(1 - n_{Tc,t}\right)\beta_F\left(\frac{P_t^* - P_t}{P_t}\right) + n_{Tc,t}\beta_{Tc}\left(\frac{P_t - P_{t-m}}{P_{t-m}}\right) + \varepsilon_t$$

The left-hand side is the forecasted variable. The first (second) term on the right-hand side represents the fundamental (technical trading) strategy. β_F and β_{Tc} are coefficients on the fundamental and technical trading strategies, respectively. For positive β_F, investors predict upward price movement if they use the fundamental strategy and the most recent price is below (above) the fundamental price. When β_{Tc} is positive, investors follow the past trend of the stock price for making their forecasts. They are contrarian when β_{Tc} is negative. P_t^* is the fundamental price, and the technical strategy depends on *m*, i.e., how far investors look back for forming the price trend. $\left(1 - n_{Tc,t}\right)$ and $n_{Tc,t}$ are the weights on the fundamental and technical trading strategy, respectively, where $n_{Tc,t}$ ranges from 0 to 1. The strategy switching suggests that this variable $n_{Tc,t}$ changes over time. In the following, we define 1) the fundamental price P_t^*, 2) lags forming the past price trend *m*, and 3) the weights on the fundamental and technical trading strategy $\left(1 - n_{Tc,t}\right)$ and $n_{Tc,t}$, in order.

2.1 Fundamental price P_t^*

Boswijk, Hommes, and Manzan (2007) reformulate the model of Brock and Hommes (1998) in terms of price to cash flow and estimate the model on yearly S&P500 data. We follow the approach by Boswijk, Hommes, and Manzan (2007) to construct a fundamental price. The market has two tradable assets: a risky stock and a risk-free bond. The risk-free bond pays a constant interest rate r_f. The risky asset is in zero net supply and pays an uncertain cash flow Y_t in each period. We define P_t as the price of the risky asset at *t*. We assume that agents select a prediction rule from fundamental and technical trading strategies. Denote the fundamental and technical trading rules as *F* and *Tc*, respectively. The expectation of rule *h* at time *t* is denoted as $E_{h,t}$ where *h* = *F* or *Tc*. Assuming CARA utility and a Gaussian distribution for cash flow and stock prices, agents selecting predictor *h* set their demand at time *t* according to:

$$(2) \quad S_{h,t} = \frac{E_{h,t}(P_{t+1} + Y_{t+1}) - (1 + r_f)P_t}{\gamma \hat{\sigma}^2_{h,t}},$$

Term $\hat{\sigma}^2_{h,t}$ is the conditional variance of prediction rule *h* at *t* and γ is a constant absolute risk aversion coefficient. We assume that it takes the same value for all agents and is constant over time, i.e., $\hat{\sigma}^2_{h,t} = \overline{\sigma}^2$, implying that the uncertainty does not influence their trading strategies. Denoting the fraction of agents using predictor *h* at time *t* as $n_{h,t}$, the market clearing condition is given by:

$$(3) \quad \sum_{h=1}^{H} n_{h,t} \frac{E_{h,t}(P_{t+1} + Y_{t+1}) - (1 + r_f)P_t}{\gamma \overline{\sigma}^2} = 0.$$

Thus, the equilibrium price is given by:

$$(4) \quad P_t = \frac{1}{1 + r_f} \sum_{h=1}^{H} n_{h,t} E_{h,t}(P_{t+1} + Y_{t+1})$$

As in Boswijk, Hommes, and Manzan (2007), cash flow is assumed to be nonstationary with a constant growth rate as:

$$(5) \quad \log Y_{t+1} = \mu + \log Y_t + \nu_{t+1} \quad , \quad \nu_{t+1} \sim i.i.d. N\left(0, \sigma^2_\nu\right)$$

Boswijk, Hommes, and Manzan (2007) show that this implies:

$$(6) \quad \frac{Y_{t+1}}{Y_t} = e^{\mu + \nu_{t+1}} = e^{\mu + (1/2)\sigma^2_\nu} e^{\nu_{t+1} - (1/2)\sigma^2_\nu} = (1 + g)Y_t$$

where $g = e^{\mu + (1/2)\sigma^2_\nu} - 1$ and $\varepsilon_{t+1} = e^{\nu_{t+1} + (1/2)\sigma^2_\nu}$, implying $E_t(\varepsilon_{t+1}) = 1$.

Assuming that all *H* prediction rules have correct beliefs on the cash flow, we have:

$$(7) \quad E_{h,t}[Y_{t+1}] = E_t[Y_{t+1}] = (1 + g)Y_t E_t[\varepsilon_{t+1}] = (1 + g)Y_t \; .$$

When all agents have rational expectations, the equilibrium pricing equation (4) can be reformulated as:

$$(8) \quad P_t = \frac{1}{1 + r_f} E_t(P_{t+1} + Y_{t+1})$$

For a case of a constant growth rate of dividend *g*, this is re-expressed in terms of the rational expectations fundamental price P^*_t as:

$$(9) \quad P^*_t = \frac{1 + g}{r_f - g} Y_t \quad \text{for} \quad r_f > g$$

We refer to P^*_t as the fundamental price. We measure the deviation of the price from the fundamental price as:

$$(10) \quad \frac{P^*_t - P_t}{P_t} = \frac{\left(\frac{1 + g}{r_f - g}\right) Y_t - P_t}{P_t}$$

2.2 Technical strategy: lags forming the past price trend m

Investors forming technical strategy refer to the past price information. We determine how far they look back the past price information *m* by estimating a following simple regression.

$$(11) \quad \left(\frac{{}_tF_{t+k,i} - P_t}{P_t}\right) = \alpha_i + \beta_i \left(\frac{P_t - P_{t-m}}{P_{t-m}}\right) + \varepsilon_t$$

where *m* = 1, 2, ….., 21, and 1 month. We estimate this model across percentiles and plot the average $\hat{\beta}_i$ and its p-value in Figures 1 and 2.

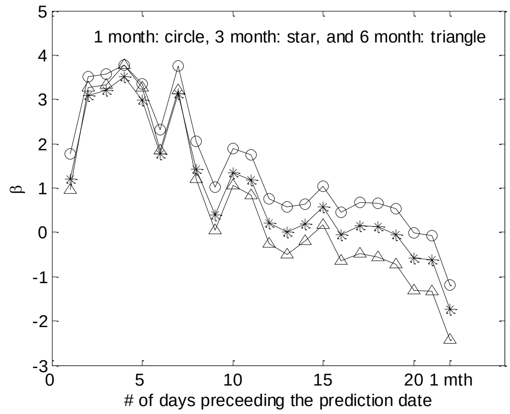

Figure 1: average $\hat{\beta}_i$ with different *m*

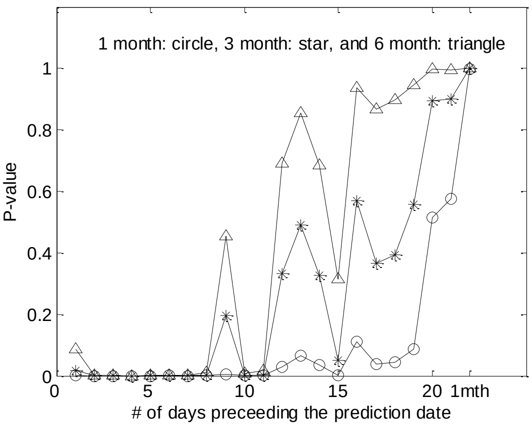

Figure 2: average *p*-value with different numbers of lags *m*

The results are summarized as follows. First, investors tend to follow the recent price trend for making their forecasts. For 1 month-ahead forecasts, the price changes from the past 19 days or later have positive impacts on the forecasts. For longer forecast horizons, investors follow the price trends from the past 11 days or later. The previous price changes from those days have negative influences on their predictions. However, p-values in Figure 2 suggest that the price trend from the past price far from the prediction date is not related to the forecasts. 3 and 6 month-ahead forecasts are not significantly related to the price trend from the past 9 days or earlier, while 1 month-ahead forecast is independent of the past trend from the past 20 days or earlier. Thus, we conclude that technical indicator in our model should only consider the price trend from the 9 days or later. We select 5 for *m* for our analysis, and later we conduct robustness checks by using different lengths of lags for *m*.

2.3 Weights on the fundamental and technical trading strategy $(1-n_{Tc,t})$ and $n_{Tc,t}$

The weight on the fundamental strategy $(1-n_{Tc,t})$ is simultaneously determined once we define $n_{Tc,t}$. Thus, the following only illustrates $n_{Tc,t}$. We analyze two versions for $n_{Tc,t}$.

We define the first version for $n_{Tc,t}$. At the end of each period, investors compare the forecast performances from their fundamental and technical trading strategies, and they put more weight on the strategy which has produced a smaller squared forecast error in the previous period. The forecast errors at *t-1* from the fundamental and technical trading strategies are given by:

$$(12)\quad \varepsilon_{F,t-1} = \left(\frac{{}_{t-1}F_{t+k-1} - P_{t-1}}{P_{t-1}}\right) - \beta_F\left(\frac{P^*_{t-1} - P_{t-1}}{P_{t-1}}\right)$$

$$(13)\quad \varepsilon_{Tc,t-1} = \left(\frac{{}_{t-1}F_{t+k-1} - P_{t-1}}{P_{t-1}}\right) - \beta_{Tc}\left(\frac{P_{t-1} - P_{t-m-1}}{P_{t-m-1}}\right)$$

We measure fitness from both strategies as the inverse of the squared forecast errors by:

$$(14)\quad fitness_{Tc,t-1} = \frac{1}{\varepsilon^2_{Tc,t-1}}$$

$$(15)\quad fitness_{F,t-1} = \frac{1}{\varepsilon^2_{F,t-1}}$$

$n_{Tc,t}$ is given by:

$$(16)\quad n_{Tc,t} = \frac{fitness_{Tc,t-1}}{fitness_{F,t-1} + fitness_{Tc,t-1}},$$

The second version of the weight $n_{Tc,t}$ is constructed by the realized profits from the fundamental and technical trading strategies. The realized profits are based on the realized excess returns and the demand of the risky asset from respective strategies. The excess return is given by:

$$(17)\quad R_{t-1} = (P_{t-1} + Y_{t-1}) - (1 + r_f)P_{t-2}$$

Thus, with the demand equation (2) and equation (17), the realized profits are expressed by:

$$(18)\quad \pi_{F,t-1} = R_{t-1}\frac{E_{F,t-2}(P_{t-1}) + (1+g)Y_{t-2} - (1+r_f)P_{t-2}}{\gamma\bar{\sigma}^2}$$

$$(19)\quad \pi_{Tc,t-1} = R_{t-1}\frac{E_{Tc,t-2}(P_{t-1}) + (1+g)Y_{t-2} - (1+r_f)P_{t-2}}{\gamma\bar{\sigma}^2}$$

Since the forecasted prices from the fundamental and technical trading strategies are respectively given by:

$$(20)\quad \left(\frac{{}_{t-1}F_{F,t+k-1} - P_{t-1}}{P_{t-1}}\right) = \beta_F\left(\frac{P^*_{t-1} - P_{t-1}}{P_{t-1}}\right)$$

and ,

$$(21)\quad \left(\frac{{}_{t-1}F_{Tc,t+k-1} - P_{t-1}}{P_{t-1}}\right) = \beta_{Tc}\left(\frac{P_{t-1} - P_{t-m-1}}{P_{t-m-1}}\right)$$

we solve them for ${}_{t-1}F_{F,t+k-1}$ and ${}_{t-1}F_{Tc,t+k-1}$ as follows:

$$(22)\quad {}_{t-1}F_{F,t+k-1} = \beta_F\left(\frac{P^*_{t-1} - P_{t-1}}{P_{t-1}}\right)P_{t-1} + P_{t-1},$$

and

$$(23)\quad {}_{t-1}F_{Tc,t+k-1} = \beta_{Tc}\left(\frac{P_{t-1} - P_{t-m-1}}{P_{t-m-1}}\right)P_{t-1} + P_{t-1}$$

The realized profits are given by plugging equations (22) and (23) into equations (18) and (19). The weight based on the realized profits is given by:

$$(24)\quad n_{Tc,t} = \frac{\exp(\pi_{Tc,t-1})}{\exp(\pi_{F,t-1}) + \exp(\pi_{Tc,t-1})}$$

where $\pi_{F,t-1}$ and $\pi_{Tc,t-1}$ are the realized profits from the fundamental and technical trading strategies, respectively.

3. Our research questions and possible results

After estimating our model by NLLS and confirming that all parameter estimates are significant, we will validate the strategy switching and provide possible sources of stock price fluctuations by answering the following questions.

- Is strategy switching observed in both definitions of weights $n_{Tc,t}$?
  - We plot the fitted value of the weights. The answer is *"yes"*, if the fitted value of the weight looks time-varying.
  - We plot the weight for the fundamental strategy in 1-month and 6-monh ahead forecasts. The answer is *"yes"*, if the weights are different. In particular, we expect that the weight is larger over time in longer time horizon, because professionals may expect that the stock price will move back to the fundamental value in the longer future.
- What are the possible causes of the stock price movements? Does the strategy switching explain the market fluctuations?
  - We compare weights of optimists and pessimists when the price goes up and down.
  - We expect the following results.
  - When price goes up, both put large weight on technical trading strategy. But optimists put larger weight on the technical trading strategy than pessimists, indicating that optimists are more strongly follow the trend. ➔ the

optimists may be the ones who lead to further price increase.

- When the price goes down, both tend to follow the tend. But pessimists put larger weight on the technical trading strategy than optimists, indicating that pessimists are more strongly follow the trend. ➔ the pessimists may be the ones who lead to further price decrease.

We then conclude that strategy switching explains the market fluctuation. Optimists are the people who intensify the increase, while the pessimists intensify the price decrease.

参考文献

[１] Boswijk, H.P., Hommes, C.H. and Manzan, S. (2007), Behavioral heterogeneity in stock prices, Journal of Economic Dynamics and Control 31, 1938-1970.

[２] Brock, W.A., Hommes, C.H., 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model. Journal of Economic Dynamics and Control 22, 1235–1274.

[３] Campbell, S., Sharpe, S., 2009., Anchoring bias in consensus forecasts and its effect on market prices. Journal of Financial and Quantitative Analysis 44, 369-390.

[４] Frankel, J.A. and Froot, K.A., (1990) Chartists, Fundamentalists and the Demand for Dollars, In: Courakis, A.S. and Taylor, M.P. (eds.), *Private behaviour and government policy in interdependent economies*, New York, Oxford University Press, pp. 73-126.

[５] Heemeijer, P., Hommes, C., Sonnemans, J., Tuinstra, J. (2009) Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation, Journal of Economic Dynamics and Control 33, 1052-1072.

[６] Hommes, C.H., 2006. Heterogeneous agent models in economics and finance. in: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics, vol. 2: Agent-Based Computational Economics. North-Holland, Amsterdam, pp. 1109–1186.

[７] Hommes, C.H., Sonnemans, J., Tuinstra, J., and van de Velden, H. (2008) Expectations and bubbles in asset pricing experiments, Journal of Economic Behavior and Organization, in press.

[８] Ito, T. (1990), Foreign exchange rate expectations: micro survey data, American Economic Review Vol. 80, 434-449.

[９] Kahneman, D., Tversky, A., 1973. On the psychology of prediction. Psychological Review 80, 237-251.

[１０] Kaustia, M., Alho, E., Puttonen, V., (2008), How much does expertise reduce behavioral biases? The case of anchoring effects in stock return, Financial Management 37, 391-412.

[１１] LeBaron, B., 2006. Agent-based computational finance. in: Tesfatsion, L., Judd, K.L. (Eds.), Handbook of Computational Economics, vol. 2: Agent-Based Computational Economics. North-Holland, Amsterdam, pp. 1187–1234.

[１２] Lux, T., 2009, "Rational Forecasts or Social Opinion Dynamics? Identification of Interaction Effects in a Business Climate Survey", Journal of Economic Behavior and Organization 72, 638-655.

[１３] Lux, T. 2010, “Sentiment dynamics and stock returns: the case of the German stock market”, Empirical Economics (forthcoming).

[１４] Nordhaus, W. "Forecasting Efficiency: Concepts and Applications." *Review of Economics and Statistics, 69 (1987) 667-674.*

[１５] Pfajfar, D., Santoro, E., 2010. Heterogeneity, learning, and information stickiness in inflation expectations. *Journal of Economic Behavior and Organization* 75,426-444.

[１６] Shiller, R.J., 1999, “Human Behavior and the Efficiency of the Financial System,” in J.B. Taylor and M. Woodford, Ed., *Handbook of Macroeconomics*, Vol. 1C.