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Abstract

This paper discusses the expectation formation process of Japanese stock market professionals and how their expectations are related to larger fluctuations of the TOPIX price than those of economic fundamentals. By utilizing a monthly forecast survey dataset on the TOPIX distributed by QUICK Corporation, we sort forecasters into buy-side and sell-side professionals. We first demonstrate that the buy-side and sell-side professionals use both fundamental and technical trading strategies throughout their expectation formation processes and that they switch between fundamental and technical trading strategies over time. We then empirically show that strategy switching is key in understanding the persistent deviation of the TOPIX from the fundamentals.

JEL Classification: G17, G12

Keywords: Strategy switching, agent-based modeling, survey data, expectations, Japanese stock market

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1. Introduction

Since the financial market liberalization of the 1990s, we have observed remarkable increase in trading volume by institutional investors in the Japanese stock market, who have been seeking short-term profits. Certain previous empirical studies show that the short-term trading, simultaneously conducted by institutional investors, is primarily responsible for destabilizing the stock markets that often involves large deviations of the stock price from the fundamental value.¹ Practitioners try to determine the sources of the unstable stock price movements for better risk management in financial markets. The liberalization of global financial markets, which increases the number of market participants, indicates that investors' expectations are more likely to be incorporated into the asset prices than in the pre-liberalization periods. Therefore, better explanations of the expectation formation process of investors and how investors' expectations are related to asset price movements can facilitate better understanding of the sources of risk in financial markets. This paper provides empirical evidence for understanding both the determinants of expectations and the causes of stock price movements by using a monthly forecast survey dataset on the TOPIX distributed by QUICK Corporation, a Japanese financial information vendor in the Nikkei Group.

We first demonstrate that the professionals involved in the Japanese stock market utilize both fundamental and technical trading strategies in their expectation formation processes and that they switch between fundamental and technical trading strategies over time. We then empirically show that the strategy switching is key in understanding the persistent deviations of the TOPIX price from the fundamental value. Our conclusions are consistent with what several agent-based models predict and are presented as follows. Recent agent-based theoretical models successfully explain the causes of stock market instability, such as larger price fluctuations than those of the fundamental price, that are still not sufficiently explained with traditional asset-pricing models using efficient market and rational expectation hypotheses.² Many agent-based theoretical models assume that agents form their expectations by combining several investment

¹ Several recent studies, such as Chen, Jegadeesh, and Wermers (2000), Nofsinger and Sias (1999), Sias (2004), and Wermers (1999) show a strong positive correlation between institutional ownership and stock returns. Shiller (1981) measures the fundamental price and demonstrates that the stock price often deviates from the fundamental price and that its variations are much greater than those of the fundamental price.

² Agent-based models also replicate volatility clustering, fat tails of return distribution, nonzero volume, autocorrelations of volume, and positive, contemporary cross-correlations between the volume and the squared returns. See, for example, LeBaron, Arthur, and Palmer (1999). Hommes (2006) and LeBaron (2006) survey the literature on agent-based computational finance and explain its usefulness in generating financial market phenomena.

strategies. Stock market instability is explained in an environment in which agents switch the level of dependence on the strategies over time. Standard agent-based models, popularly exemplified by a model created by Brock and Hommes (1998), assume that agents combine fundamental and technical trading strategies in their forecasting. Investors using the fundamental strategy expect that future prices will always hover around the fundamental or intrinsic value of the asset, which is often measured by a firm's earnings or dividends. The technical trading strategy is developed using past price information, and it suggests that expectations are positively correlated to recent price movements if agents are momentum traders and that they are contrarians when the relation is negative. The models demonstrate that when most agents select the technical strategy, the stock market tends to be unstable, which explains the phenomena of the larger deviations from the fundamental price such as bubbles and crashes. Conversely, when most agents adopt the fundamental strategy, the market will be stabilized, moving the market price back to the fundamental price and leading the market to be informationally efficient. Standard agent-based theoretical models demonstrate that investors interchangeably utilize the two strategies over time, and this "strategy switching" is a major factor in explaining unstable price movements of financial assets.³ Our paper provides empirical evidence on strategy switching in Japanese stock markets, and we further demonstrate that the strategy switching explains persistent price deviations from economic fundamentals well.

We explore them by sorting forecasters into buy-side and sell-side professionals.⁴ Buy-side professionals are those who work for investment institutions, such as mutual funds, pension funds, and insurance firms, which purchase securities on their own account. Sell-side professionals work for companies that sell investment services to asset management firms, or buy-side professionals, and provide research including their recommendations to their clients.⁵ We empirically identify the strategy switching of buy-side and sell-side professionals, and we demonstrate that their strategy switching explains persistent price deviations from economic

³ Kirman (1991), Lux and Marchesi (1999; 2000), and Gaunersdorfer, Hommes, and Wagner (2008) also explain the strategic interactions and volatility. In addition, Chiarella, Iori, and Perelló (2009) and Farmer and Joshi (2002) show that trend-following strategies amplify noise and cause stylized phenomena in financial markets such as excess and clustered volatility.

⁴ Pfajfar and Santoro (2010) sort forecasters' expectations in each period in ascending order with respect to value, and they construct time series of percentiles from the empirical distribution. They adopt the approach of investigating the effect of strategy switching on inflation expectations.

⁵ For more information on the different activities in which buy-side and sell-side professionals engage, see Groysberg, Healy, and Chapman (2008) and Busse, Green, and Jegadeesh (forthcoming).

fundamentals. Previous studies on expectation formations focus on measuring the characteristics of the central tendency of the forecasts.⁶ However, the distribution of the forecasts may not be symmetrical, and the distribution may vary over time. Thus, if we use the measure of the central tendency of the forecast series, we cannot characterize the expectation formation of professionals forecasting differently from the average, and will not be able to identify the types of professionals who are actually destabilizing the market.

Most significantly, this paper contains the following five contributions. First, this paper validates the strategy switching and demonstrates the significant relation between the strategy switching and stock market instability, which is an important contribution of several agent-based models to the literature. Some laboratory experiments with human subjects support this important observation in theoretical agent-based stock markets.⁷ In addition, some survey studies in financial markets provide evidence of strategy switching among the market professionals.⁸ Although we have seen theoretical and laboratory work, direct evidence is still required to empirically support strategy switching and its contribution in generating the empirical features of stock markets.

Second, we empirically identify the types of professionals who actually switch the strategies and destabilize the market. Previous research on agent-based models concludes such investors' behavior to be key in explaining several empirical features in stock markets. Nonetheless, those papers identify neither the type of financial institutions to which those agents specifically belong nor their respective business categories.

Third, we empirically analyze the strategy switching by both buy-side and sell-side professionals. Several papers, such as Clement (1999) and Hong and Kubik (2003), investigate the behavior of sell-side investors from a cross-sectional viewpoint, but they exclusively focus on the sell-side professionals. Accordingly to Groysberg, Healy, and Chapman (2008), this is due to a lack of data on buy-side professionals. Within the relatively limited amount of research conducted on buy-side professionals, Cowen, Groysberg, and Healy (2006) and Groysberg,

⁶ For example, see Branch (2004), Brown and Cliff (2004; 2005), Lux (2009; 2010), and Verma, Baklaci, and Soydemir (2008).

⁷ See, for example, Hommes, Sonnemans, Tunstra, and van de Velden (2008) and Heemeijer, Hommes, Sonnemans, and Tuinstra (2009).

⁸ In the literature on foreign exchange markets, Frankel and Froot (1990), Westerhoff and Reitz (2003), and Gilli and Winker (2003) empirically show strategy switching, while Boswijk, Hommes, and Manzan (2007) investigate it in the US stock market. In the literature on inflation expectations, Branch (2004) and Pfajfar and Santoro (2010) provide empirical evidence that agents switch prediction regimes using a survey on inflation expectations.

Healy, and Chapman (2008) examine the forecasts made by both buy-side and sell-side professionals but do not characterize the strategy switching by buy-side and sell-side professionals. In addition, by analyzing the expectation formations by types, we can characterize the forecast behavior of professionals expecting different from the cross-sectional average of the forecasts.

Fourth, we validate the strategy switching in the Japanese stock market at a monthly frequency. Boswijk, Hommes, and Manzan (2007) find strategy-switching behavior at a yearly frequency. But it still remains unknown at what frequency stock investors actually change their strategies.

Fifth, we demonstrate that the professionals in the Japanese stock market have systematic prediction biases and anchoring in some observable priors, contradicting the prediction of the efficient market hypothesis. Our results indicate that professional forecasters combine technical and fundamental strategies, meaning that they refer to past price information in predicting future prices. The efficient market hypothesis suggests that a market is informationally efficient when the market price, or current price, already reflects all known information at any point in time. The beliefs of all investors regarding future prices are fully incorporated into the current price. Thus, the market price is an unbiased estimate of the true asset value in the sense that past price information cannot be further used to predict future prices. While Shiller (1999) argues that past price information helps to explain current prices in stock markets, several studies that examine this hypothesis by using survey data for professional forecasters have indicated systematic prediction biases.⁹ Our empirical results are consistent with the findings of laboratory studies conducted by Kahneman and Tversky (1973). Thus, our results help to improve the robustness of the findings of these studies by using survey data for Japanese stock markets.

Boswijk, Hommes, and Manzan (2007) provide evidence of strategy switching in stock markets. They estimate Brock and Hommes's (1998) type of agent-based model in which agents

⁹ For example, Nordhaus (1987) finds a significant positive autocorrelation of forecast revisions on GDP growth. When new information arrives, forecasters do not incorporate it into their new expectations immediately but rather gradually adjust their view in accordance with the new information. Campbell and Sharpe (2009) also investigate Money Market Services (MMS) consensus forecasts and find that expectations are systematically biased and anchored on recent past values. A survey study of financial market professionals and university students conducted by Kaustia, Alho, and Puttonen (2008) provides evidence that professionals and university students anchor their long-term stock return expectations to an initial value. In survey studies on foreign exchange markets, for example, Frankel and Froot (1990), Lui and Mole (1998), and Menkoff and Taylor (2007), professionals often combine technical trading strategies with the fundamental strategy in their forecasting.

switch their strategies between fundamental and trend-following regimes based on recent past performance. They use the yearly S&P 500 and the corresponding 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 using earnings data, while the fundamental strategy tends to revert the prices back to their historical mean.

Our paper differs from that of Boswijk, Hommes, and Manzan (2007) as follows. First, we characterize expectation formations of the buy-side and sell-side professionals. Thus, we demonstrate the mechanisms of the strategy switching by different types of professionals. Second, Boswijk, Hommes, and Manzan (2007) assume an agent-based model in estimating strategy switching such that 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. However, our estimation equation is not an equilibrium pricing equation; rather, it uses forecast survey data for stock market professionals to investigate strategy switching. Thus, compared to Boswijk, Hommes, and Manzan (2007), we impose fewer assumptions in validating strategy switching.

The rest of the paper is structured as follows: Section 2 introduces our dataset of professionals' forecasts on the TOPIX and disaggregates the forecasts into those of buy-side and sell-side professionals. Section 3 presents our empirical models. Section 4 provides empirical evidence on strategy switching, and Section 5 discusses the relation between strategy switching and price fluctuations in the Japanese stock market. The final section presents a conclusion to this paper.

2. Data

We utilize a monthly panel dataset gathered in surveys conducted by QUICK Corporation, which covers a period of 117 months (from June 2000 through February 2010) and includes the one-month-ahead expectations for the TOPIX, provided by a total of 1,132 professionals. The average number of respondents each month is 182.0, and each forecaster replied an average of 20.5 times. The survey is usually conducted at the beginning of each month over the course of three consecutive days, with the last of these days taking place on the first Thursday of the month and the survey report released on the following Monday. The published report solely includes

summarized survey results, such as the mean, standard deviation, median, minimum and maximum of the forecasts, and so forth. Although not all of the professionals replied to the survey for the full time period of the study, our dataset contains the survey results of each respondent as well as information such as the individual code and company code of each respondent, enabling us to track the forecast record of individuals over time.

2.1. Buy-side and sell-side professionals

We categorize the respondents into buy- and sell-side professionals, using the information for each respondent presented in two columns of the dataset, which are labeled “assigned work” and “business category.”¹⁰ With respect to the “assigned work” column, a respondent is categorized as a buy-side professional if he or she is in charge of managing (1) his or her company’s own funds, (2) pension funds, (3) funds placed in trust (excluding pension purposes), (4) funds placed in trust (including pension purposes), (5) investment trust, or (6) proprietary trading. (These subcategories are denoted B1, B2, B3, B4, B5, and B6, respectively). A respondent is defined as a sell-side professional if he or she is involved in (7) brokerage of agency trades or (8) brokerage of principal trading and agency trades (denoted as S7 and S8, respectively).

If a forecaster works for (9) research and information, (10) planning for investment management, or (11) other, we look at a column labeled “business category.” If the professional works at a domestic security company or foreign security company, then he or she is categorized as a sell-side professional (denoted as S1 or S2, respectively). Otherwise, for example, if he or she works at an investment trust, commercial bank, trust bank, in life insurance, postal life insurance, pension fund, or other, or if the professional is an investment advisor, then he or she is categorized as a buy-side forecaster (B9, B10, and B11, respectively).

Our dataset includes 826 buy-side and 306 sell-side professionals. The average number of respondents each month is 130.1 buy-side and 52.0 sell-side professionals. Each buy-side professional replied an average of 19.8 times, and each sell-side professional replied an average of 21.5 times throughout the sampling period. There are 9 types of buy-side professionals (B1–B6 and B9–B11) and 4 types of sell-side professionals (S1–2 and S7–8). Throughout our sample periods, the average fractions of these types in percentage are as follows: 18.6 percent for B1, 6.9

¹⁰ This categorization is primarily based on the previous papers, such as that of Groysberg, Healy, and Chapman (2008). In addition, we asked various Japanese market professionals about our categorizations into buy-side and sell-side professionals. In particular, we thank Hidetoshi Ohashi (Morgan Stanley) for his helpful suggestions.

percent for B2, 4.6 percent for B3, 9.3 percent for B4, 10.0 percent for B5, 9.2 percent for B6, 7.3 percent for B9, 3.2 percent for B10, 2.4 percent for B11, 19.2 percent for S1, 2.4 percent for S2, 3.3 percent for S7, and 3.7 percent for S8.

2.2. Forecast series

We utilize one-month ahead forecast series from QUICK Corporation and denote that ${}_tF_{t+1}^i$ is the average one-month-ahead forecast made by type i at t where i = buy-side professionals or sell-side professionals. We define P_t as a monthly stock price and the stock price preceding the prediction date.¹¹ As the survey is released at the beginning of each month, we assume that P_t is the price information available before the release of the survey, meaning the price information that is available at the end of the preceding month. Thus, $\ln\left(\frac{{}_tF_{t+1}^i}{P_t}\right)$ represents unconditional and expected percentage price changes from the most recent stock price.¹² Figure 1 plots the difference of the cross-sectional averages of one-month-ahead forecasts from TOPIX. Figure 1 indicates that professionals usually have upward biases in their predictions, and the biases are persistently observed in our sample, suggesting that the forecast variable at time t , $\ln\left(\frac{{}_tF_{t+1}^i}{P_t}\right)$, is auto-correlated; thus, the estimation model should include its autoregressive components.

Although certain previous studies on expectation formations in stock markets analyze the behavior of the central tendency of the forecasts, this paper sorts forecasts in each period into buy-side and sell-side professionals and investigates the strategy switching in each type.¹³ If the

¹¹ We use this index from Datastream.

¹² We avoid using the beginning-of-month price for this. The survey is usually conducted for three days in the first week of each month, ending with the first Thursday, but the survey period shifts back and forth for a few days if any of the first three days overlaps a Japanese holiday. Thus, if we use a certain price at the beginning of the month, the forecasts ${}_tF_{t+1}^i$ could be made before forecasters obtain the information on the stock price. This contradicts the definition of P_t , which uses the most recent price before the prediction date. We assume that P_t is the past price information that all professionals observe and refer to in making their forecasts.

¹³ Since professionals sometimes move from buy-side business to sell-side business, or vice-versa, certain professionals may be categorized as buy-side professionals in some periods and as sell-side professionals in other periods, or they may move from one type to another within the buy-side professional side. However, as shown in empirical studies conducted by Curtin (2005) and Pfajfar and Santoro (2008), agents in the same category behave similarly, leaving the intrinsic characteristics of the category unchanged. As Pfajfar and Santoro (2010) explain, analyses that include time series of types are in line with the conceptual structure of overlapping generation models.

forecasts in each period are asymmetrically distributed and the distribution varies over time, analyses using only the central tendency cannot characterize professionals' expectations forecasting as different from the average. Figure 2 confirms asymmetrical and time-varying distribution of the forecasts. The star shows the cross-sectional standard deviation of the forecasts, measuring the expectation heterogeneity. We observe that the expectations are heterogeneous and vary over time. The thick line and dots in the figure show the skewness and kurtosis of the forecasts, respectively. The skewness and kurtosis are also time-varying and do not typically exhibit normal distribution. The distribution almost always has fatter tails than a standard normal distribution, indicating that certain types of professionals tend to have more optimistic or conservative views on the future than the others. The skewness is usually not zero, indicating asymmetry in the forecast distribution. Forecasts are skewed to the left when the skewness is negative, meaning that certain professionals are more conservative in forecast. Positive skewness indicates a small portion of professionals predicting more optimistic views than others. The first moment and the higher moments of the forecast distribution clearly confirm the asymmetrical and time-varying features of the forecast distribution.

To further understand the characteristics of the forecast distribution, Figure 3 plots the differences of buy-side and sell-side forecasts from cross-sectional mean of the forecasts. Three points should be emphasized here. First, the forecasts of buy-side professionals are often lower than the mean, while the forecasts of sell-side professionals are often higher than the mean. Second, the sell-side professionals' forecasts are more volatile than those of buy-side professionals. The first and second points are consistent with general observations of the forecast behavior of sell-side and buy-side professionals. Sell-side professionals usually make optimistic forecasts to sell their investment services, while buy-side professionals are generally considered relatively conservative in their forecasts. In addition, as described by Cheng, Liu, and Qian (2006), sell-side professionals have an incentive to differentiate their investment services from those of other sell-side professionals, hoping to establish a reputation on the market by making unique forecasts. This incentive generates forecasts that are more volatile than those of buy-side professionals.

Third, the differences between buy-side and sell-side forecasts explain the distribution of the entire forecasts in Figure 2. The standard deviations of the entire forecasts in Figure 2 tend to be greater, as sell-side professionals make higher forecasts and buy-side professionals make

lower forecasts than the mean. The skewness and kurtosis of the entire forecasts in Figure 2 vary significantly when sell-side professionals change their forecasts in greater magnitude. To summarize, Figure 3 confirms that the forecasts by buy-side and sell-side professionals are different from the average, and their forecasts characterize the non-normal distribution of the forecasts in our sample. This suggests that the investigation of the forecasts by buy-side and sell-side professionals may, in some way, explain the forecasting behavior that is not characterized in an analysis using the averaged forecast series.

3. Empirical model

We estimate the following model for each type i to validate the strategy switching.

$$\ln\left(\frac{F_{t+1}^i}{P_t^i}\right) = \alpha_0^i + \sum_{n=1}^N \alpha_n^i \ln\left(\frac{F_{t+1-n}^i}{P_t^i}\right) + (1 - n_{Tc,t}^i) \beta_F^i \ln\left(\frac{P_t^*}{P_t^i}\right) + n_{Tc,t}^i \beta_{Tc}^i \ln C_t^i + \varepsilon_t^i \quad (1)$$

The left-hand side is the forecasted variable. The first and second terms in the right-hand side are a constant term and the lagged observations with order N , respectively. We add autoregressive components because the forecasts are likely to have persistently upward biases, as observed in Figure 1. We focus on the one-month-ahead forecast to avoid the overlapping forecast problem, in spite of the fact that the QUICK dataset contains one-month-, three-month-, and six-month-ahead forecasts. The third term on the right-hand side represents the fundamental strategy, while the fourth term on the right-hand side represents the technical strategy. $\ln\left(\frac{P_t^*}{P_t^i}\right)$ is a fundamental indicator measuring the deviation of the preceding price from the fundamental or intrinsic value P_t^* , while $\ln C_t^i$ is a technical indicator measuring the recent price trend, both of which will be defined in more detail in the following subsections.

β_F^i and β_{Tc}^i are coefficients of the fundamental and technical trading strategies, respectively, for type i . When β_F^i is positive, forecasts based on the fundamental strategy are made around the fundamental value. For example, if professionals use the fundamental strategy and the most recent price is below the fundamental price, they expect that the future price will move back toward the fundamental price, so they predict upward price movement, and vice versa. When β_{Tc}^i is positive, investors extrapolate the future path of the stock price in accordance with

the past trend. They are contrarians when β_{Tc}^i is negative, predicting a turning point in the price trend. We assume that professionals utilize both fundamental and technical trading strategies to reflect investors' realistic behavior, as found in some studies on surveys of financial market participants, such as Lui and Mole (1998) and Menkoff and Taylor (2007).

$(1 - n_{Tc,t}^i)$ and $n_{Tc,t}^i$ are the fractions of professionals in type i , who utilizes the fundamental and technical trading strategies in forecasting, respectively, ranging from 0 to 1. The strategy switching suggests that this variable $n_{Tc,t}^i$ changes over time. In the following subsections, we define the details regarding (1) the fundamental price P_t^* ; (2) technical indicator $\ln C_t^i$; (3) the fractions of the fundamental and technical trading strategies $(1 - n_{Tc,t}^i)$ and $n_{Tc,t}^i$; and (4) order N in the autoregressive components, in order.

3.1. Fundamental price P_t^*

We define a fundamental price by closely following the approach of Boswijk, Hommes, and Manzan (2007), which is the present value model with rational expectations of future real dividends discounted by a constant real discounted rate, which is the so-called static Gordon growth model (Gordon, 1962). The market has two tradable assets: a risky stock and a risk-free bond. The risk-free bond pays a constant interest rate of r_f . The risky asset is in zero net supply and pays an uncertain cash flow of Y_t in each period. We define P_t as the price of the risky asset at t . Agents select a prediction rule from the fundamental and technical trading strategies. The expectation of strategy h at time t is denoted as $E_{h,t}$ where $h = F$ (fundamental strategy) or Tc (technical trading strategy). Assuming a constant absolute risk aversion (CARA) utility and a Gaussian distribution for cash flow and stock prices, agents selecting predictor h set their demand at time t according to:

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

$\hat{\sigma}_{h,t}^2$ refers to the conditional variance estimate of prediction rule h at t , and γ is a constant absolute risk aversion coefficient. We assume that all agents have homogeneous expectations on the conditional variance; thus, $\hat{\sigma}_{h,t}^2 = \hat{\sigma}_t^2$. Denoting the fraction of agents using predictor h at time

t as $n_{h,t}$ and assuming a zero net supply of the risky asset, the market clearing condition is given by:

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

The equilibrium price is given by:

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

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

$$\ln Y_{t+1} = \mu + \ln Y_t + \nu_{t+1}, \quad \nu_{t+1} \sim i.i.d.N(0, \sigma_\nu^2) \quad (5)$$

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

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

where $g = e^{\mu + (1/2)\sigma_\nu^2} - 1$ and $\varepsilon_{t+1} = e^{\nu_{t+1} - (1/2)\sigma_\nu^2}$. This implies that $E_t(\varepsilon_{t+1}) = 1$ and $V_t(\varepsilon_{t+1}) = e^{\sigma_\nu^2} - 1$.

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

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

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

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

In the case of a constant growth rate in cash flow of g , equation (8) is expressed in terms of the rational expectations' fundamental price P_t^* as:

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

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

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

In our empirical analyses, we utilize a monthly dividend series of TOPIX, which is distributed by the Tokyo Stock Exchange, for the cash flow Y_t . Figure 4 plots TOPIX and its fundamental price, defined by equation (9). We follow the practice of Shiller (1981) and Boswijk, Hommes, and Manzan (2007) in using the CPI to deflate the nominal variables. Since dividends are usually paid in May or June in Japan, seasonal cycles are generated in series, so we smooth them out using an exponential moving average as follows:

$$EMA_t = \alpha EMA_{t-1} + (1 - \alpha) Y_{t-1} \quad (11)$$

where we set a constant smoothing parameter at 0.9.¹⁴ Figure 4 suggests that the stock price often deviates from the fundamental price but shows a tendency to revert to the fundamental value. The stock price has co-movement with the fundamental value within our sample periods, but it does not perfectly explain the stock price dynamics that are a consistent feature observed in U.S. data, popularly in the work of Shiller (1981).

3.2. Technical indicator $\ln C_t^i$

$\ln C_t^i$ refers to a technical indicator in equation (1), which measures the past price trend. We examine whether professionals look at the past price trend in forming their expectations. Technical indicators used in several agent-based models are based on a one-period price change,¹⁵ while real stock investors may use more complicated and sophisticated rules. Thus, we select a variety of simple but slightly sophisticated rules for the trend indicator and empirically determine which rule better fits the technical indicator for each type of professional by estimating:

$$\ln \left(\frac{F_{t+1}^i}{P_t} \right) = \delta^i + \phi^i \ln C_t^i + \varepsilon_t^i \quad (12)$$

Here, we consider the following three types of technical indicators representing the past trend:

$$\ln C_t^i = \ln \left(\frac{P_t}{P_{t-m}} \right) \quad (13)$$

¹⁴ Shiller (1981) detrends the stock price and fundamental price by dividing by a long-run exponential growth factor, while Campbell and Shiller (2005) smooth them using 10-year moving averages.

¹⁵ See, for example, Anufriev and Panchenko (2009).

where P_t is the end-of-month price and m represents how many days (m) each type i considers past price information in forming the trend indicator, and $m = 1, 2, \dots, 19$, and one month.¹⁶ We also consider two trend indicators that reflect price deviations from the monthly mean price. The first one is the deviation of the end-of-month price from the mean price, which is:

$$\ln C_t^i = \ln \left(\frac{P_t}{\text{monthly mean price}} \right) \quad (14)$$

where P_t is the end-of-month price and the monthly mean price is calculated by averaging all daily prices observed for the month. The other one utilizes the price at the beginning of the month, which is given by:

$$\ln C_t^i = \ln \left(\frac{\text{monthly mean price}}{P_t} \right) \quad (15)$$

where P_t is the beginning-of-month price¹⁷ and the monthly mean price is calculated as in equation (14).

Another type of trend indicator measures the monthly price change by using the monthly average price, which is:

$$\ln C_t^i = \ln \left(\frac{\bar{P}_t}{\bar{P}_{t-1}} \right) \quad (16)$$

where \bar{P}_t is the monthly mean price, calculated by averaging all daily prices observed at t . Note that our technical indicators at t are constructed using daily data within a month, or they are monthly price changes, to avoid the overlapping sample problem. This means that our technical indicators at t are independent from those at the most recent preceding and following months.

We have 23 trend variables, and we estimate equation (12) for each type of professional using these 23 variables. For each type, we conduct a univariate regression for each of the 23 variables, meaning that we run a total of 46 regressions. We use the Newey-West consistent standard error (Newey and West, 1987; 1994) to evaluate the significance of $\hat{\phi}^i$ because, quite possibly, the expectations can also be explained by other variables, suggesting that we observe

¹⁶ On average, 21.7 prices are recorded each month; the minimum and maximum are 20 and 23, respectively. Thus, if we set m to be equal to or more than 20, $\ln C_t^i$ may be serially correlated with that of the preceding or following month.

¹⁷ For equation (15), we use the price at the beginning of the preceding month from the forecast date.

certain serially correlated patterns in the residuals. We select a trend variable for each type when the Newey-West corrected p -value is less than 0.05. If multiple trend variables are chosen with this criterion, we randomly select one of them. If none of them fulfills this criterion, we choose the one that generates the lowest p -value. Table 1 shows the result.

We highlight two results here. First, the estimates of $\hat{\phi}^i$ are all positive, meaning that buy-side and sell-side professionals are trend-followers. Second, both types of professionals look over the past 1 month when forecasting the future price. Our results suggest that professionals tend to utilize past price information in making their forecasts. This contradicts the implication of the efficient market hypothesis that we cannot accurately predict future prices using past price information because the current price already contains all available information in the market. If that were the case, nobody would use past price information to predict future prices. Our results on prediction being anchored in some observable priors are consistent with certain survey studies on macroeconomic forecasts. For example, Campbell and Sharpe (2009) show that forecasts of macroeconomic variables, such as CPI and industrial production, are anchored not only in the previous month's release but also in the average of the three previous months' releases.¹⁸

3.3. Fractions of the fundamental and technical trading strategy $(1 - n_{Tc,t}^i)$ and $n_{Tc,t}^i$

The fraction of the fundamental strategy $(1 - n_{Tc,t}^i)$ is simultaneously determined with $n_{Tc,t}^i$. Thus, the following illustrates only $n_{Tc,t}^i$. At the end of each period, investors compare the forecast performances from their fundamental and technical trading strategies, and they switch their strategies to the one that produced the smaller squared forecast error during the previous period. As assumed in several agent-based models, such as Brock and Hommes (1998), we assume that type i chooses strategies according to:

$$\max(\text{fitness}_{F,t-1}^i - C_F + \omega_{i,t}, \text{fitness}_{Tc,t-1}^i + \varpi_{i,t}) \quad (17)$$

¹⁸ Among several articles, those of Aggarwal, Mohanty, and Song (1995), Nordhaus (1987), and Schirm (2003) are other examples. In addition, professional forecasters of macroeconomic variables refer to older information—such as the past three months in the work of Campbell and Sharpe (2009)—than the forecasters in our sample do. Forecasted values of macroeconomic variables are typically released every month, while stock prices are disclosed to the public much more frequently. Thus, professional forecasters of macroeconomic variables may update their information set much more slowly than the forecasters of stock prices, and they may retain the old information in their information set for a while, suggesting that macroeconomic forecasters may look at older information for their forecasts.

where C_F , assumed to be positive, is the cost that type i pays for acquiring the information on the fundamental value. $\omega_{i,t}$ and $\varpi_{i,t}$ are random variables that are independent and extreme-value distributed. Then, type i chooses the technical trading strategy by the logit model probability as follows:

$$n_{Tc,t}^i = \frac{\exp(\beta \times fitness_{Tc,t}^i)}{\exp(\beta \times (fitness_{F,t}^i - C_F)) + \exp(\beta \times fitness_{Tc,t}^i)} \quad (18)$$

Parameter $\beta \geq 0$ is called the intensity of choice and measures the sensitivity of the switch between fundamental and technical trading strategies. The higher the intensity of choice, the more rapidly professionals switch their strategies to the one that produced better performance in the previous period. The lower β indicates that type i changes his strategy only when there is a large difference in the performance in the two strategies. The intensity of choice is inversely related to the variance of the noise terms $\omega_{i,t}$ and $\varpi_{i,t}$. We measure the fitness from both strategies in terms of the squared forecast error by:

$$fitness_{F,t}^i = -(\varepsilon_{F,t}^i)^2 \quad (19)$$

$$fitness_{Tc,t}^i = -(\varepsilon_{Tc,t}^i)^2 \quad (20)$$

The forecast errors at t from the fundamental strategy $\varepsilon_{F,t}^i$ and technical trading strategy $\varepsilon_{Tc,t}^i$ for type i are given by:

$$\varepsilon_{F,t}^i = \ln\left(\frac{P_t}{P_{t-1}}\right) - \beta_F^i \ln\left(\frac{P_{t-1}^*}{P_{t-1}}\right) \quad (21)$$

$$\varepsilon_{Tc,t}^i = \ln\left(\frac{P_t}{P_{t-1}}\right) - \beta_{Tc}^i \ln\left(\frac{P_{t-1}}{P_{t-2}}\right) \quad (22)$$

It is assumed that professionals evaluate past performance every month, meaning that they update the strategies every period, hoping to obtain better performances in the future.

3.4. Order N in an autoregressive component

Since our empirical model includes the autoregressive components of forecasted variable $\ln\left(\frac{F_{t+k}^i}{P_t}\right)$, we need to determine the appropriate order N to be estimated. We utilize the Akaike

Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to determine the appropriate lag length. Since we cannot decide which criterion is better, we leave the model selection issue undecided and proceed with our subsequent analyses using candidate models selected by both criteria. Since we have two types and use two criteria, four candidate models are chosen by the AIC and BIC. The lag length selected by the AIC is likely to be larger than that selected by the BIC, but the lags selected by the AIC and BIC are one month for both buy-side and sell-side professionals.

4. Evidence of strategy switching

This section provides evidence of strategy switching in the Japanese stock market. We first estimate our empirical model, i.e., equation (1), by nonlinear least squares (NLLS). After confirming the significance of the fundamental and trend-following parameters, we plot the fitted value of $n_{Tc,t}^i$ (i.e., fraction of professionals in type i utilizing the technical trading strategy). We validate the strategy switching by examining whether the fitted value of $n_{Tc,t}^i$ varies by time.

We estimate the parameters in equations (1), such as those of fundamental and technical trading strategies and intensity of choice, with appropriate lag lengths selected independently by AIC and BIC for buy-side and sell-side professionals. Thus, we conduct NLLS four times. Table 2 summarizes the results. As seen in Table 2, the parameters of the fundamental and technical trading strategies are significantly positive for buy-side and sell-side professionals in both of the AIC and BIC models.¹⁹

The results indicate that, on the one hand, the forecasts based on the fundamental strategy tend to revert to the fundamental value. On the other hand, technical traders are all trend followers. They forecast that the price change will be proportional to the latest observed change. In cases where the price has increased in the past, they expect that the future price will go up, and that it will go down when the price has decreased.²⁰

¹⁹ In addition, we have conducted two statistical tests on the residuals: the Jarque-Bera test, where the null hypothesis is that the residuals follow a normal distribution, and the Ljung-Box test, where the null is that the residuals are not autocorrelated. For both tests in the AIC and BIC models, the test statistics are usually in a range of insignificance at the 95% confidence level. The null hypothesis in the Jarque-Bera test is not rejected for buy-side and sell-side professionals, while, in the Ljung-Box test, the residual autocorrelations do not exist for both types. Thus, we conclude that the residuals are normally distributed without autocorrelations.

²⁰ We selected technical indicators from only 23 choices in Section 3.2. In reality, professionals may refer to other and more complicated technical indicators. Thus, if we adopt other (and possibly more complicated) rules for

The parameters of the intensity of choice are all positive but usually not significant.²¹ As explained by Boswijk, Hommes, and Manzan (2007), the parameter in the transition function is hardly significant, because large variations in the intensity of choice cause only small changes in the fraction $n_{Tc,t}^i$. As emphasized by Boswijk, Hommes, and Manzan (2007) and Teräsvirta (1994), the significant heterogeneity in the estimated strategies is more important than the insignificance of the estimate of the intensity of choice.

Our estimate of the intensity of choice for buy-side professionals is very large (170.8) compared to that of inflation expectations, as indicated in Branch (2004), possibly because buy-side professionals generally employ passive investment strategies, which are very common in the Japanese stock market. The passive management adopted by the majority of the Japanese institutional investors, such as investors in pension funds and life insurance, is the fund management method that utilizes major stock indices, such as TOPIX, as a benchmark and seeks an investment performance similar to the returns from the benchmark.^{22,23} Our results suggest that many of the buy-side professionals employ passive investment strategies and, thus, adjust their strategies to the TOPIX price movements. Their intensity of choice is strong, indicating that they quickly and frequently adjusted their strategies to the very volatile movements of the TOPIX during our sample periods.

In addition, the sell-side professionals also indicate strong intensity of choice (185.2), possibly because, as Yamamoto and Hirata (2011) demonstrate, the sell-side professionals tend to utilize buy-side professionals' ideas about future prices to ingratiate themselves to their clients, that is to say, buy-side professionals.

Now we validate the strategy switching by plotting the fitted value of $n_{Tc,t}^i$ in the upper figure in Figure 5. We plot the weighted average of the fraction that weights the fractions of buy-side and sell-side professionals by the number of respondents in each type, denoted as $\bar{n}_{Tc,t}$. This clearly shows a time-varying feature. Since the parameter estimates of the fundamental and

selecting appropriate technical indicators, we may select different rules. However, our results indicate that these rules that we may possibly select will also be in a form similar to that of trend-following indicators, because the rules we selected here are statistically significant.

²¹ In both of the AIC and BIC models, the p -values for the estimates of the intensity of choice are 0.13 for buy-side professionals and 0.13 for sell-side professionals.

²² As opposed to passive management, active investment looks for better trading performances than the returns from the benchmark.

²³ See, for example, Ohba (2001), who documents the passive management systems in the Japanese stock market.

trend-following strategies are significant for both types, we conclude that buy-side and sell-side professionals adjust their strategies between the fundamental and trend-following strategies over time. While professionals on average put more weight on the trend-following component, since the weight is larger than 0.5, they switch their strategies and put more weight on the fundamental strategy when it has generated a better forecast performance in the past.

Figure 5 suggests that the stock price would be related to the strategy switching by buy-side and sell-side professionals. Since our parameter estimates of the technical trading strategies are positive, it is clear that more professionals tend to choose trend-following strategies when the price follows the trend, and therefore, the price trends are further intensified. However, the positive parameter estimate of the fundamental strategy indicates that professionals tend to predict that the price will revert to the fundamental value when the deviation of the price from the fundamental price becomes larger. As more professionals choose the fundamental strategy, the price tends to move back to the fundamental price.

We observe that the fundamentalist strategy suddenly gains more weight during certain periods. Such switching behavior would be also related to certain big market events in Japanese markets and in global markets.²⁴ The examples include (1) the Resona shock in May 2003; (2) the UFJ shock in August 2004, which refers to the merger of the Mitsubishi Tokyo Financial Group and UFJ Holdings, triggered by the problems of huge, nonperforming loans; (3) the litigation of the insider trading charges of the Japanese famous hedge fund, the Murakami fund, in June 2006; (4) the unexpected sudden resignation of Prime Minister Abe in September 2007; and (5) certain issues that occurred months prior to the Lehman shock in September 2008, such as the Bear Stearns shock in March 2008 and the Subprime shock in summer 2008. The bottom figure in Figure 5 plots the TOPIX and its fundamental value and indicates the period of the above-mentioned events. The Resona shock and the UFJ shock hit the Japanese economy in a way that moved the price back to the fundamental price. During those periods, professionals switched their strategies to that of fundamentalist. This suggests that those events calmed down the Japanese stock market and made investors realize that the market would go back to fundamental prices. When they switched their strategies, the price seemed to revert to the fundamental value. The other events, such as the litigation of the Murakami fund, the stepping

²⁴ The switching behavior is also observed when the markets go bullish (for example, summer 2003, summer 2004, and spring 2005). Shibata (2011) identifies the timings of bull and bear markets in the case of Tokyo stock exchange by using DDMS-ARCH model.

down of Prime Minister Abe, the Bear Stearns shock, and the Subprime shock also appeared to be correlated to the movement of $\bar{n}_{Tc,t}$. As the Japanese economy experienced those shocks, the investors tended to think that the price would not further deviate from the fundamental price. Thus, they would switch to the fundamental strategies, and the price would move back to the fundamental price.²⁵

Those observations suggest that the fluctuations of the fraction of professionals in the market, utilizing trend-following strategies, would be related to the deviation of the stock price from the fundamental price, as previous agent-based models suggest. In the next section, we statistically investigate this relation in the Japanese stock market. We will demonstrate that the strategy switching employed by buy-side and sell-side professionals actually drives the fluctuations of the Japanese stock market.

5. Strategy switching and market fluctuations from 2000 to 2010

Standard agent-based models, such as that of Brock and Hommes (1998), predict that the trend-following strategy can be a key factor generating unstable phases in the economy, while the fundamental strategy contributes to stabilizing price fluctuations. As more agents adopt trend-following strategies, the price moves away from the fundamental price and the price deviations persist. During the period of persistent price movements, the trend-following strategies produce better forecast performances, which results in more investors choosing the trend-following strategies. Thus, the trend-following strategies reinforce the deviations. When the price deviates much from the fundamental price, agents tend to predict the price reverting to the fundamental price. As more agents choose the fundamental strategy, the price goes back to the fundamental price. This implies that there is a positive correlation between the fraction of professionals *in the market* utilizing the trend-following strategy, that is to say, $\bar{n}_{Tc,t}$, and the price deviation from the fundamental price.²⁶ The following investigates the dynamic relation between the fraction $\bar{n}_{Tc,t}$ and the price deviation from the fundamental price. We measure the price deviation from the

²⁵ When the Lehman shock hit the market, professionals thought that the price would deviate from the fundamental price. Thus, more professionals utilized the trend-following strategies. This indicates that the Lehman shock confused the market, intensifying the decrease in the stock price.

²⁶ Recall that $\bar{n}_{Tc,t}$ is the weighted average of the fraction using the numbers of respondents in buy-side and sell-side professionals as weights.

fundamental price as the absolute value of the log difference of TOPIX from the fundamental price: $abs\left(\ln\left(\frac{P_t}{P_t^*}\right)\right)$.

We have conducted Augmented Dickey-Fuller tests and found that the fraction and price deviations are nonstationary, with different lengths of lags.²⁷ However, the first differences in $\bar{n}_{Tc,t}$ and $abs\left(\ln\left(\frac{P_t}{P_t^*}\right)\right)$ appear to be stationary. Thus, we estimate a bivariate VAR model to investigate the dynamic relation by utilizing the first differences of the two variables.²⁸ We model our VAR model as follows:

$$Y_t = V + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + U_t \quad (23)$$

where $Y_t = \left(\Delta \bar{n}_{Tc,t}, \Delta abs\left(\ln\left(\frac{P_t}{P_t^*}\right)\right) \right)'$. V is a 2 x 1 vector of the intercept terms, the A_k are 2 x 2 coefficient matrices with entries $a_{n,j}^h$, where n is the row, j is the column number, h is the lag order, and U_t is a vector of disturbances.

Before estimating the parameters, we determined the appropriate order of the VAR models using the AIC and BIC, and we found that the lags selected by the AIC and BIC are eight and three months, respectively.

We estimate the VAR model with the appropriate lags and conduct Granger causality tests to investigate the implied causal structures of the fraction $\bar{n}_{Tc,t}$ and the price deviations from the fundamental price, $abs\left(\ln\left(\frac{P_t}{P_t^*}\right)\right)$. We first explain the results of the Granger causality test in Panels A and B in Table 3. Consistent with earlier research on agent-based theories, we find a significant influence of the fraction on the price deviation from the fundamental value for both

²⁷ For example, the ADF test statistics are -0.33 and -0.09 for the fraction when the lags are 1 and 2, respectively. The ADF test statistics for the absolute price deviation are -1.13 and -1.21 when the lags are 1 and 2, respectively.

²⁸ The ADF test statistics are -10.68 and -8.68 for the first difference of the fraction when the lags are 1 and 2, respectively. The ADF test statistics for the first difference of the absolute price deviation are -6.65 and -5.43 when the lags are 1 and 2, respectively.

the AIC and BIC models. In addition, Panel B in Table 3 demonstrates significant causality from the price deviations to the fraction for both the AIC and BIC models as well.

The parameter estimates are summarized in Panels A and B in Table 4. In Panel A in Table 4, we find that in both of the AIC and BIC models, switching strategies to trend-following strategies by buy-side and sell-side professionals causes the price to deviate from the fundamental price (i.e., positive coefficient estimates at a lag of one month). When more professionals select trend-following strategies, the price tends to deviate from the fundamental value. The price reverts to the fundamental value when more professionals choose the fundamental strategies. Panel B in Table 4 shows that the coefficient estimates of the price deviation are usually significant at a one-month lag, meaning that the price deviations from the fundamentals are persistent over a month, which fits our observation on the real data.

6. Conclusion

This paper has demonstrated that the buy-side and sell-side professionals in the Japanese stock market utilize both fundamental and trend-following strategies in their forecasting and that they switch strategies over time. We have demonstrated that strategy switching by buy-side and sell-side professionals has a significant impact on the TOPIX price deviations from the fundamental value. Our findings help to validate strategy switching as well as its influences on the persistent deviations of the price from the fundamentals, which are important results in standard agent-based models, such as that of Brock and Hommes (1998).

Finally, we conclude our discussion with certain possible extensions of our research. We have related the stock price forecast series to the stock price dynamics. Therefore, our results suggest that the stock price forecast series can possibly be utilized to identify the shape of the return distribution. Since practitioners calculate the probability of large and small price movements from the tail of the return distribution, the thickness of the tail indicates important information for better risk management. Therefore, the forecast series can serve to provide a better understanding of the sources of risk in stock markets. One possible extension of our work involves relating the forecasts to the probability of the large stock price movements, and it is the subject of our future work.

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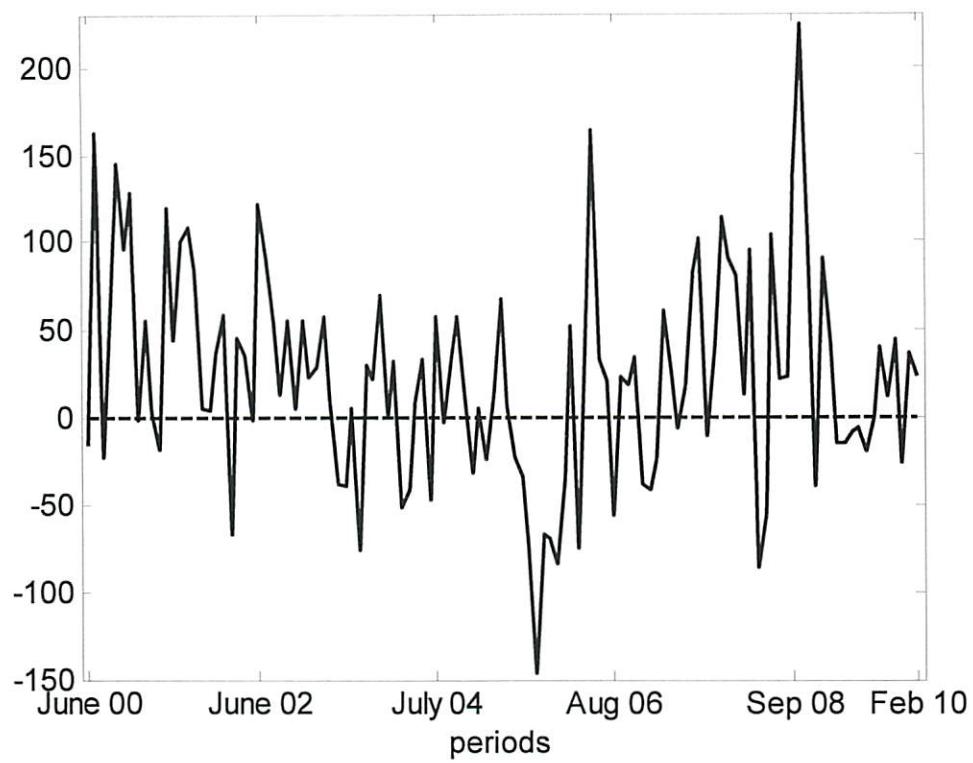


Figure 1: Differences of the forecasts from TOPIX

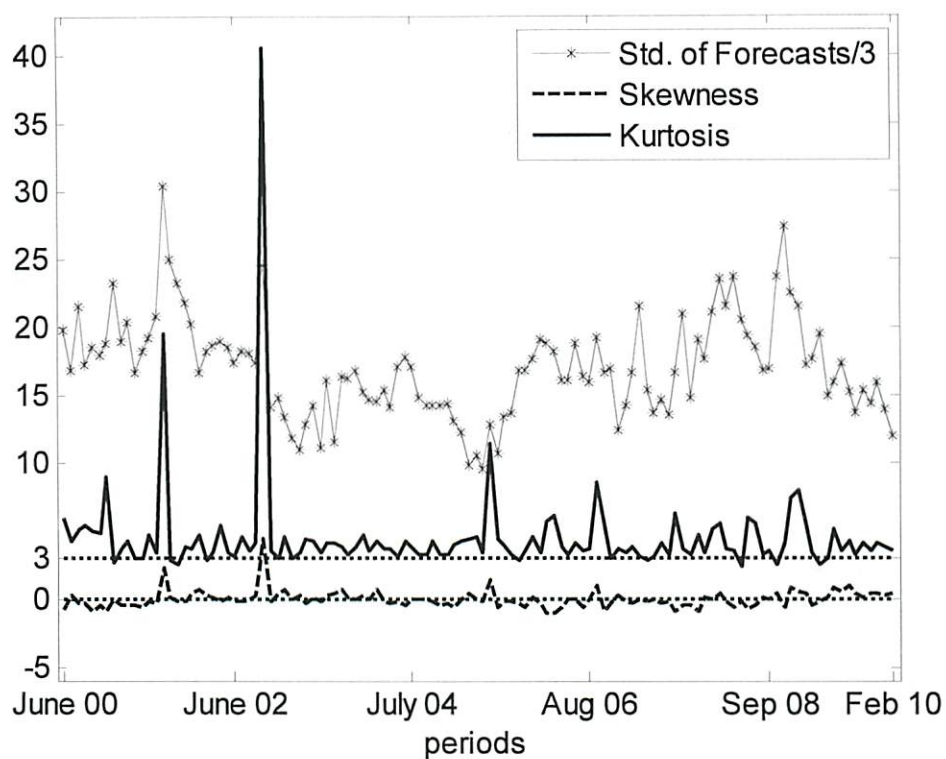


Figure 2: Cross-sectional standard deviation, skewness, and kurtosis of forecasts

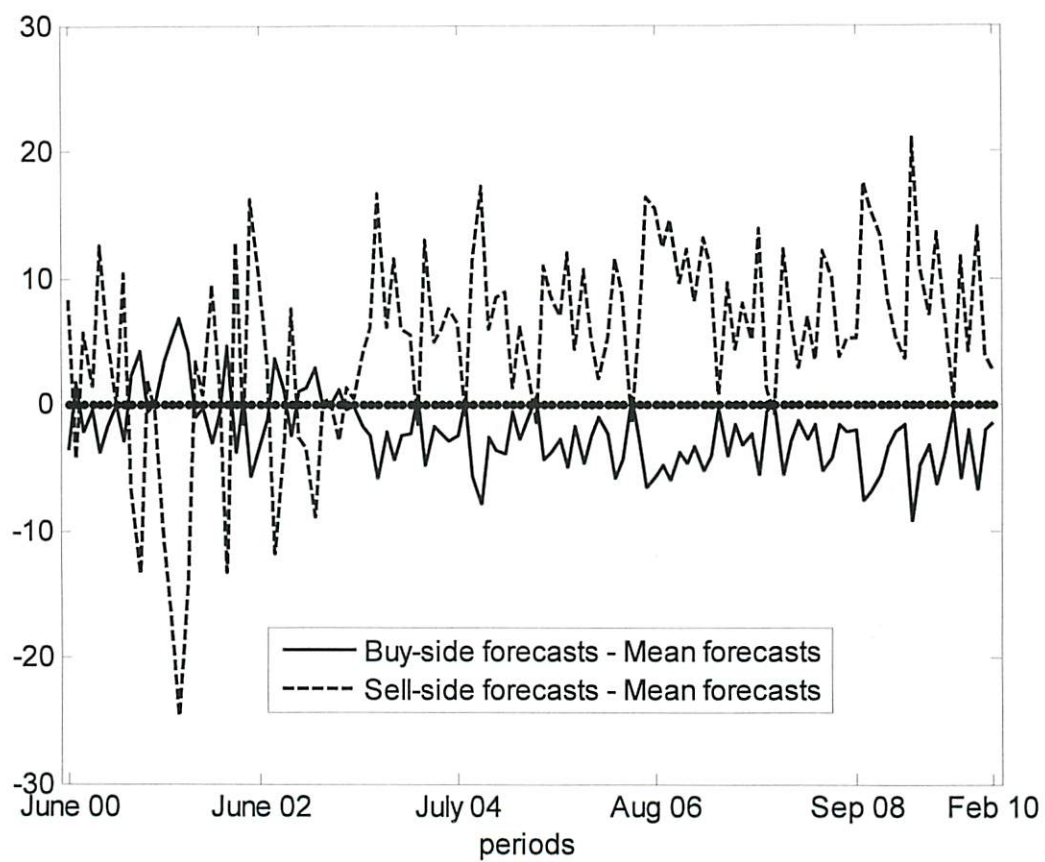


Figure 3: Differences between the mean forecasts and the buy-side professionals' forecasts and sell-side professionals' forecasts

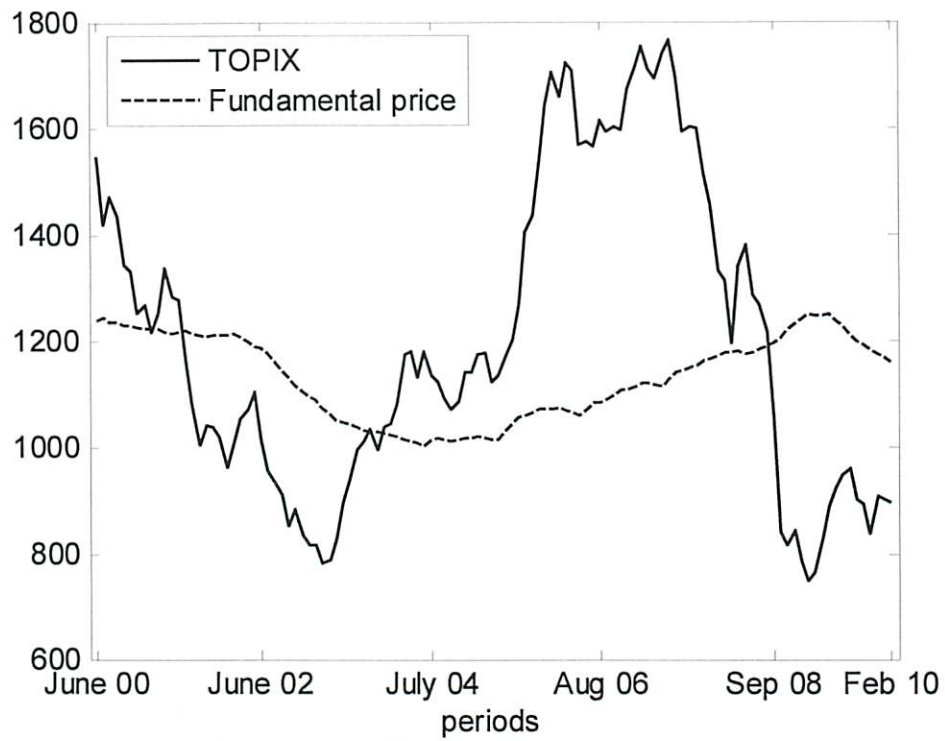


Figure 4: TOPIX and fundamental price

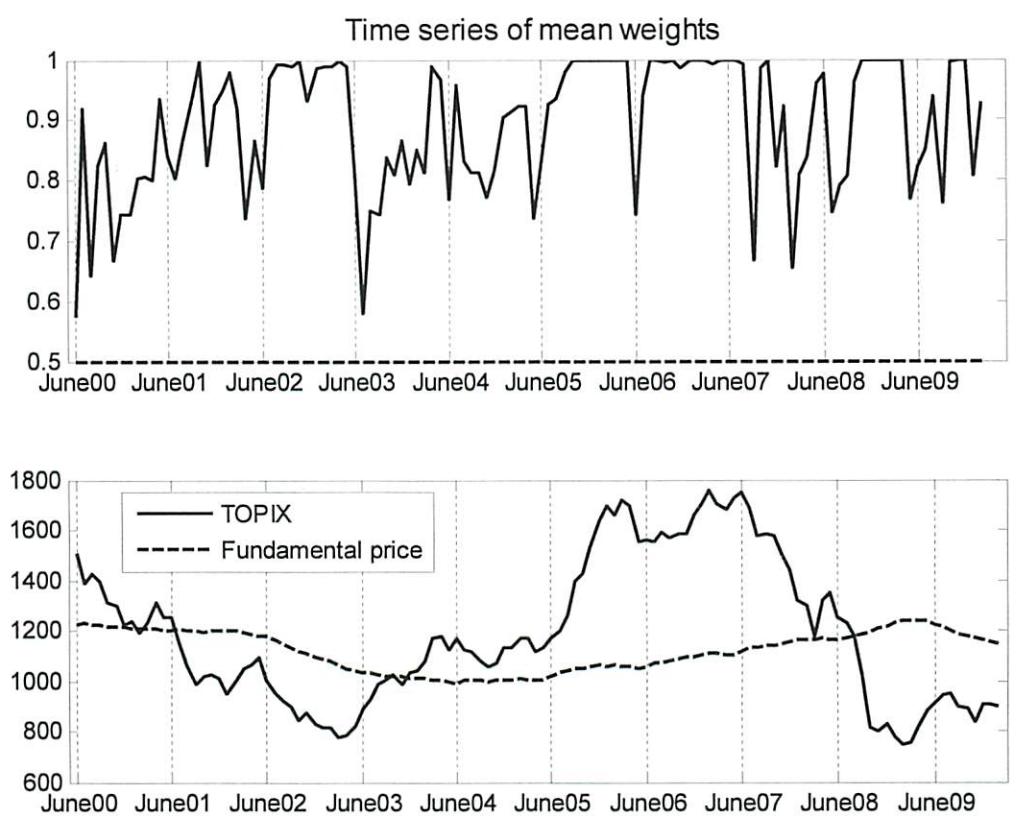


Figure 5: Time series of mean fraction, TOPIX, and the fundamental price

Table 1: Parameter estimates for trend indicators

Type of professionals	Rules selected	$\hat{\phi}^i$	<i>p</i> -value
Buy-side professionals	Trend over a month (mean price)	0.117	<0.01
Sell-side professionals	Trend over a month (mean price)	0.115	0.02

Table 2: Parameter estimates

AIC	Buy-side Professionals	Sell-side professionals
Fundamentalist	0.42***	0.39***
Technical trading	0.25***	0.20**
Intensity of switch	170.8	185.2

BIC	Buy-side Professionals	Sell-side professionals
Fundamentalist	0.42***	0.39***
Technical trading	0.25***	0.20**
Intensity of switch	170.8	185.2

Note: *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 3: Causality tests

Panel A:**Fraction → Deviation from the fundamental price**

	AIC	BIC
<i>F</i> -value	3.01	5.09
<i>p</i> -value	<0.01	<0.01

Panel B:**Deviation from the fundamental price → Fraction**

	AIC	BIC
<i>F</i> -value	19.41	38.04
<i>p</i> -value	<0.01	<0.01

Table 4: Coefficient estimates of VAR models

Panel A:

Dependent variable: Deviation from the fundamental price at t

Independent variable: Fraction

lags	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$
AIC	0.161**	-0.109	-0.047	-0.059	0.109	0.175*	0.083	-0.007
BIC	0.164***	-0.084	-0.005					

Panel B:

Dependent variable: Deviation from the fundamental price at t

Independent variable: Deviation from the fundamental price at previous period

lags	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$
AIC	0.261**	-0.274*	0.321**	0.047	-0.011	-0.235*	-0.318**	-0.013
BIC	0.329***	-0.284**	0.256**					

Note: *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.