

# Herding and Speculation in Experimental Asset Markets

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## **Abstract**

I conduct an experiment to observe individual traders' beliefs and desired behavior in a partial-equilibrium asset market. Isolated traders trade a risky asset in a market with exogenous prices. The price series exhibits a "bubble," diverging strongly from the expected dividend yield. Before trading, traders predict the asset's price in the upcoming period, the price in the final period, and the asset's current fundamental value. I find that beliefs about fundamentals are strongly influenced by observed price movements, even when the stochastic process governing the fundamental is perfectly known. This suggests the possibility of herd behavior in experimental asset markets. Beliefs about both upcoming and final-period prices closely track observed prices, even for traders who understand the fundamental value. Price predictions diverge strongly from predictions of fundamentals, demonstrating that traders do not believe in market rationality in the short-term or long-term. A clear relationship between asset demand and beliefs cannot be determined, even when beliefs are highly accurate. Asset demand is strongly positive just after the peak of the bubble, and turns strongly negative only in the final period. The findings imply that market prices, instead of aggregating traders' information, may provide traders with misinformation. This in turn may contribute to the phenomenon of asset bubbles.

# 1 Introduction

## 1.1 Background and Motivation

Of all phenomena in asset markets, the "bubble" is the most dramatic, arguably the most dangerous, and perhaps the most frustratingly inexplicable. Many economists believe that rapid runups and crashes in asset prices, such as the South Sea Bubble of the 1700s, the U.S. stock bubble of the 1920s, and the U.S. housing bubble of the 2000s, have severe negative effects on real economic output (Malkiel 2010). Without an understanding of the causes of this phenomenon, however, we appear doomed to repeat it.

There is much controversy over whether "bubbles" are rational reactions to the possibility of rapidly increasing fundamental values, or whether they represent market failures. But if it is the latter, what is the market failure? There are (at least) two classes of theories in which market failures generate a runup-and-crash price pattern. First, there are theories of *speculation*. Rational investors, knowing they are witnessing a bubble, choose to temporarily "ride" the bubble instead of betting against it. Theories of this type usually focus on the interaction between irrational "noise traders" and rational "arbitrageurs," showing how the latter may be tempted to speculate on the coordinated mistakes of the former (e.g. DeLong et. al. 1990a and 1990b, and Abreu and Brunnermeier 2003). There is some empirical evidence supporting this explanation - see, for instance, Brunnermeier and Nagel (2004).

A second phenomenon that may lead to bubble-like outcomes is *herd behavior*. If traders believe that rising asset prices are a signal that asset values have increased, they may unwittingly buy into a bubble (the error then compounds itself as prices rise further). Avery and Zemsky (1998) create a model in which multiple sources of uncertainty combine to bring about this outcome. Of particular importance is "composition uncertainty" - i.e., uncertainty over whether other traders are better-informed or worse-informed than oneself. If traders mistakenly conclude that their own information is poorer than that of the market, they may over-rely on prices as signals of value, creating a situation in which "the blind lead the blind" into a bubble. \*\*\*empirical evidence\*\*\*

Note that these two explanations for bubbles differ in one crucial respect. In a speculative

bubble, rational investors believe that they are in a bubble, while in a herding bubble, they do not<sup>1</sup>.

The difficulty that we face is that data from real-world markets doesn't tell us what investors believe. Without reliable belief data, we can observe what appears to be speculation or herding, but there are always alternative explanations for the behavior that rely on rationality. In fact, the problem runs deeper: real-world data cannot even tell us if bubbles are market failures at all, because asset fundamentals are not observed *ex ante*. For this reason, some researchers conclude that bubbles don't even exist.

This is where experiments can be of great use. In a laboratory asset market, the experimenter knows the fundamental value, and can examine the conditions under which prices deviate from these. Also, an experimental setting allows the collection of data on traders' beliefs. Finally, experiments allow us to test the effects of various institutional changes on bubbles without adversely impacting real-world markets. These advantages make experiments an important complement to real-world empirics in the study of bubbles.

The purpose of the current paper is to investigate the role of herd behavior and speculation in asset bubbles. I set up an experiment in which asset prices are constrained to follow a bubble path, and observe how traders react to this price path. By observing traders' *beliefs* about both prices and fundamentals, I am able to ascertain whether or not traders truly believe a bubble is occurring, and whether this belief changes when prices move. By correlating these beliefs with traders' *actions*, I am able to shed light on which types of behavior induces traders to buy into a bubble. I find that when prices diverge from fundamental values, errors about fundamentals increase and tend to move in the direction of observed prices. This belief is consistent with herd behavior. I also find that even traders who understand the fundamental value tend to believe that prices will never converge to fundamental values, and tend to buy into a bubble. This behavior is consistent with speculation.

In the remainder of this section, I describe the existing literature on experimental investigations of bubbles, and explain how my approach differs from these past studies. In Section 2, I lay out and motivate my hypotheses. Section 3 describes the experimental setup and treatment groups. In

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<sup>1</sup>Note that this does not mean the two concepts are mutually exclusive. Speculative models with noise traders generally need some reason for the noise traders to coordinate their actions; herd behavior might provide this reason.

Section 4 I present my results, test hypotheses, and discuss interpretations. Section 5 concludes with a discussion of the implications of the results.

## 1.2 Related literature

Experiments have been used to study bubbles in the past. The most famous laboratory investigation into the bubble phenomenon is an experiment by Smith, Suchanek, and Williams (1988) (henceforth SSW). In that study, small groups of subjects traded a single short-lived risky asset against cash (a riskless asset) using a continuous double auction market. The asset paid a dividend after every trading period, and the i.i.d. stochastic process governing the amount of each dividend was known to all traders. The result was a large bubble, in which the price of the asset diverged strongly from the fundamental value and then crashed at the end of the market. The effect disappeared when subjects repeated the market several times. In the following years, this bubble result was replicated by many other experimenters, and shown to be robust to many changes in market institutions and asset fundamentals<sup>2</sup>.

The question of why this result occurs so reliably is still open. SSW conjecture that speculation is involved, and a 2007 experiment by Haruvy, Lahav, and Nossair seems to support this interpretation<sup>3</sup>. However, an experiment by Lei, Noussair, and Plott (2001) showed that the bubbles occur even when resale of the asset (and, hence, speculation) is not allowed. That has led many researchers to conclude that the bubbles that occur in these experiments are simply a cognitive error on the part of subjects. Fisher (1998) hypothesizes that the bubbles are due to an initial misunderstanding about the dividend process that is corrected over time. This appears to be supported by an experiment by Lei and Vesely (2009), in which subjects who are allowed to experience the dividend process before the experiment generate no bubbles; and by Kirchler, Huber, and Stockl

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<sup>2</sup>See, for example, King, et. al. 1993; Van Boening, Williams, and LaMaster 1993; Porter and Smith 1994 and 1995; Ackert & Church 1998; Caginalp, Porter, and Smith 1998; Smith, van Boening, and Wellford 2000; Noussair, Robin, and Ruffieux 2001; Ackert et. al. 2006a and 2006b; Oechssler, Schmidt, and Schnedler 2007; and Noussair and Tucker 2008.

<sup>3</sup>In that experiment, the researchers solicited price predictions from all traders for all future periods. They found that after the first market, traders predicted a runup and crash in prices, and attempted to sell out before the crash - which, of course, moved the crash earlier in time. However, the authors do not provide an explanation for why bubbles appear so strongly in the *first* round, in which price predictions are generally flat.

(2010), in which framing the asset in a more natural way dramatically reduces bubbles<sup>4</sup>.

A third hypothesis - herd behavior - has not yet been formally examined in this literature, but there are some tantalizing hints. Camerer and Weigelt (1991) find that when traders believe that other traders may be insiders, overpricings can develop even when no insiders are actually present. Dufwenberg, Lindqvist, and Moore (2005) find that when two experienced traders are introduced into an experienced group in a SSW-type setup, bubbles disappear. Both of these results indicate the possibility that composition uncertainty, as defined in Avery and Zemsky (1998), can cause bubbles, since both indicate that inexperienced traders follow the pricing decisions of others.

Accurate data on trader beliefs about both prices and fundamentals, coupled with data on traders' desired actions, would resolve this controversy and clarify this literature immensely. If speculation is the key, we should expect to see traders who believe that prices exceed fundamentals buying into the bubble. If mistakes about fundamentals are the culprit, we would expect to see bubble trading among the subset of traders who make initial errors about fundamentals, followed by the bubbles deflating as traders began to understand the true nature of the fundamental.

I gather these data in the current experiment, but I use a different setup from SSW.

The SSW-type experiment described above has some clear limitations. In a small group (typically 6 subjects), market quantities - prices and volumes - are endogenous to individual beliefs and actions. This is not only because one subject's orders can move prices, but because a subject's actions in the market can send signals that affect others' beliefs. Hommes, et. al. (2005 and 2007) have observed very strong "coordination effects" in laboratory asset markets, where feedback effects between prices and beliefs tend to eliminate within-group differences over time, even as between-group differences remain large<sup>5</sup>. This sort of effect means that, when analyzing the impact of an experimental treatment in a group bubble experiment, each group must be treated as a single observation, making large samples extremely expensive. It also means that isolating the determinants of individual behavior can be very difficult, since these may interact with the group

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<sup>4</sup>The authors hypothesize that experimental subjects expect "stocks" to rise in value over time. It is easy to show that any asset with a fixed lifetime and strictly positive dividends must fall in value over time. Hence, the authors relabeled the asset "stock in a depletable gold mine," and found that bubbles were dramatically reduced in size.

<sup>5</sup>Interestingly, this happens despite the fact that in their setup, traders' cannot directly observe each others actions.

effects.

The experiment in the current paper therefore studies the bubble phenomenon using a different setup from SSW. Instead of studying the behavior of markets under general equilibrium, I study the behavior of individual traders under partial equilibrium. I first obtain price and dividend series from a SSW-type group bubble experiment, and then present these to each experimental subject individually. Each period, a subject makes predictions about the future values of prices, and also about the future value of dividends (with payment for accurate predictions). He or she is then allowed to buy and sell as many shares as he or she desires and can afford at the fixed market price. Thus, while a SSW-type experiment examines the aggregate outcomes of markets, I simulate the experience of a small trader in a large, liquid market.

Both this partial-equilibrium setting and the solicitation of predictions about fundamentals are new methodologies in the bubble experiment literature. Many researchers have studied individuals' ability to make predictions about the future values of exogenous time series (see, for example, Schmalensee 1976 and Dwyer 1993); however, to my knowledge, this technique has not been applied in an asset market experiment<sup>6</sup>. Also, although many experimenters make conjectures regarding subjects' beliefs about fundamentals, to my knowledge none has ever sought to elicit these directly. Obtaining knowledge about beliefs enables me to identify whether the necessary conditions for herding and/or speculation exist.

## 2 Hypotheses

Hypothesis 1: Beliefs about fundamentals adjust to follow observed prices.

This is a necessary condition for herding. I define herding in financial markets as "trading based on information about fundamentals obtained from observation of the actions of others."<sup>7</sup> In other

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<sup>6</sup>At least, not in the experimental economics. It would surprise me greatly if someone, somewhere, has not done this in some context!

<sup>7</sup>Avery and Zesky (1998) define herding as "when agents imitate the prior actions (buying or selling) of others." However, in their setup, they assume that traders will buy and hold, and that traders do not interact strategically. In a more general setup, "buying when others buy" can also be done for speculative reasons, with the intent of selling out later. I update Avery and Zesky's definition to ensure that herders obtain information about fundamentals from prices.

words, simply buying because one sees others buying is not necessarily herding; a herder must buy *because* (s)he thinks the asset's fundamental value has risen. Since in many financial markets (and in the one in this experiment) prices are the only action of others that a trader observes, herding requires that beliefs about fundamentals change when prices change. More specifically:

Hypothesis 1a: The likelihood of a trader making an error about the fundamental value increases as prices increase, and declines as prices decline.

Hypothesis 1b: Predicted fundamental values are adjusted in the direction of prices.

Hypothesis 1c: Traders who make mistakes about fundamental values trade based on believed fundamentals.

Hypothesis 1a is important because it addresses the widespread notion that lab bubbles are simply a misunderstanding on the part of experimental subjects. If subjects simply start out misunderstanding the fundamentals but then learn through experience, we should see beliefs about fundamentals converging, basically monotonically, to the correct value. But if herd beliefs are at work, we should see *decreased* understanding of fundamentals as prices seem to go "the wrong way."

Hypothesis 1b is more specific, since it specifies *how* fundamental beliefs adjust. Note that this hypothesis is sufficient, but not necessary, for herding. If observed mispricings simply make traders less confident about their beliefs about fundamentals, they may abandon fundamental-based trading for momentum trading, speculation, or some other strategy.

Hypothesis 1c is even more specific, since it is about one specific type of herd behavior. This hypothesis is neither necessary for herd behavior (for the same reason as 1b), nor sufficient (since non-herding mistakes about fundamentals could also influence trading), but it would help establish a link between herd beliefs and herd behavior.

Hypothesis 2: Traders who understand fundamentals exhibit speculative beliefs and behavior.

This hypothesis is a test of whether or not noise trader models describe this experimental market. Since I gather belief data about fundamentals, I can observe which traders are "well-informed". If these traders buy into a bubble, they must be buying for reasons other than the fundamentals. Those reasons can be broadly classified as "speculative." More specifically:

Hypothesis 2a: Traders who understand the fundamental value will not predict that prices will

track fundamentals in the short term.

Hypothesis 2b: Traders who understand the fundamental value will not predict that prices will revert to fundamentals in the long term.

Hypothesis 2c: Traders who understand the fundamental value will not tend to sell at the beginning of a bubble.

Hypothesis 2d: Expectations of short-term price gains will be correlated with asset buying.

Hypothesis 2e: Expectations of long-term price gains will be correlated with asset buying.

Hypothesis 2a is necessary for what I will define as "short-term speculation," in which speculators overpay for an asset in the expectation of a short-term price gain, even though they expect a long-term price decline (i.e., they try to time the market). Similarly, Hypothesis 2b is necessary for what I define as "long-term speculation," in which traders who do not believe in the rationality of the market overpay for an asset in the expectation of being able to earn a capital gain at any time in the future.

Hypothesis 2c is simply the hypothesis of non-fundamental trading, which can be broadly defined as speculative.

Hypothesis 2d and 2e are simply descriptions of specific types of speculative asset buying.

## 3 Experimental Setup

### 3.1 Source of the parameters

Before the experiment, I obtained a series of prices and dividends from a previous asset experiment, conducted on June 6, 2011 at the University of Michigan. That study was a "group bubble experiment," extremely similar in nature to the original SSW setup. For the details of that previous study, see "Overconfidence in asset markets: an experimental investigation (Noah Smith, forthcoming)"<sup>8</sup>. The prices and dividends (each corresponding to 1 share of the asset) can be seen in Figure

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<sup>8</sup>Briefly, groups of 6 subjects traded a single risky asset with a lifetime of 10 periods, in a continuous double auction market. Each share of the asset paid an i.i.d dividend each period, with a 50% chance of 10 cents and a 50% chance of 0 cents (dividends were identical across all shares in a period). The prices used for the current experiment are the average prices from the control group of that previous experiment. The control group was chosen because the setup was closest to the original SSW setup.

1, along with the fundamental value of the asset. It is clear that Market 1 produced a bubble; prices start out at slightly over the fundamental value, then start rising rapidly in Period 3. Prices peak in Period 5, then decline, but the gap between prices and fundamentals remains large, and the bubble never disappears completely. Market 2<sup>9</sup> produced what might be called a bubble; prices start at fundamentals, stay flat (so that the asset is overpriced), and then decline, but again fail to reach fundamental value by the end of the market. Both markets are exemplary of the classic SSW patterns for inexperienced and once-experienced groups.

### **3.2 Subjects and compensation**

The experiment was conducted on five days, between July 15 and July 31, 2011, at Aoyama Gakuin University in Tokyo, Japan. There were 83 experimental subjects, all Japanese. The majority (73) of these were university students from Aoyama Gakuin University, Keio University, and Sophia University. The rest were graduate students and staff at the same universities, except for one subject who was a business owner. The mean age of participants was just under 22 years. Five subjects had participated in economics experiments before, though none had participated in an asset market experiment. Seven had experience trading assets in a real financial market. Thirty-eight, or slightly less than half, had taken a finance class of some kind. The average total payment to each subject was 4323 yen, or about \$56 at the then-prevailing exchange rate. Of this, 2500 yen was paid as a "show-up fee," and the rest, averaging 1823 yen per subject, as experimental incentives.

### **3.3 Experimental procedures**

There were five experimental sessions, each two hours long, including the time to read and explain the instructions (approximately 40 minutes). The number of subjects in each session is listed in Table 1. The experiment was carried out using the z-Tree software package (Fishbacher 2007). An English translation of the experimental instructions is provided in Appendix A.

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<sup>9</sup>The subjects who participated in Market 2 were the same subjects as those in Market 1.

Subjects participated in two experimental "markets," each of which lasted 10 periods<sup>10</sup>. In each market, a subject was given an initial endowment of cash totaling 450 yen, and an initial endowment of five shares of a risky asset (called simply "the asset"). Each period, the subject was given the opportunity to buy or sell shares of the asset at a fixed "market price." After observing the period's price, as well as the "high" and "low" (see below), the subject submitted an order to either buy or sell shares at that price. The total number of shares in each one-person market was therefore not constant, but was determined by the subject's buying and selling decisions. Subjects were not allowed to sell more shares than they owned (no short selling), nor to buy more shares than they could afford at the market price, given the cash in their account (no margin buying). After the subject submitted his or her order, his or her account (amount of cash and number of shares) was adjusted accordingly. Each trading period lasted 90 seconds, except for the first two periods of Market 1, which were each 180 seconds<sup>11</sup>.

This setup is intended to simulate the situation of a small individual investor in a large, liquid market. Small investors' offers and trades do not affect market prices. Also, in general, small investors do not see the flow of individual orders. In real-world markets, even large investors' may not substantially affect the movements of entire stock indices like the S&P; thus, this setup may also shed light on the behavior of institutional investors deciding what positions to take in a broad asset class such as U.S. stocks. Because this setup eliminates all feedback effects from investor choices to the market, it allows us to study how individuals react to aggregate outcomes.

After trading, a subject received a dividend payment for each share of the asset that he or she held in his or her account. The dividends were stochastic, and each period's dividend was determined according to an i.i.d distribution. Each period the dividend had a chance of being 10 yen per share, and a 50% chance of being 0 yen per share<sup>12</sup>. The dividends differed from period

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<sup>10</sup>The term "market" is a bit of a misnomer, since the subjects did not interact with one another, but only with a computer.

<sup>11</sup>This was done despite the fact that a demonstration of the interface was conducted before the experiment. As it turned out, nearly no subjects used the entire 180 seconds in the first or second trading periods of Market 1, nor all of the 90 seconds in any subsequent trading period.

<sup>12</sup>These dividend values and probabilities, and indeed all parameters of the current experiment, are nearly identical to the prior experiment from which the data was obtained. The single difference is that the values for the current experiment are in yen, and the values for the previous experiment were in cents. Because the Japanese after-tax median income in yen is very similar to the American median income in cents, the per-dividend levels of risk and reward involved in the two experiments are extremely similar.

to period, but were the same for each share within a period. The asset had no buyout value; that is, at the end of the tenth and final period, after the tenth dividend was collected, all shares of the asset vanished<sup>13</sup>. Therefore the asset's fundamental value per share in period  $t$  is given by:

$$FV(t) = 55 - 5t \tag{1}$$

Great care was taken to ensure that the subjects understood the process for the determination of dividends<sup>14</sup>. Subjects were made to understand that the prices and dividends they were observing were taken from a previous group experiment at the University of Michigan, as described above<sup>15</sup>.

In addition to the market price, while making his or her trading decision each subject had the following additional information: A) a "high" and "low" price, at which the subjects were *not* allowed to trade, B) a history of the market price, high, and low in past period (empty in the first period), and C) a graph displaying the market price in each past period (empty in the first period). It was explained that the "high" and "low" prices were the highest and lowest prices for which the asset had traded in the corresponding period of the experiment from which the prices and dividends were obtained<sup>16</sup>.

Therefore, in addition to the experimental parameters, a trader's information set while trading in Period  $j$  included:

1.  $\{p_1, p_2, \dots, p_n\}$ , where  $p_j$  is the market price of one share of the asset in Period  $j$ ,
2.  $\{h_1, h_2, \dots, h_n\}$ , where  $h_j$  is the "high" in Period  $j$ ,
3.  $\{l_1, l_2, \dots, l_n\}$ , where  $l_j$  is the "low" in Period  $j$ , and
4.  $\{d_1, d_2, \dots, d_{n-1}\}$ , where  $d_j$  is the dividend per share paid to holders of the asset in Period  $j$ .

Before each trading period, each subject was given a 90-second<sup>17</sup> period in which to make three

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<sup>13</sup>Although the experimenters took care to explain that there was a buyout cost on every day of the experiment, students often asked questions to confirm this explicitly. In fact, many subjects asked "So, the asset is worthless in the last period?" To which the experimenters replied "Well, after you trade in the last period, you still get the final period's dividend for any shares that you still have. But after that, the asset just disappears."

<sup>14</sup>although, as we will see, this was not entirely successful.

<sup>15</sup>Subjects had difficulty understanding this, so great care was taken to make them understand the source of the price and dividend series, and to confirm that they had in fact understood.

<sup>16</sup>Again, great care was taken to explain that subjects could NOT trade at the "high" and "low" prices, only at the market price.

<sup>17</sup>180 seconds in the first two periods of Market 1.

predictions. Each was asked to predict:

P1: the price of the asset in the upcoming trading period,

P2: the price of the asset in the final trading period, and

P3: the total amount of dividend income that someone would receive from 1 share of the asset, if (s)he were to buy that share in the upcoming period and hold onto it until the end of the experiment.

This final prediction is equal to the expected value of one share of the asset, i.e. the fundamental value<sup>18</sup>.

Therefore, in addition to the experimental parameters, a trader's information set while making predictions in Period  $j$  included:

1.  $\{p_1, p_2, \dots, p_{n-1}\}$
2.  $\{h_1, h_2, \dots, h_{n-1}\}$
3.  $\{l_1, l_2, \dots, l_{n-1}\}$
4.  $\{d_1, d_2, \dots, d_{n-1}\}$

An explanation of the flow of the experiment can be seen in Figure 2.

It is worth taking a moment to point out the implications of this sequential structure for the analysis. Because predictions were made before trading, yet market prices were observed only during trading, we must assume that a trader updates his/her beliefs after seeing the market price but before making his/her trading decision. Thus, we must associate trading in period  $n$  with predictions made at the beginning of period  $n + 1$ . The only new information a trader receives between trading in in Period  $n$  and making predictions at the beginning of Period  $n + 1$  is the Period  $n$  dividend. Period- $n + 1$  predictions are not a perfect proxy for Period- $n$  beliefs, since dividend realizations may cause traders to change their predictions<sup>19</sup>. However, as we will see later, it is probably a good proxy, since dividend realizations usually do not have a measurable effect on predictions.

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<sup>18</sup>Since this prediction is somewhat difficult to understand, the experimenters attempted to confirm students' understanding by repeating the explanation twice or three times, asking subjects directly if they understood, and pop-quizzing individual subjects on what was being asked in this third prediction. Still, as we will see, many students made mistakes regarding the nature of this prediction.

<sup>19</sup>A trader who believes the market to be rational and who knows the dividend process will not believe that prices and future fundamentals are conditional on past dividends; however, most traders in the current experiment probably do not believe the market to be rational, as we will see later. Also, traders in Treatment 2 do not completely know the dividend process, so Bayesian updating about fundamentals may take place between trading and making predictions.

Subjects were paid for making accurate predictions. For each of the three predictions made in each period, subjects were paid according to the following formula:

$$Payment = 25\text{¥} - 2\text{¥} \times |prediction - actual\ value| \quad (2)$$

This absolute-deviation payment scheme leaves no incentive for subjects to do anything other than to choose their best point estimate for each prediction.

The total maximum prediction incentive per period was equal to or greater than that in Haruvy, Lahav, and Noussair (2007). In that paper, the authors pay for the *percentage* accuracy of predictions, while I pay for absolute accuracy. I do this because natural cognitive error makes more precise predictions more difficult<sup>20</sup>. The theoretical maximum amount of money available for a subject who makes perfect predictions throughout the experiment was therefore equal to 1500 yen, or 100 yen more than the combined value of the subject's initial endowments in the two market repetitions. Thus, the incentive for predicting well was roughly the same as the incentive for trading well (this was mentioned to the subjects). The total amount of money that would be received only for the third prediction (fundamentals), if that subject were to predict the ex ante correct value every time, would be 455 yen, which is considerably larger than the trading profits made by the average subject. Thus, this experiment features a larger incentive to make accurate predictions than has been used in any similar experiment.

Each subject participated sequentially in two markets, Market 1 and Market 2. All parameters for the two markets were identical except for the prices, dividends, highs and lows. Subjects were not told that the prior-experiment subjects who generated the prices for Market 2 were the same as the prior-experiment subjects who generated the prices for Market 1 (in fact, they were the same). This information was withheld for the purpose of preserving the correspondence to "small traders"; in real-world asset markets, small traders generally do not know much about the characteristics of the other traders in the market in which they trade. Henceforth, I refer to Market 2 traders as

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<sup>20</sup>A truly "fair" prediction payment scheme, in which ex post payments were roughly equal across predictions, would probably be some combination of the two payment schemes. However, such a hybrid scheme would be difficult to explain to subjects. Even the payment scheme used in this experiment had to be explained multiple times before subjects understood.

"experienced" traders, and Market 1 traders as "inexperienced" traders.

### 3.4 Experimental Treatments

The above description completely describes the experimental setup for Treatment 1, which I will also call "Basic." 64 of the subjects participated in this treatment. In addition, there were two other experimental treatment conditions, Treatment 2 and Treatment 3, which encompassed 20 and 19 subjects, respectively.

In Treatment 2, which I will call Uncertain, the probabilities of the dividend values were withheld from the subjects. Subjects were told that the dividends were i.i.d., that 10 yen and 0 yen were the only possible values, and they knew that the probabilities were constant every period and in both markets; however, they did not know the values of the probabilities. This treatment was included to assess the behavior of beliefs about fundamentals under Bayesian learning. In this treatment, we would expect boundedly-rational traders to condition their beliefs about fundamentals on observed prices if they believed that prior participants had been more skilled at Bayesian updating than themselves. However, we would still not expect rational traders in this Uncertain setup to predict fundamental values above 100, since they know that the maximum dividend each period is 10. The hypotheses associated with this treatment are:

Hypothesis U1: In the Uncertain treatment, the variance of beliefs about fundamentals will be greater than in the other treatments. 2\*

Hypothesis U2: In the Uncertain treatment, mistakes about fundamentals will be no greater than in the other treatments. 1\*

In Treatment 3, which I will call Pictures, subjects were shown images of price and dividend series from several other markets in the same bubble experiment from which the actual price and dividend series were taken<sup>21</sup>. Three out of the four price series demonstrated clear bubble-and-crash patterns; one was consistent with rational pricing. The idea was to convey the basic

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<sup>21</sup>Actually, these series were not entirely representative of what the traders would encounter in the actual market. The pictures shown to the traders came from markets in which traders received private forecasts of dividend value, which was part of the experimental procedure of Smith (forthcoming). However, subjects in the current experiment were not told this.

message that bubbles and crashes occur, and to give subjects some experience of the dividend process. We would therefore expect traders to A) speculate more than traders in other treatments, B) predict prices that rise above fundamentals and then crash, C) exhibit less of a tendency to "belief-herd" than traders in other treatments, and D) make more accurate predictions about fundamentals than traders in other treatments. The hypotheses associated with this treatment are:

Hypothesis S1: In the Pictures treatment, asset demand will be more positive in the runup phase of a bubble than in the other treatments.

Hypothesis S2: In the Pictures treatment, next-period price predictions will diverge more from predictions about fundamentals than in the other treatments.

Hypothesis S3: In the Pictures treatment, beliefs about fundamentals will be more accurate than in the other treatments.

The basic idea behind the inclusion of these treatments is to examine the two behaviors that I believe may underlie the formation of bubbles: speculation, and herd behavior. The Uncertain treatment provides more of an incentive for boundedly rational traders to herd, since prices may give some information about the true fundamental value if one's own calculation abilities are limited<sup>22</sup>. The Pictures treatment gives subjects an artificial form of experience, showing them that speculation can be profitable. Rejecting any of the treatment-conditional null hypotheses listed above would give us information about which, if either, of these processes are operating on an individual level in bubble situations.

## 4 Results

The results from this experiment are categorized into three sections, corresponding to the three types of output variables: beliefs about fundamentals, beliefs about prices, and trading behavior. Taken together, these three things give us a picture of whether the necessary conditions exist for herd behavior and/or speculation, and whether these behaviors can be detected in traders' asset

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<sup>22</sup>Or if, as happens to be true in this case, the traders who formed the price series knew the fundamental probabilities!

demands. I find that the necessary conditions do in fact exist in the belief data for both speculation and herd behavior, and that there is some evidence in the trading data that both behaviors are occurring.

#### 4.1 Beliefs about fundamentals

There is strong evidence that observation of mispricings leads to increased mistakes in beliefs about fundamentals, and that expected fundamentals move in the direction of observed prices.

Define the average belief about fundamentals as  $E_t [FV_t]$ , and an individual  $i$ 's belief as  $E_{it} [FV_t]$ . Let the difference between an individual's belief about fundamentals and the true fundamental value - i.e., the individual's *mistake* about the underlying value of the asset - be defined as:

$$M_{it} \equiv E_{it} [FV_t] - FV_t \tag{3}$$

Also, let  $M_t$  be the average mistake across any group under consideration in a given market period. The average mistake for all subjects in the experiment is shown in Figure 3, alongside the lagged actual overpricing (i.e. the most recent overpricing that traders observed). It is clear that many subjects made large mistakes at the beginning of Market 1, and many continued to make mistakes in Market 2. The decline over time suggests a learning process and/or an understanding that the fundamental declines over time. However, the upward bulge in the early period hints at the presence of herd behavior.

Now I investigate the hypothesis that observing rising prices leads to increasing mistakes about fundamentals (Hypothesis 1a above). First, I define three indicator variables, each of which is intended to capture whether a subject's beliefs about fundamentals were mistaken or not, in increasing order of strictness about what constitutes a "mistake".

First, define  $NOMIS_{it}$  as an indicator variable representing whether subjects were completely mistaken about the fundamental value. Being "completely mistaken" means that the subject's prediction for the total received dividends was not possible given the experimental parameters.

Thus:

$$NOMIS_{it} = \begin{cases} 0 & |M_t| > FV_t \\ 1 & |M_t| \leq FV_t \end{cases} \quad (4)$$

Next, define  $NOTOFF_{it}$  as an indicator variable representing whether subjects' error regarding the fundamental was within a fraction  $\sigma$  of the correct *ex ante* value, except in the last period, in which it is defined as being within 100% of the correct value<sup>23</sup>:

$$NOTOFF_{it} = \begin{cases} 0 & |M_t| > \sigma FV_t \\ 1 & |M_t| \leq \sigma FV_t \end{cases} ; t < 10 \quad (5)$$

$$NOTOFF_{it} = \begin{cases} 0 & |M_t| > FV_t \\ 1 & |M_t| \leq FV_t \end{cases} ; t = 10$$

I arbitrarily choose  $\sigma$  to be 0.5 unless otherwise stated<sup>24</sup>.

Finally, define  $COR_{it}$  as an indicator variable representing whether subjects made any error at all when guessing the fundamental value, except in the last period, in which it is defined as being within 100% of the correct value:

$$COR_{it} = \begin{cases} 0 & |M_t| > 0 \\ 1 & |M_t| = 0 \end{cases} ; t < 10 \quad (6)$$

$$COR_{it} = \begin{cases} 0 & |M_t| > FV_t \\ 1 & |M_t| \leq FV_t \end{cases} ; t = 10$$

Also, define  $NOMIS_t, NOTOFF_t$ , and  $COR_t$  to be the sum of these values across subjects in a given market period.

In Figure 4 are displayed the total numbers of subjects in each period of Market 1 for whom

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<sup>23</sup>This is because some subjects may have slightly misunderstood the incentive scheme, so that they preferred a risky guess about the dividend in the final period to an average guess. Guessing 10 or 0 for the final period's dividend yields possible rewards of 25 yen and 0 yen, while guessing 5 yields a certain reward of 15 yen.

<sup>24</sup>For all analyses performed on the variable  $NOTOFF_{it}$ , I repeated the analysis with  $\sigma = 0.8$  and  $\sigma = 0.2$  as robustness checks. The results were never different.

each of these three indicator variables equals 1 (i.e., who in some sense get the fundamentals right), plotted alongside the one-period-lagged overpricing (i.e. the overpricing that was observed just before the prediction about fundamentals was made). It is obvious that, for the two less stringent criteria, the number of non-mistaken subjects goes *down* significantly from the beginning of the market through Period 6. This means that as time goes on, fewer people are getting the fundamentals right. The trend reverses around Period 6 or Period 7 (noticeably, shortly after prices have begun to fall). Even for the most stringent criterion - perfect ex ante prediction of the fundamental - the number of subjects who gets it right holds flat or falls through Period 7, and only then begins to rise.

According to the hypothesis that subjects are gradually learning about fundamentals, this should not happen. As subjects observe more and more dividends, the true dividend process should become apparent, and mistakes should decrease more or less monotonically. Instead we find mistakes increasing for half the duration of the experiment. Since prices and dividends are the only new information traders receive over the course of the market, any updating of their beliefs should be due to the act of processing this information.

Interestingly, the pattern persists in Market 2. Although the number of subjects who understand the dividend process is higher overall - learning has taken place - the number still decreases with time, then increases near the end of the market.

The intuition from these pictures can be confirmed econometrically. I use fixed-effects logit models to model the dependence of the three binary variables  $NOMIS_{it}$ ,  $NOTOFF_{it}$ , and  $COR_{it}$  on the lagged overpricing (defined as  $OVERP_{t-1} \equiv P_{t-1} - FV_{t-1}$ ). The results of these estimations for the three outcome variables and various subsamples can be seen in Table 2. In Market 1, there is a significant negative relationship between both  $NOMIS_{it}$  and  $NOTOFF_{it}$  on recently observed overpricing; for  $NOTOFF_{it}$ , this is true even when the sample is restricted to subjects who believe that fundamentals go down from Period 1 to Period 2 ( $E_{i2}[FV_2] < E_{i1}[FV_1]$ )<sup>25</sup>. However,  $COR_{it}$ , the number of subjects who entered exactly the ex ante correct fundamental value, does not show a dependence on the price. This suggests that there is a "hard core" of subjects (about 25% of the

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<sup>25</sup>This is done in order to rule out the alternative hypothesis that mistakes are due to a fixed belief that fundamentals go up over time.

total) who understand the dividend process very well, and who do not question their understanding after observing overpricing in the market.

In Market 2, the dependence of mistakes on observed overpricing is also present, but weaker. Although  $NOMIS_{it}$  continues to show a relationship to price,  $NOTOFF_{it}$  no longer shows a significant correlation when the sample is restricted to subjects who were informed about the dividend probabilities, and who believe that fundamentals go down from Period 1 to Period 2

Subjects' increasing degree of mistakenness about fundamentals over time can also be seen by plotting  $M_t$  - that is, the average mistake about fundamentals - over time for various subsets of the sample. Figure 5 shows a plot of  $M_t$  for two "near-rational" subsamples of traders. The first subsample includes traders who made no large mistakes about fundamentals in Period 1 or Period 2 ( $NOTOFF_{i1} = NOTOFF_{i2} = 1$ ). The second subsample includes traders who A) did not predict impossible values for the fundamental in the first period ( $NOMIS_{i1} = 1$ ), and who B) predicted falling fundamentals between Period 1 and Period 2 ( $E_{i2}[FV_2] < E_{i1}[FV_1]$ ). The most recently observed mispricing is shown for comparison. In Market 1, beliefs about fundamentals appear strongly to track prices, while in Market 2, no such relationship is apparent. Also, the average mistake for this subgroup is far smaller in Market 2 than in Market 1. Recall that if subjects were learning about fundamentals during Market 1, the line representing  $M_t$  in Market 1 would be expected to go down over time, as subjects corrected their mistakes.

Figure 6 shows the same plots as Figure 5, but for  $M_{it}$  averaged over *shares traded in a period* instead of over subjects. Call this average  $TWM_t$ . Plotting  $TWM_t$  gives a picture that combines beliefs and trading activity; it shows what "the money in the market" believes the fundamental value to be. In one sense, using this measure weights beliefs by how much confidence is behind them. If traders who make mistakes are less confident about their beliefs about fundamentals, and if this lack of confidence stops them from trading, then we should expect to see the relationship between beliefs and overpricing disappear when beliefs are averaged across shares traded. However, the relationship is still clearly apparent in Market 1, and even shows some indication of existing in Market 2. These pictures show that the shares being traded by those who understood the fundamentals at the beginning of the market are being traded by traders whose beliefs track observed prices.

To formally model the "pull" that observed prices exert on beliefs about fundamentals, I first define a variable that weights an individual's mistakes about fundamentals by that individual's percentage of the total trading activity within a market period:

$$TWM_{it} \equiv M_{it} * \frac{\# \text{ of shares traded by trader } i \text{ in period } t}{\text{total } \# \text{ of shares traded by all traders in period } t} \quad (7)$$

$TWM_{it}$ , or a trader's "trade weighted mistake" about fundamentals, combines the size of a trader's mistake with his/her significance in the market in a given period. To model the idea that this quantity moves in the direction of observed prices, I use a partial adjustment model:

$$TWM_{it} = \alpha + c_i + \beta P_t + (1 - \beta)TWM_{i,t-1} + \varepsilon_{it} \quad (8)$$

This is similar to an adaptive expectations model, except that expectations "adapt" to a different quantity (price). Estimates of  $\hat{\beta}$  for the full sample, as well as for various subsamples, and for both markets, are shown in Table 3. The null that  $\hat{\beta} = 0$  is strongly rejected in Market 1. The point estimate of  $\hat{\beta}$  is positive and less than 1, indicating partial adjustment. The effect is much less clear in Market 2.

Thus, it seems that there is strong evidence suggesting that what I call *herd beliefs* are present, particularly for the inexperienced traders of Market 1. For all but the most well-calibrated traders, observing an incorrect market price increases both the likelihood and the size of traders' mistakes about fundamentals. This is in direct contradiction to the notion that subjects' mistakes are due to mistaken prior beliefs that vanish over time through a process of learning; it means that mistakes can *increase* over time, and that mistakes depend on conditions in the market. This is a necessary (though not sufficient) condition for herd behavior.

## 4.2 Beliefs about prices

Beliefs about both next-period and final-period prices are strongly adaptive, and expectations are generally for flat prices. Traders do not assume that prices will equal fundamentals in the long run.

Figure 7 shows beliefs about prices in Market 1 and Market 2. Define:

$$PRN_{it} \equiv E_{it}[P_t] \tag{9}$$

$$PR10_{it} \equiv E_{it}[P_{10}]$$

Also, define  $PRN_t$  and  $PR10_t$  as the averages of these beliefs across subjects in a given period.

In Figure 7, two results are immediately apparent. First, except for the first two periods of Market 1, traders believe that prices will not change much from the present period until the end of the market. This is especially the case in Market 2; traders anticipate flat prices despite the fact that the traders had all seen the price drop in Market 1. Even when price begins to fall in both markets, traders continue to predict flat prices.

Second, both short-term and long-term price predictions appear highly adaptive. That is, they both appear to closely track the most recently observed price. To test this latter idea, I define two standard adaptive-expectations models, calling the adjustment parameters  $\gamma$  and  $\delta$ , respectively:

$$PRN_{it} = \alpha + c_i + \gamma P_t + (1 - \gamma)PRN_{i,t-1} + \varepsilon_{it} \tag{10}$$

$$PR10_{it} = \alpha + c_i + \delta P_t + (1 - \delta)PR10_{i,t-1} + \varepsilon_{it}$$

The first of these is simply the classic adaptive-expectations model of Cagan (1956) with a fixed-effect term. The second is the same functional form, applied to predictions about the far future instead of the near future; it expresses the idea that people make update their predictions about far-future prices in the direction of the most recently observed price.

Regression estimates for  $\hat{\gamma}$  and  $\hat{\delta}$  can be found in Table 4. The null hypotheses that  $\hat{\gamma} = 0$  and  $\hat{\delta} = 0$  are both strongly rejected. The point estimates are positive and close to 1 in Market 1, and the model fit (R-squared) is very high (as high as 0.99), indicating a strong adaptive process for both expectations (though somewhat weaker in Market 2). A Wooldridge-Drukker test for serial correlation failed to reject the null of no autocorrelation in the regressors. I conclude that the

adaptive model is an extremely good description of price belief formation in these markets<sup>26</sup>.

A third result is that even subjects who understand the fundamental value very well do not predict that prices will converge to fundamentals in the long run. Figure 8 shows price and fundamental predictions for the "rational" subset of traders for whom  $NOMIS_{it} = 1$  for all  $t$ <sup>27</sup>. Fundamental predictions are essentially completely correct, but price predictions follow an adaptive path similar to that followed by the average of all traders. This result means that even well-calibrated traders do not believe that the market is rational; that is, they do not believe that prices will converge to fundamentals *even in the long term*. In fact, they substantially underpredict the degree to which prices actually converge.

This result is very interesting in light of the contention of Lei, Noussair, and Plott (2001) that lack of common knowledge of rationality is not responsible for the bubbles observed in laboratory asset markets. The current result shows that lack of common knowledge of rationality is very much in existence. Lack of belief in the rationality of the market is necessary for rational speculation, so I will call this type of belief a "speculative belief."

### 4.3 Trading Behavior

I find that overall trading patterns in both Market 1 and Market 2 are consistent with support for a bubble. First, I define some indices of trading activity:

$$BUY_{it} = \text{shares bought by trader } i \text{ in period } t \tag{11}$$

$$SELL_{it} = \text{shares sold by trader } i \text{ in period } t$$

$$NETBUY_{it} = BUY_{it} - SELL_{it}$$

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<sup>26</sup>An alternative model, the extrapolative trend-following model used in Haruvy Lahav, and Noussair (2007) was also tried. The fit of this model was much lower than for the adaptive-expectations model (R-squared of about 0.15), and those authors' result that price predictions in experienced markets follow past market trends was not replicated.

<sup>27</sup>This result is not altered if the subsample is restricted to traders for whom  $COR_{it} = 1$  for all  $t$  (i.e., subjects who make exactly zero mistakes about fundamentals).

Additionally, I define three indicator variables to represent whether a trader bought, sold, or held shares in a given period:

$$\begin{aligned}
 BOUGHT_{it} &= \begin{cases} 0 & NETBUY_{it} \leq 0 \\ 1 & NETBUY_{it} > 0 \end{cases} ; \\
 SOLD_{it} &= \begin{cases} 0 & NETBUY_{it} \geq 0 \\ 1 & NETBUY_{it} < 0 \end{cases} ; \\
 HELD_{it} &= \begin{cases} 0 & NETBUY_{it} \neq 0 \\ 1 & NETBUY_{it} = 0 \end{cases} ;
 \end{aligned} \tag{12}$$

Finally, define  $NETBUY_t$  as the average of  $NETBUY_{it}$  for a given group within a given market period.

Figure 9 shows plots of  $NETBUY_t$  for both markets. Figure 10 shows the same thing, but restricted to include only the "rational" traders who understand the fundamental value well ( $NOMIS_{it} = 1$  for all  $t$ ). The basic pattern in Market 1 is remarkably constant across subsamples of traders: A) net buying at the outset, B) zero net buying or even some net selling at the height of the bubble, C) strong net buying just after the peak of the bubble, and D) strong net selling in the final period<sup>28</sup>. In general, this pattern may or may not be consistent with support for a bubble; because these traders did not interact, this cannot be known. However, the strong net selling just after the peak of the bubble - a feature that is present in many different subgroups of traders, and in both Market 1 and Market 2 - strongly suggests a mechanism by which a bubble might be sustained. It also conflicts with the idea that traders try to sell out at the peak of bubbles<sup>29</sup>; even experienced traders in this experiment tend to buy when the price is already on its way down. Also, note that the strong net buying activity at the beginning of both Market 1 and Market 2 represents behavior that would tend to initiate a runup in prices.

The next question is whether or not herd beliefs feed through into traders' asset demands. If

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<sup>28</sup>This pattern is the same if the the number of traders who bought or sold is plotted on the y-axis instead of the number of shares that were bought or sold.

<sup>29</sup>Put fort, for example, in Haruvy, Lahav, and Noussair (2007).

this is happening, we should expect to see a positive correlation between net buying activity and changes in the size of (positive) mistakes about fundamentals. As a measure of increasing mistakes, define:

$$DM_{it} = M_{i,t+1} - M_{it} \tag{13}$$

In order to capture only those whose belief about fundamentals is too high and getting higher, I restrict the sample to only those observations for which  $M_{i,t+1} > 0$  and  $M_{it} > 0$ . I then regress  $NETBUY_{it}$  on  $DM_{it}$  (regression results are in Table 5). The relationship is not significant in Market 1, indicating that there is no measurable effect of increasing mistakes on net asset demand in that market. In Market 2, there appears to be a positive relationship, but the effect is not significant at the 1% level (p-value of 0.011). Thus, there is slight evidence that herd beliefs are causing traders to buy more in Market 2.

Another way that herding should show up in asset demand is if traders who misunderstand fundamentals trade based on their perceived fundamental values. For a measure of traders' beliefs that the asset is overpriced in period  $t$ , I define:

$$PRBUB_{it} = P_t - E_{i,t+1}[FV_{t+1}] - 5 \tag{14}$$

First, I restrict the sample to traders who misunderstand fundamentals in more than eight of the ten periods ( $\sum_t NOMIS_{it} < 2$ )<sup>30</sup>. Regressing  $NETBUY_{it}$  on  $PRBUB_{it}$ , I find that the relationship is not significant in Market 1, but is significantly negative in Market 2 (see Table 6). In other words, traders who misunderstand fundamentals do trade based on their mistaken beliefs about fundamentals in Market 2.

Thus, I find no evidence that herd beliefs are causing the patterns of demand seen in Market 1. This does not mean that the herd beliefs found in Section 4.1 do not cause bubbles. Because this experiment asks only for asset demand at the given price, and not at a range of hypothetical prices, it is perfectly possible that beliefs about fundamentals influence the price that subjects are *willing*

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<sup>30</sup>The result holds, and is actually stronger, if this number of "well-calibrated" periods is varied.

to pay in Market 1. Since buying patterns are essentially identical for traders who understand vs. misunderstand fundamentals (see Figure 10), if herd beliefs lead to increased willingness to pay, this would directly cause bubbles.

Next, I investigate whether speculation is taking place among traders who understand fundamentals well. The definition of speculative behavior that I use is: "buying based on anticipated price movements by traders who do not believe that prices reflect fundamentals." Since we have already seen that traders who understand fundamentals well do not believe that prices and fundamentals converge in the short or long term, we can observe speculative behavior in this data set simply by measuring the correlation between trading behavior and beliefs about future price movements.

Beliefs about future price movements can be broken down into A) a belief that the asset will rise in price from the current period to the next period (a "short-term rise"), and B) a belief that the asset will rise in price from the next period to the final period (a "long-term rise"). These can be formalized as:

$$PRSTRISE_{it} = E_{i,t+1}[P_{t+1}] - P_t \quad (15)$$

$$PRLTRISE_{it} = E_{i,t+1}[P_{10}] - P_t$$

In order to examine the behavior of traders who understand the fundamentals relatively well, I restrict the sample to traders who make mistakes about the fundamentals in fewer than two out of ten periods ( $\sum_t NOMIS_{it} > 8$ )<sup>31</sup>. I then regress net buying behavior on the two kinds of beliefs about future price appreciation, as well as on beliefs about fundamentals:

$$NETBUY_{it} = \alpha + c_i + \beta_f PRBUB_{it} + \beta_s PRSTRISE_{it} + \beta_l PRLTRISE_{it} + \varepsilon_{it} \quad (16)$$

Regression results are given in Table 6, along with the same regression for traders who make substantial mistakes about fundamentals ( $\sum_t NOMIS_{it} < 2$ ). In Market 1, traders who understand fundamentals demonstrate both fundamental-based trading and short-term speculation, but not

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<sup>31</sup>Again, these results are robust to the number of periods used for this cutoff.

long-term speculation. In Market 2, none of these behaviors is in evidence.

So there is evidence that "rational" traders - at least, rational enough to understand the fundamentals - engage in both arbitrage and short-term speculation in Market 1. This is consistent with the predictions of noise-trader models. However, the fit of the model is not substantial (within-panel R-squared of about 0.06). A simple model of fundamental-based arbitrage and short-term speculation is not sufficient to explain the dramatic swings in buying and selling that we observe in Market 1. Additionally, in Market 2, "rational" traders do not seem to trade based on fundamentals at all, but also do not seem to be engaging in the most simple kinds of speculation.

This is something of a puzzle. Why do active traders trade neither on the belief that prices will appreciate, nor the belief that assets are over-valued? What is causing their trading? It seems that a more complex relationship between beliefs and trading exists<sup>32</sup>. It is also possible that even experienced traders have very little confidence in their predictions about either prices or fundamentals, and thus trade based on other factors, such as momentum.

In fact, there is evidence that traders do trade based on momentum. Price momentum at one, two, and three lags is significant as an explanatory variable for buying activity in Market 1; in Market 2, one-period-lagged momentum is significant (see Table 7). However, even in Market 1, momentum trading cannot explain the bulk of trading behavior. A more sophisticated model is required to explain asset demand. It is almost certain that testing such a model will require more cross-subject variation in price histories, thus placing it beyond the scope of this experiment.

#### 4.4 Experimental Treatment Effects

There were two predictions for the Uncertain treatment, in which subjects were not shown the exact probabilities associated with the two per-period dividend possibilities. One prediction was that the per-subject volatility of predictions about prices and fundamentals would be greater in this treatment. I define the volatility of a trader's predictions as the standard deviation of predictions

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<sup>32</sup>It is possible to find examples of easily-understood behavior. For example, one subject, who participated in the Pictures treatment (and hence had seen examples of dividends and prices series), bought shares in the first and second period of Market 1, held them, and sold them in Period 5 at the peak of the bubble, earning a substantial profit. This subject's predictions for the next period's price closely - and correctly - track the bubble, while his/her predictions of the fundamental value are completely ex ante correct. However, this is an isolated case.

over one market:

$$VOLF_i = \sqrt{Var(E_{it}[FV_t])} \quad (17)$$

$$VOLN_i = \sqrt{Var(E_{it}[P_t])}$$

$$VOL10_i = \sqrt{Var(E_{it}[P_{10}])}$$

Regressing these on a dummy for the Uncertain treatment, I find that the null hypothesis (no difference in prediction volatility) is not rejected for any of the three predictions in Market 1, and is rejected only for the prediction of fundamentals in Market 2 (see Table 8). Thus, withholding information about dividend probabilities does decrease learning about fundamentals from Market 1 to Market 2, but this does not increase the variance of price predictions. That is to be expected, given the lack of any clear connection between beliefs about fundamentals and beliefs about prices, as reported above.

The second prediction for the Uncertain treatment was that subjects in this treatment, because they knew the maximum and minimum possible per-period dividends, would be no more likely to exhibit mistakes about dividends than subjects in the other treatments. Using  $\sum_t NOMIS_{it}$  and  $\sum_t COR_{it}$  as measures of the total # of mistakes made by a subject, I regress this total on a dummy variable for the Uncertain treatment. The null of no more mistakes in the Uncertain Treatment is not rejected for Market 1, but is rejected for Market 2 for both mistake measures (see Table 9). This result is not easily explained, as subjects in the Basic and Pictures treatment receive no more information about dividends between Market 1 and Market 2 than do subjects in the Uncertain treatment. It appears that uncertainty about dividend probabilities spills over into uncertainty about dividend possibilities. This is an interesting target for future research into behavioral information processing. It also raises the possibility that finance experiments in which dividend probabilities are not known (as they are not known in real markets) may be more externally valid than experiments in which probabilities are known. In particular, real markets (and the

Uncertainty treatment in this experiment) may suffer from a variant of ambiguity aversion, in which the fact that probabilities are not known leads agents to discard other kinds of information that they possess about random processes.

There were three predictions for the Pictures treatment. The first was that asset demand should be more positive during the runup phase of a bubble, as traders used their knowledge (that a runup-and-crash pattern was possible in this type of market) to speculate. To assess this, I simply regress  $NETBUY_{it}$  on a dummy variable for the Pictures Treatment, with the sample restricted to periods before the peak of the bubble ( $t < 6$  in Market 1,  $t < 7$  in Market 2). The null hypothesis of no difference between the treatments is not rejected (p-values of 0.617 and 0.484 for Market 1 and Market 2, respectively)<sup>33</sup>. Thus, I find that simply seeing examples of runups and crashes does not induce traders to speculate. This is contrary to the hypothesis put forth in Haruvy, Lahav, and Noussair (2007), which states that traders base their trading decisions on price patterns that they have observed in the past.

The second prediction for the Pictures treatment is that traders in this treatment should predict greater divergence between next-period prices and fundamentals than traders in the other treatments. This reflects the idea that, having seen examples of prices diverging strongly from fundamentals, traders in the Pictures treatment would expect this to happen again. To test this hypothesis, I define:

$$PROVER_i = \sum_t (E_{it}[P_t] - E_{it}[FV_t]) \quad (18)$$

I then regress  $PROVER_i$  on a dummy variable for the Pictures treatment. The null is not rejected for either market (p-values of 0.127 and 0.200, respectively). Having seen examples of bubbles does not make subjects more likely to predict one.

The third prediction for the Pictures treatment is that beliefs about fundamentals should be more accurate for traders who have actually seen examples of dividend series. This hypothesis is due to the results of Lei & Vesely (2009), who found that traders who passively experienced

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<sup>33</sup>This result is robust to variation of the "peak" by one period in either direction.

one market worth of dividend realizations produced no bubbles when allowed to trade. Defining  $M_i = \sum_t M_{it}$  and regressing  $M_i$  on a dummy variable for the Pictures treatment, I find that the null cannot be rejected in either market (p-values of 0.210 and 0.175). Regressing  $\sum_t NOMIS_{it}$  and  $\sum_t COR_{it}$  on the dummy for the Pictures treatment, I find that subjects in this treatment are not significantly more likely to understand fundamentals in Market 1, but ARE significantly more likely to understand fundamentals in Market 2 (see Table 10). This implies that direct experience of dividends, as opposed to simply viewing time series, is important in the process of learning. This has important implications for future experimental finance research. It means that direct experience with a time-series process is crucial for understanding the process; unless subjects have experienced the process in real time, experimenters should not assume that subjects will internalize information about the process that they have been given by the experimenter. The result also holds possible importance for the finance literature in general, since it hints that knowledge of the history of markets may not be a perfect substitute for direct personal experience of those markets. This may imply, for example, a role for employee turnover in fund performance.

## 5 Conclusion

The results presented here have implications both for the study of bubbles in general, for the "bubble experiments" literature, and for the methodology used in asset-pricing experiments.

In this experiment, it was found that even experienced traders who understand fundamental values very well do not believe that market prices will eventually converge to fundamental values. It was also found that, on average, these traders' trading behavior is not significantly different from that of traders who misunderstand fundamentals. If these result hold true for real-world markets, our basic understanding of why bubbles occur must change. In currently existing theories of bubbles, prices fall when either A) previously unknown information about fundamentals gets revealed, or B) the actions of rational arbitrageurs "pops" the bubble. The results of this study show that these may be an insufficient explanation for why bubbles end. Models in which rational traders assume that markets will *temporarily* diverge from fundamentals, such as the model of Abreu &

Brunnermeier (2003), use the final return to fundamentals as an equilibrium condition. Instead, the results of this experiment show that rational traders may think that bubbles will never end. That implies that the popping of bubbles may come before *any* trader expects. It may be that the popping of bubbles is due to aggregate constraints, such as global liquidity constraints. The popping of bubbles may also be an emergent phenomenon; rational traders' actions may send out signals that give other traders a slight nudge in the direction of rationality. Theories of bubbles that incorporate these effects would represent an interesting direction for research.

Also, the finding that beliefs about fundamentals are affected by prices has important implications. Most current theories of asset pricing involve either learning (for example, theories of heterogeneous priors), or mistakes that remain constant in time (differences-of-opinion models, over-confidence models, and noise trader models). Only the literature on information cascades entertains the notion that mistakes may *increase* in time, as an endogenous result of market outcomes. These models, however, tend to rely heavily on pure rationality, and to have rigid setups (e.g. sequential trading) upon which the model's outcome crucially depends. More general models of endogenously increasing mistakes, of the kind that would be needed to explain the results presented in this study, would be a good addition to the study of bubbles.

This experiment also has important implications for the interpretation of the bubbles commonly seen in SSW-type "bubble experiments." A consensus has been building that the bubbles observed in these experiments are simply due to mistakes about fundamental values (for example, the notion that asset prices always go up). In this view, the eventual disappearance of the bubbles, as traders replay the experiment, is due to subjects learning how the fundamental value process really works. The results of the present study, which is the first in this literature to directly elicit beliefs about fundamentals, should lead to a questioning of that consensus. Mistakes about fundamentals tend to *increase* as a market progresses. This strongly suggests that "herd beliefs" are at least partially responsible for the bubbles encountered in the laboratory, making these bubbles more interesting than many have recently come to believe. Alternatively, explanations of bubbles based on the notion that traders try to "sell out" just before the anticipated (single) peak of a bubble are not supported by the markets observed in this experiment, in which traders buy strongly *after* the market price has

begun to decrease. Future "bubble experiments" should test the effects of *composition uncertainty*, which may exacerbate bubbles by encouraging herd behavior and/or speculation.

This experiment introduced two methodological departures from the traditional experimental asset pricing literature. The first of these is the use of an "isolated trader" setup - i.e., partial equilibrium. Although this method sacrifices the ability to observe aggregate market outcomes, it gains the experimenter the ability to observe the determinants of traders' beliefs without the interference of feedback effects. It also allows large-sample cross-sectional statistics to be used in order to assess the effect of experimental treatments on trader's beliefs, and on traders' *desired* behavior. This makes partial-equilibrium asset pricing experiments very important in modeling the decision-making processes of individual traders. Since understanding traders' decision-making processes is crucial to making microfounded models of asset markets, partial-equilibrium experiments should be regarded as an important complement to group-by-group general equilibrium experiments. In addition, this approach may have external validity that small-group experiments lack, since it better simulates the behavior of small traders in large, liquid markets.

This experiment's second methodological departure is to ask traders directly about their beliefs about fundamentals. Asset market experiments generally either assume that traders properly understand fundamentals, assume that they will learn over time, or use market performance itself as a proxy for whether traders understand fundamentals. As the results of the current experiment show, all of these may fail to capture important features of fundamental beliefs. In general, experimenters should not assume that traders understand the things they are supposed to understand, even after time has passed and traders have gained experience. When practical, it is always best to confirm what traders do and do not understand; and to figure out the causes of any misunderstandings.

There are two additional experimental approaches that would strongly complement these results, and therefore should be directions for future research. The first is to vary the observed price patterns across individuals; in particular, inexperienced traders' beliefs in a no-bubble market would be interesting to compare with their beliefs in a bubble market. This would allow a heuristic confirmation of the result that beliefs follow observed prices. Second, a variant of this experiment using a "call market" setup, in which traders make contingent trading decisions *before* observing

prices (but simultaneously with making predictions) would provide data on traders' willingness to pay. This would allow a clarification of the mechanisms by which beliefs give rise to market prices.

The methodology explored in this study, however, has applicability far beyond the traditional bubble experiment literature. Observing beliefs in a partial-equilibrium setting has potential applicability to a diverse array of open questions in the finance literature. The phenomena of under- and over-reaction to earnings, announcements, for example, could be better understood if the reaction of traders' beliefs to these announcements could be directly observed in a stark setting. The phenomenon of inefficient over-trading, is hypothesized to be due to individual overconfidence (for example, in Barber and Odean 2000); this could most easily be tested in a partial-equilibrium setting, where interactions between individuals of different confidence levels can be eliminated. Finally, some macroeconomic phenomena - for example, saving behavior - may be strongly influenced by individuals' beliefs about financial markets, even if those individuals do not manage their investments themselves. Observing how the beliefs of experimental subjects react to observation of real, historical financial market data may enable construction of better microfoundations for macro models.

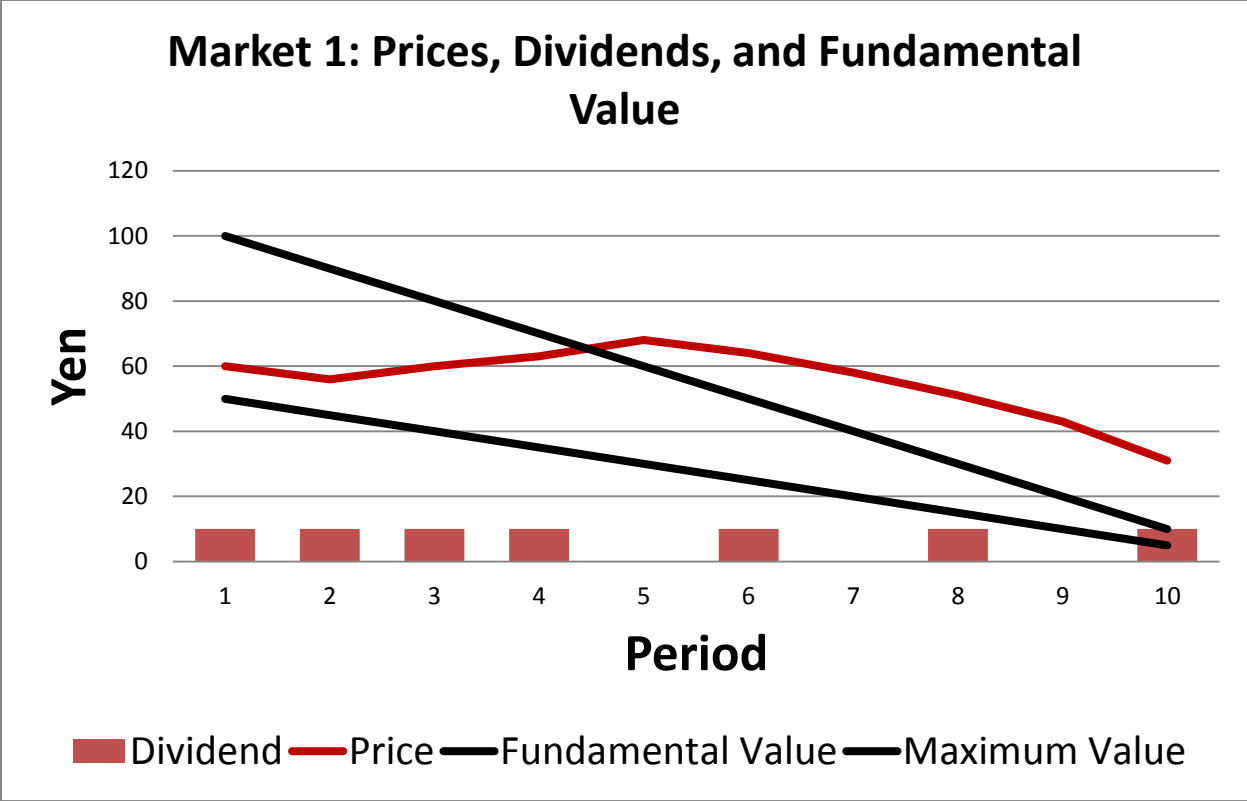


Figure 1a: Prices and Fundamentals in Market 1

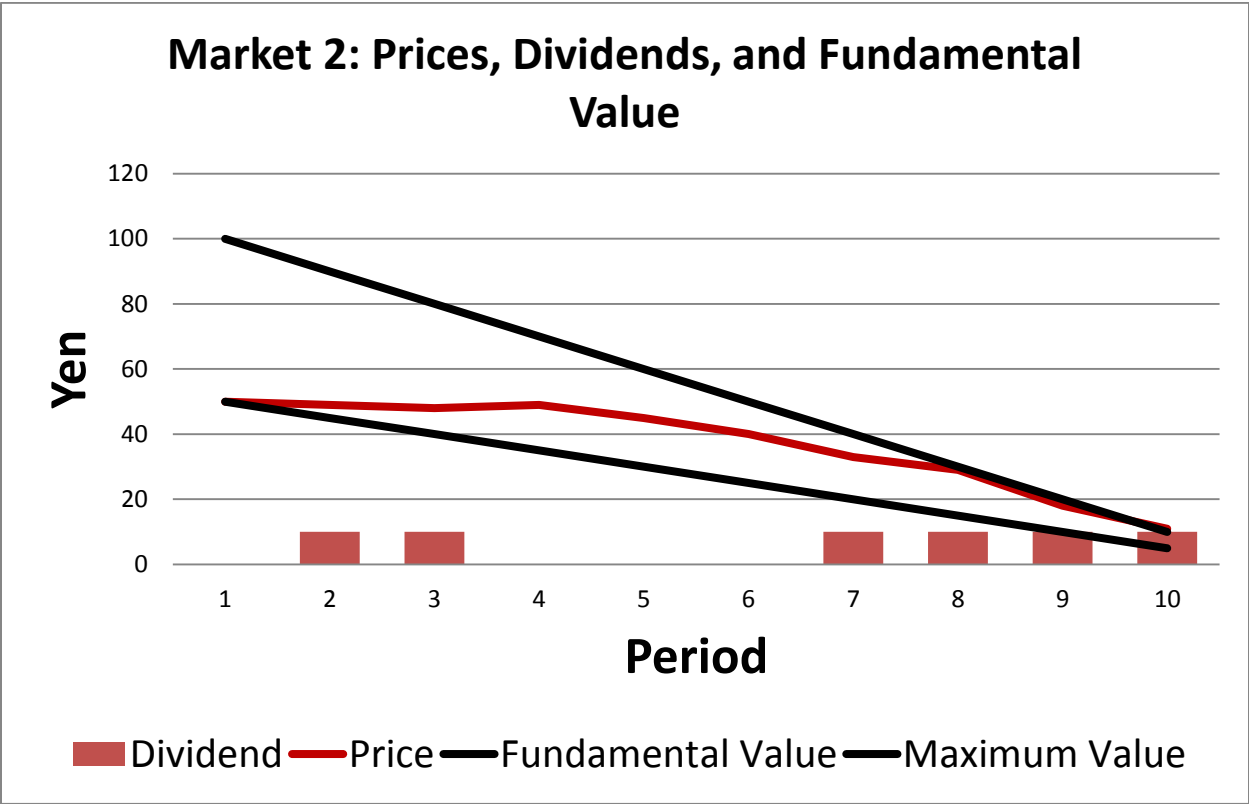


Figure 1b: Prices and Fundamentals in Market 2

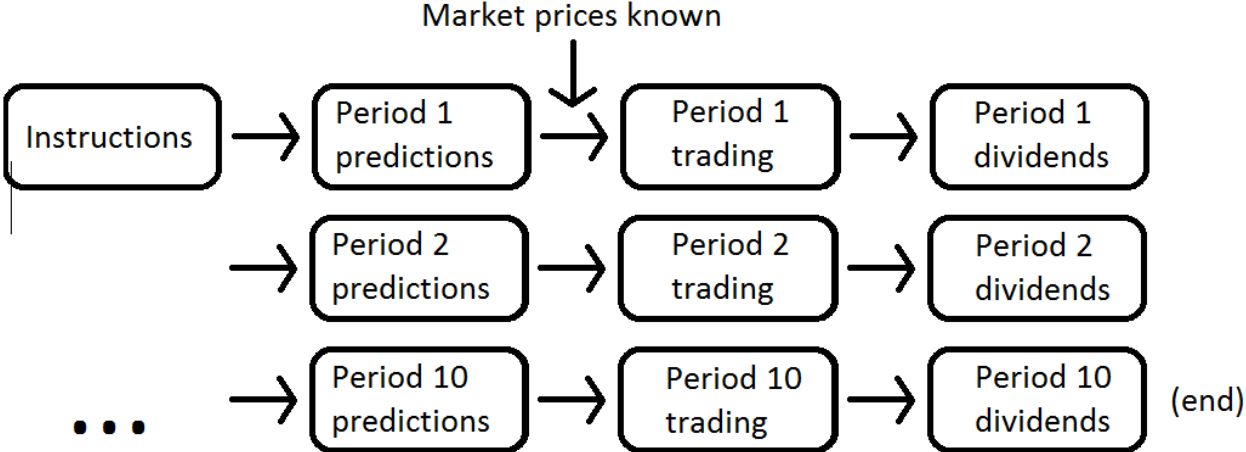


Figure 2: Diagram of the Experimental Procedure

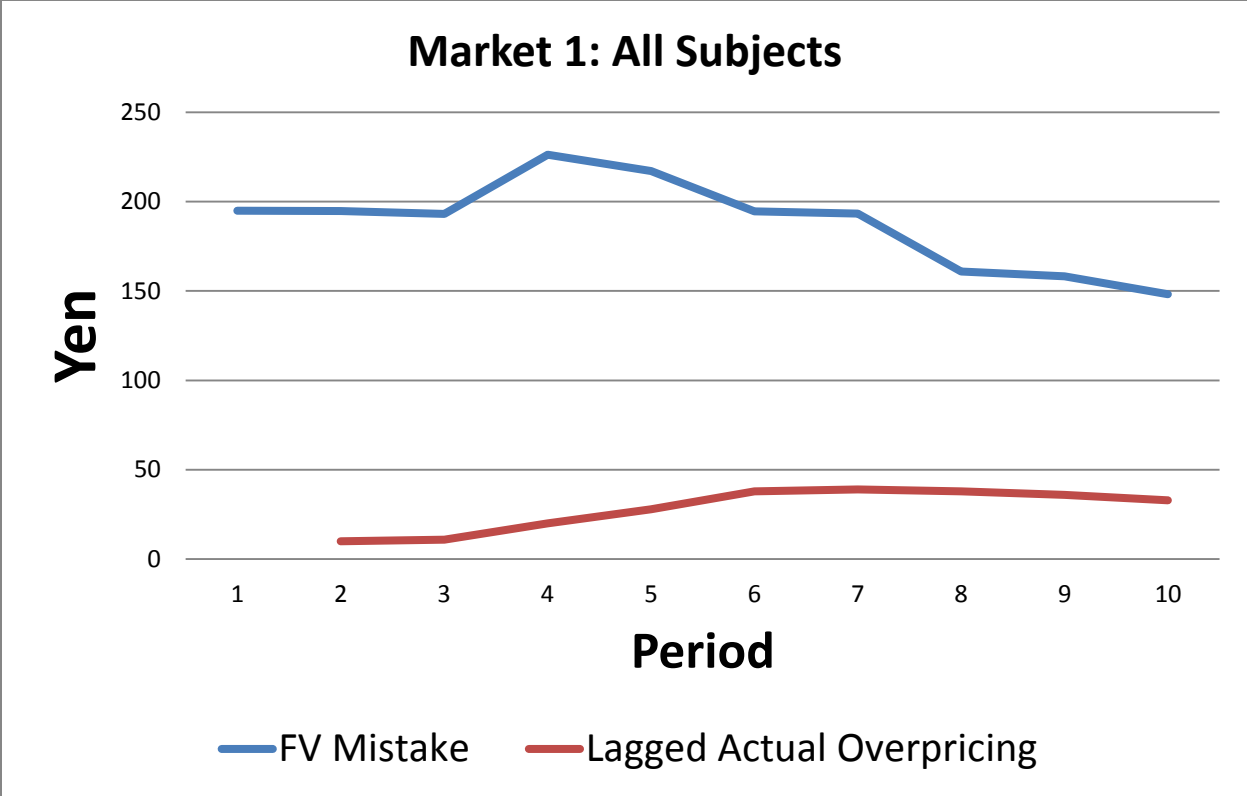


Figure 3a: Traders' Mistakes About Fundamentals in Market 1

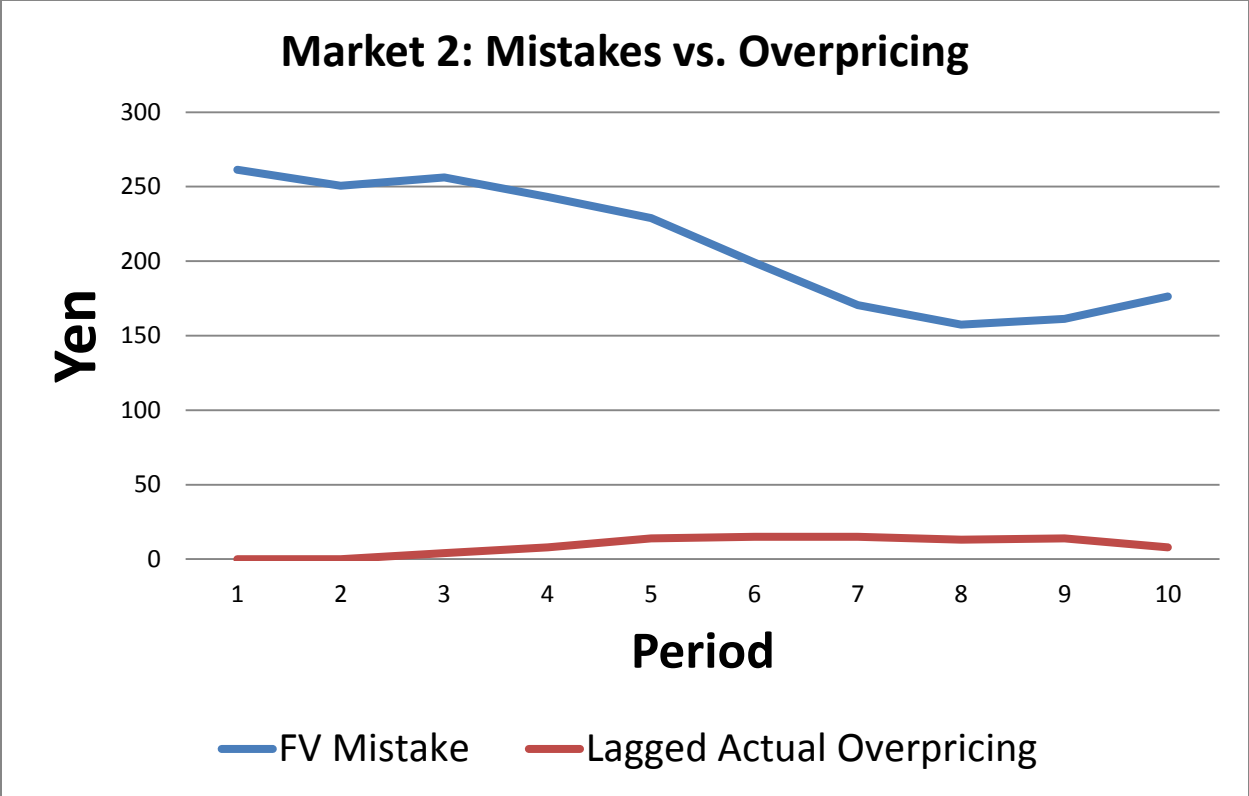


Figure 3b: Trader's Mistakes About Fundamentals in Market 2

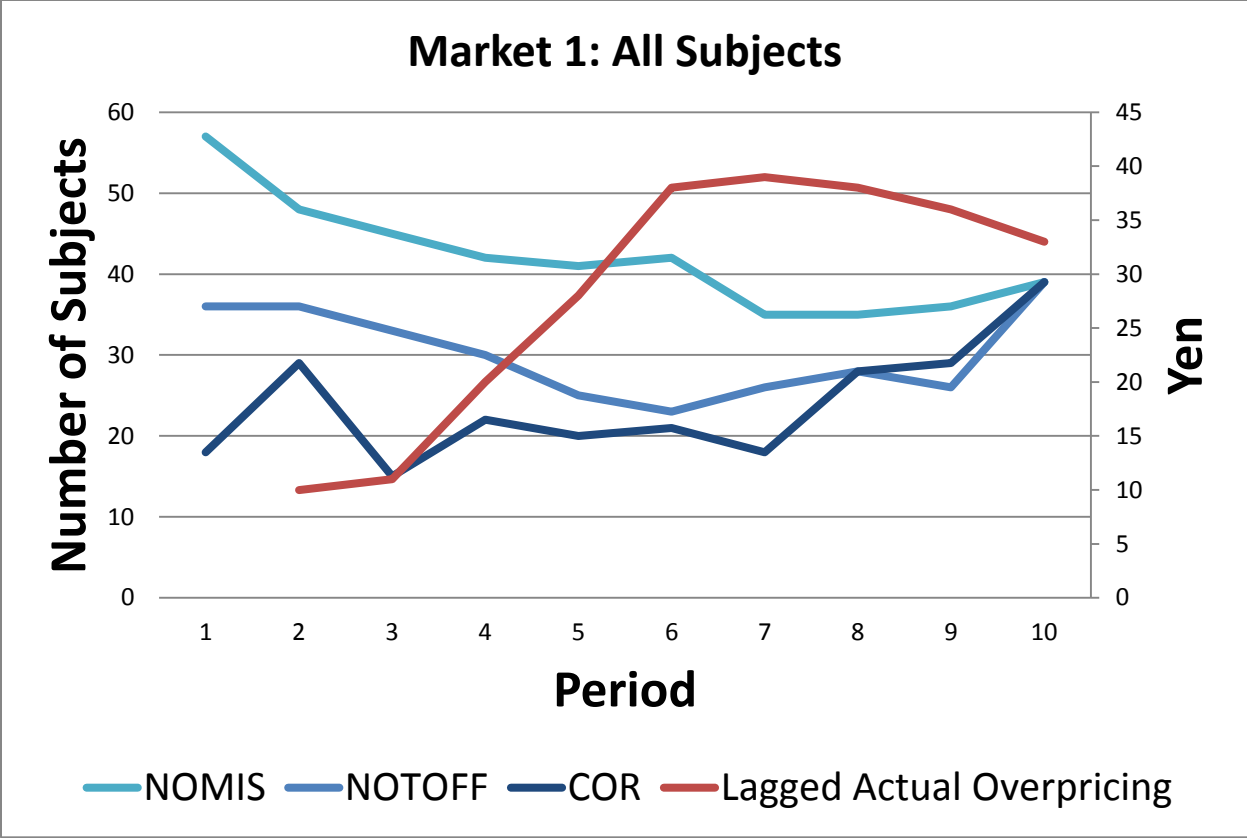


Figure 4a: Number of Traders Making Mistakes About Fundamentals in Market 1

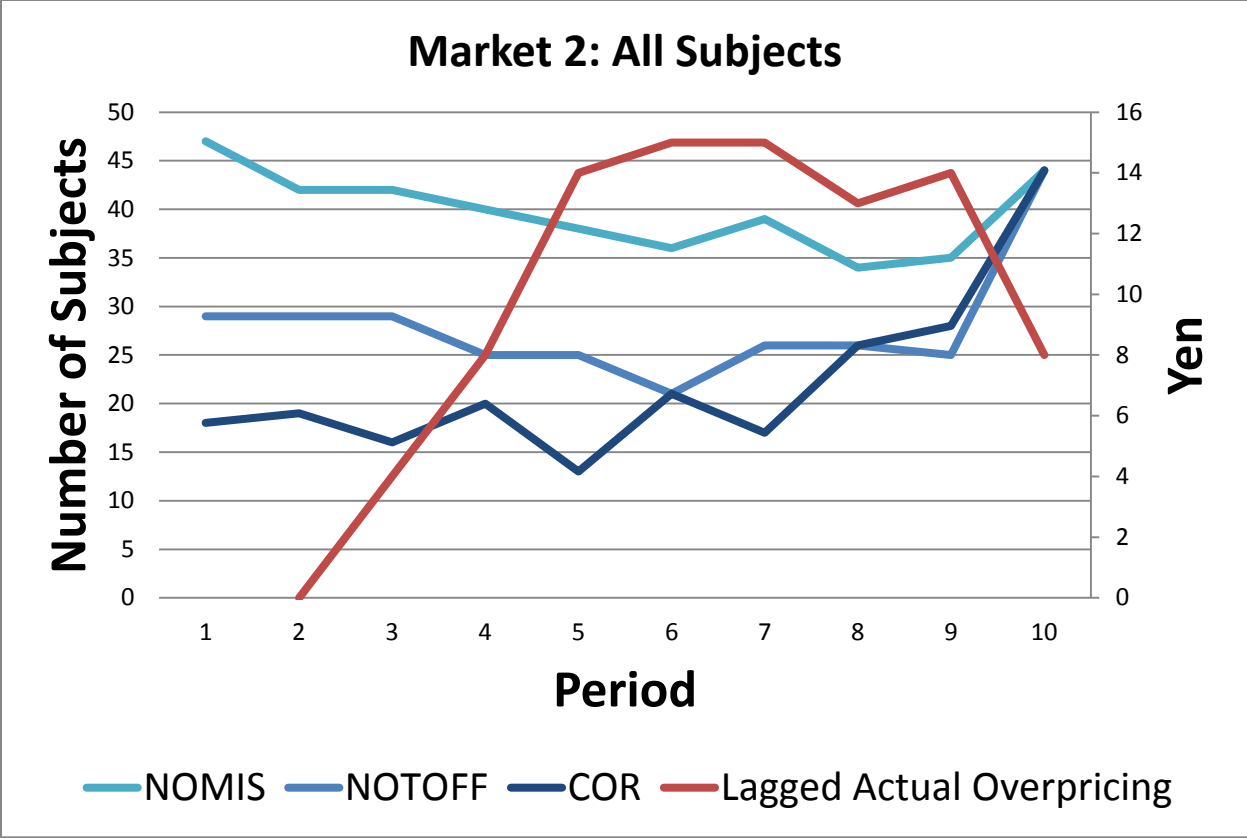


Figure 4b: Number of Traders Making Mistakes About Fundamentals in Market 2

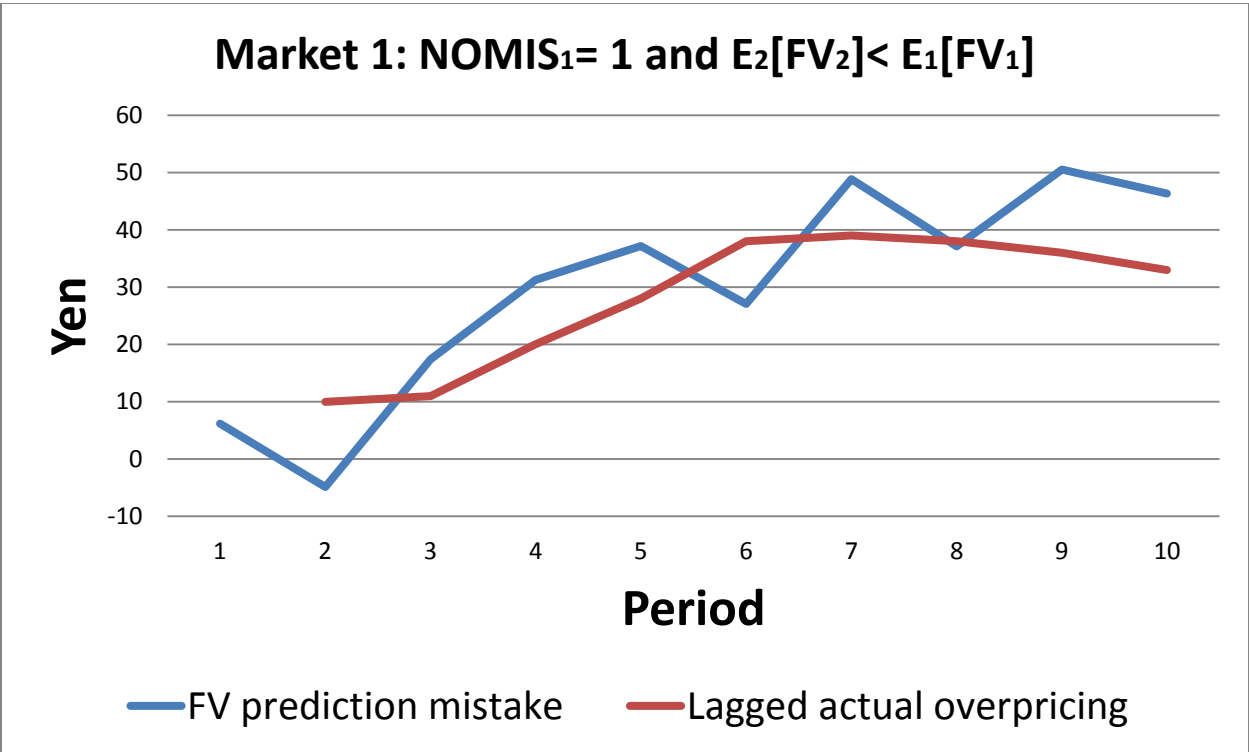
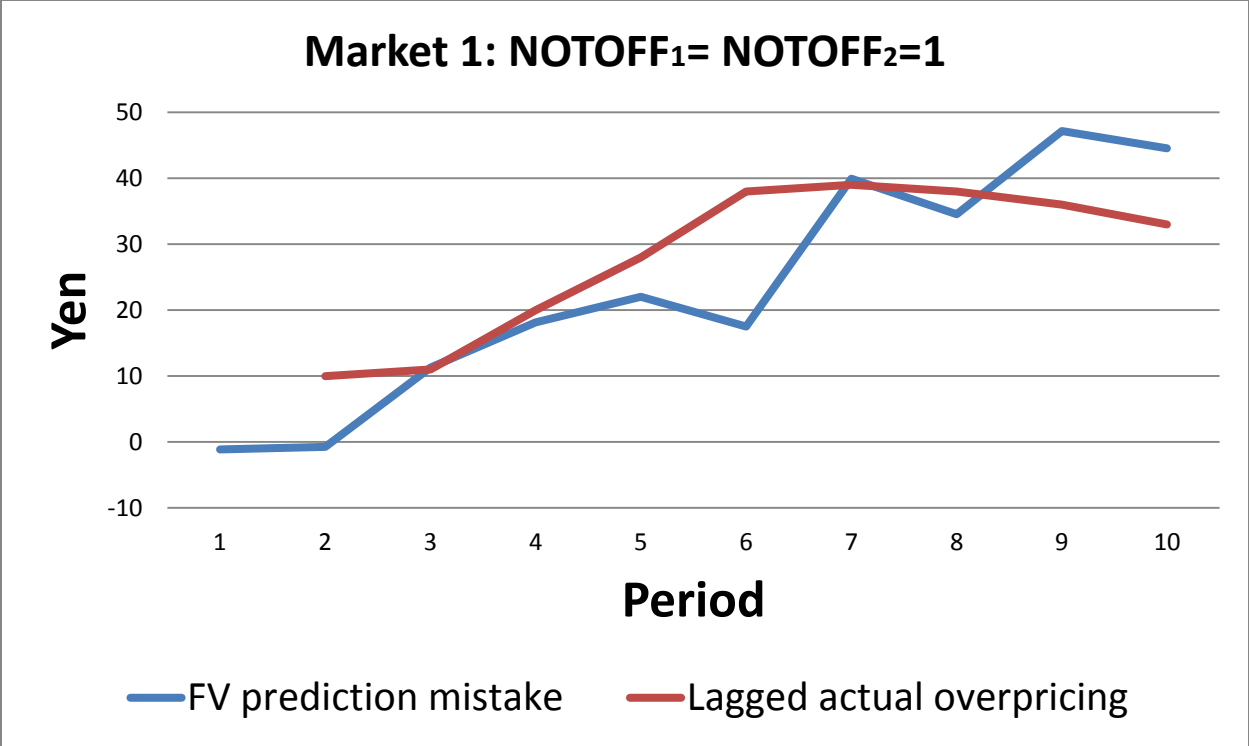
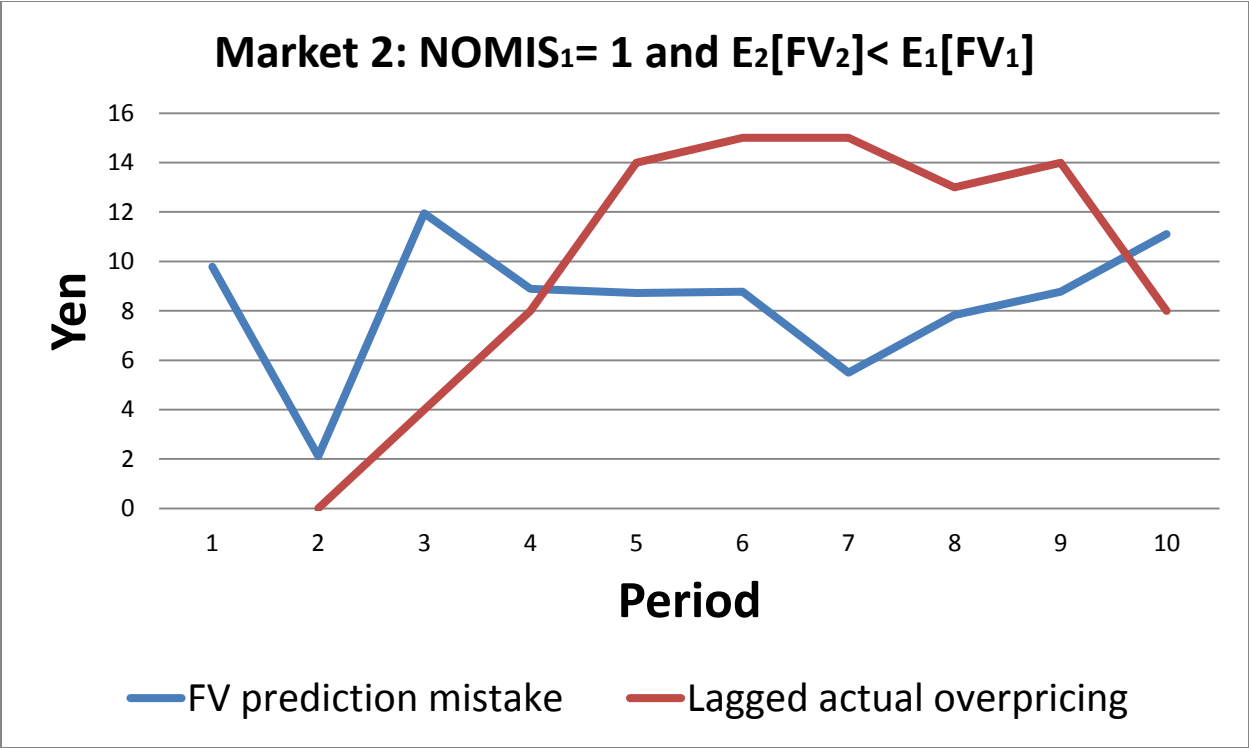
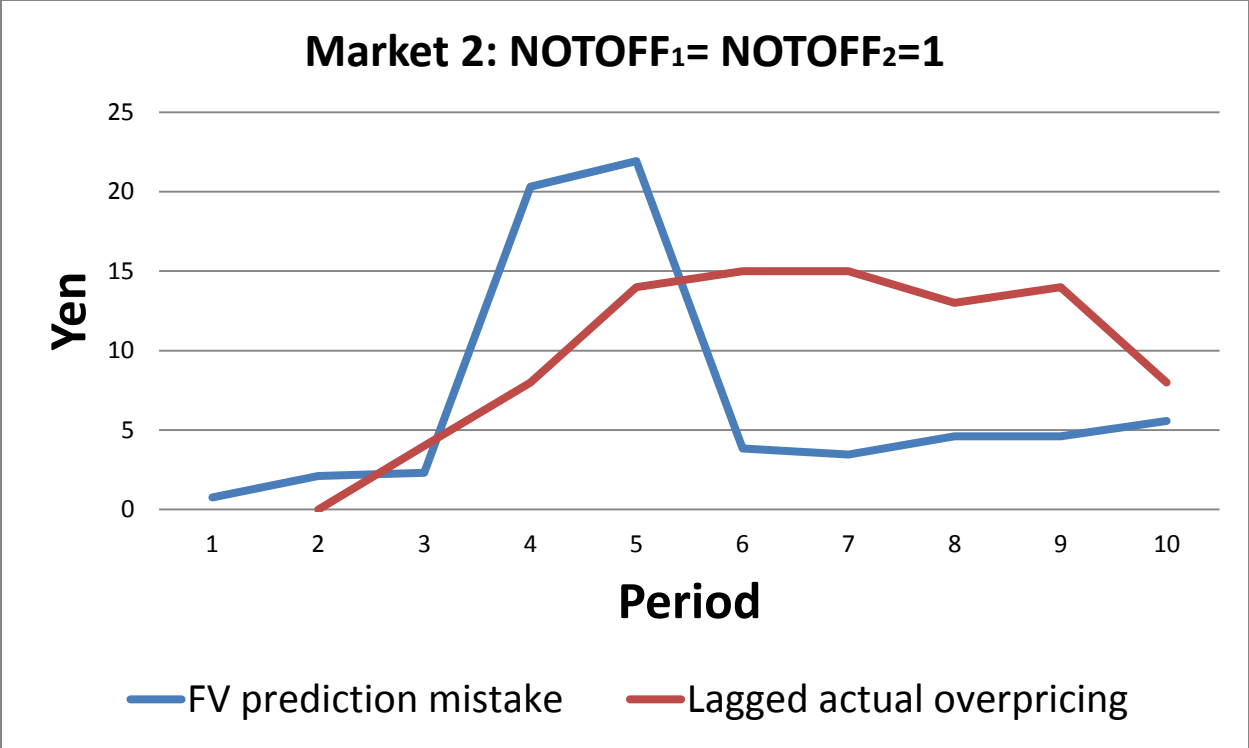
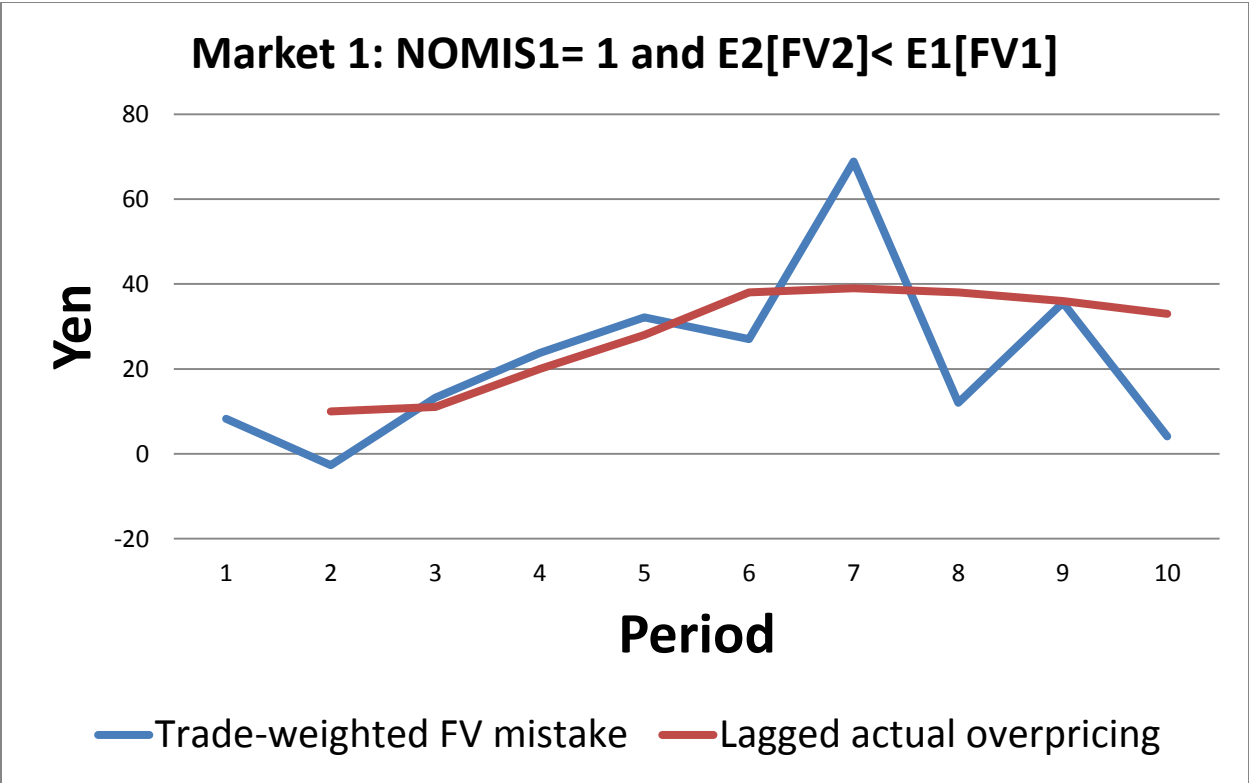
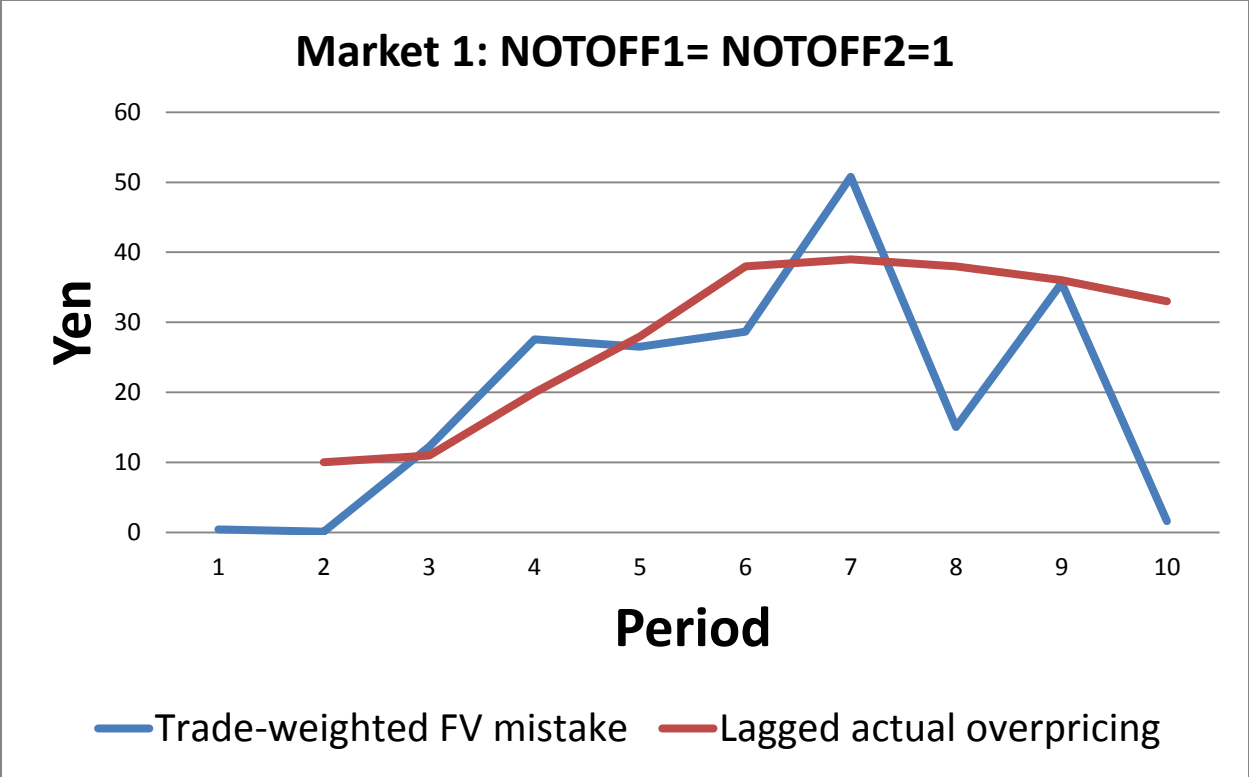


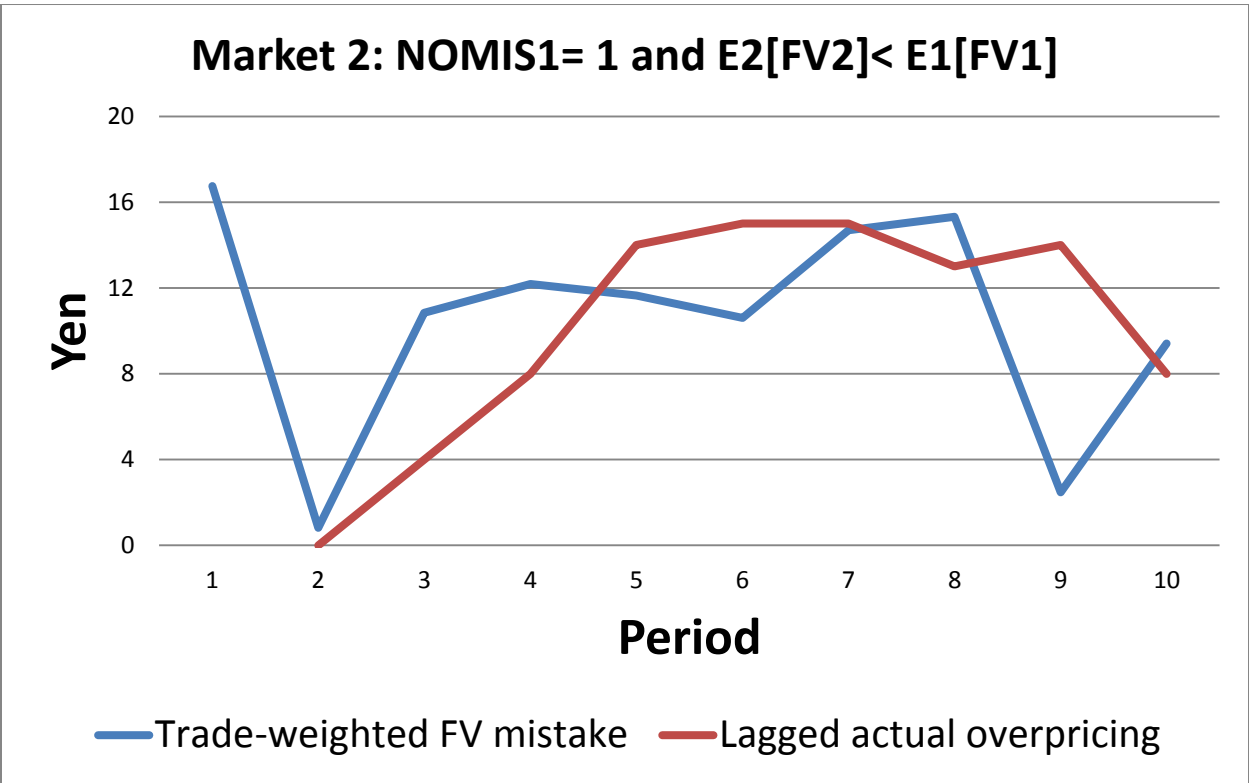
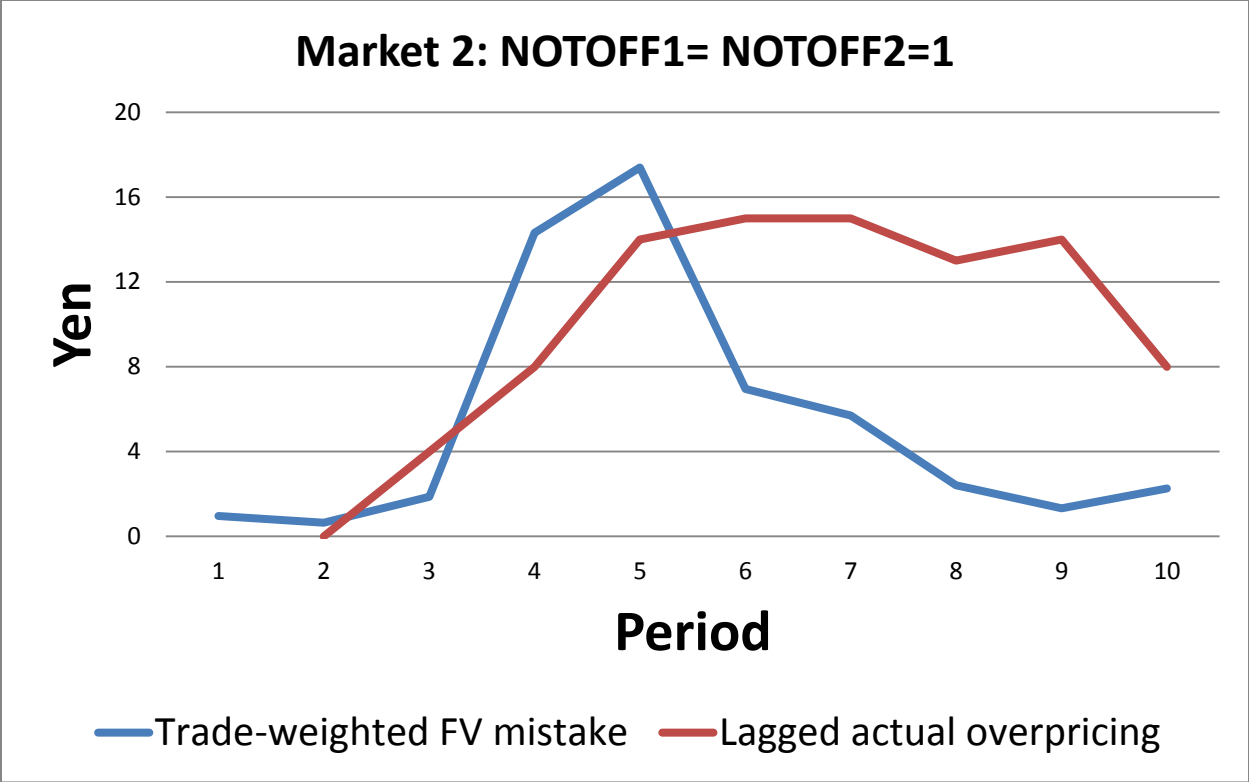
Fig. 5a: Mistakes About Fundamentals vs. Lagged Overpricing, Market 1, Selected Subsamples



**Fig. 5b: Mistakes About Fundamentals vs. Lagged Overpricing, Market 2, Selected Subsamples**



**Fig. 6a: Trade-Weighted Mistakes About Fundamentals vs. Lagged Overpricing, Market 1, Selected Subsamples**



**Fig. 6b: Trade-Weighted Mistakes About Fundamentals vs. Lagged Overpricing, Market 2, Selected Subsamples**

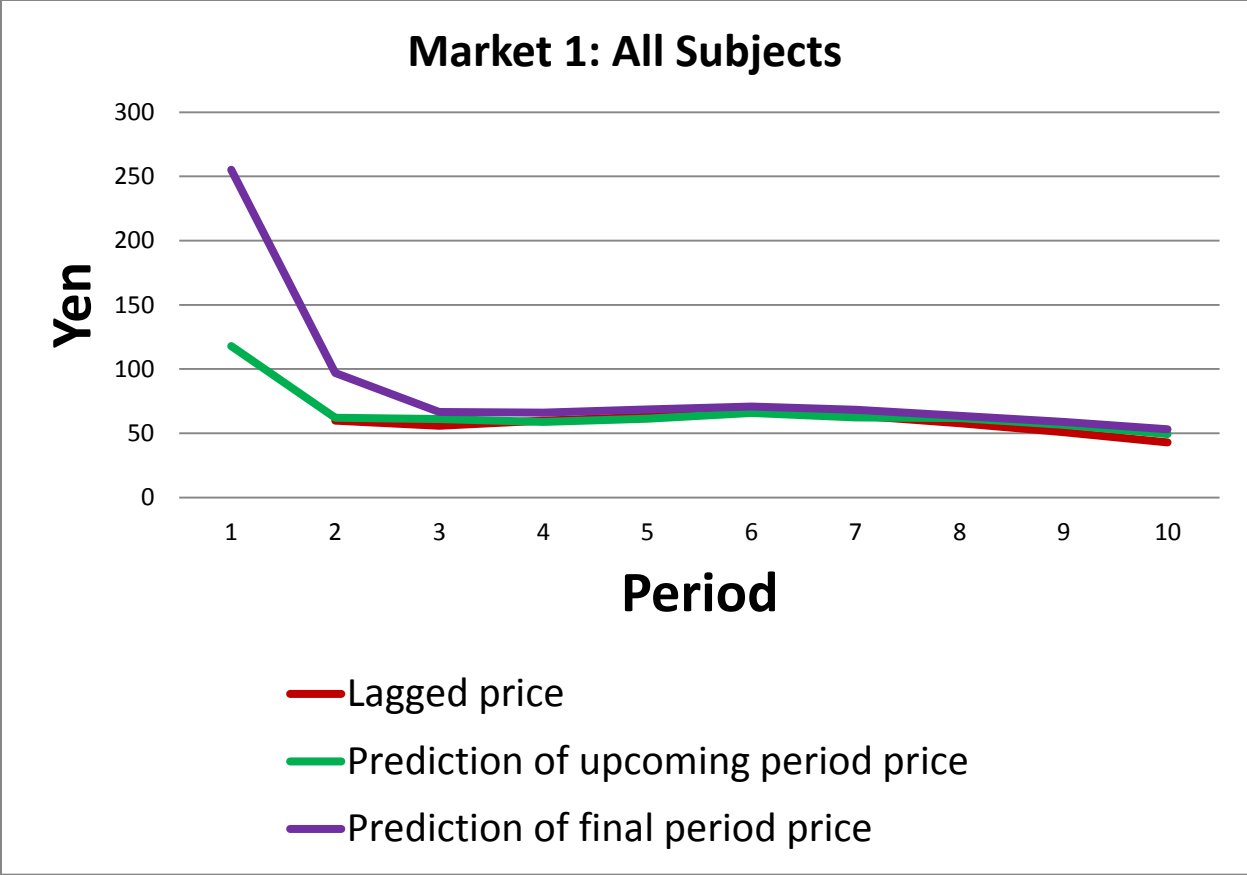


Fig. 7a: Price Predictions vs. Lagged Prices, Market 1, All Subjects

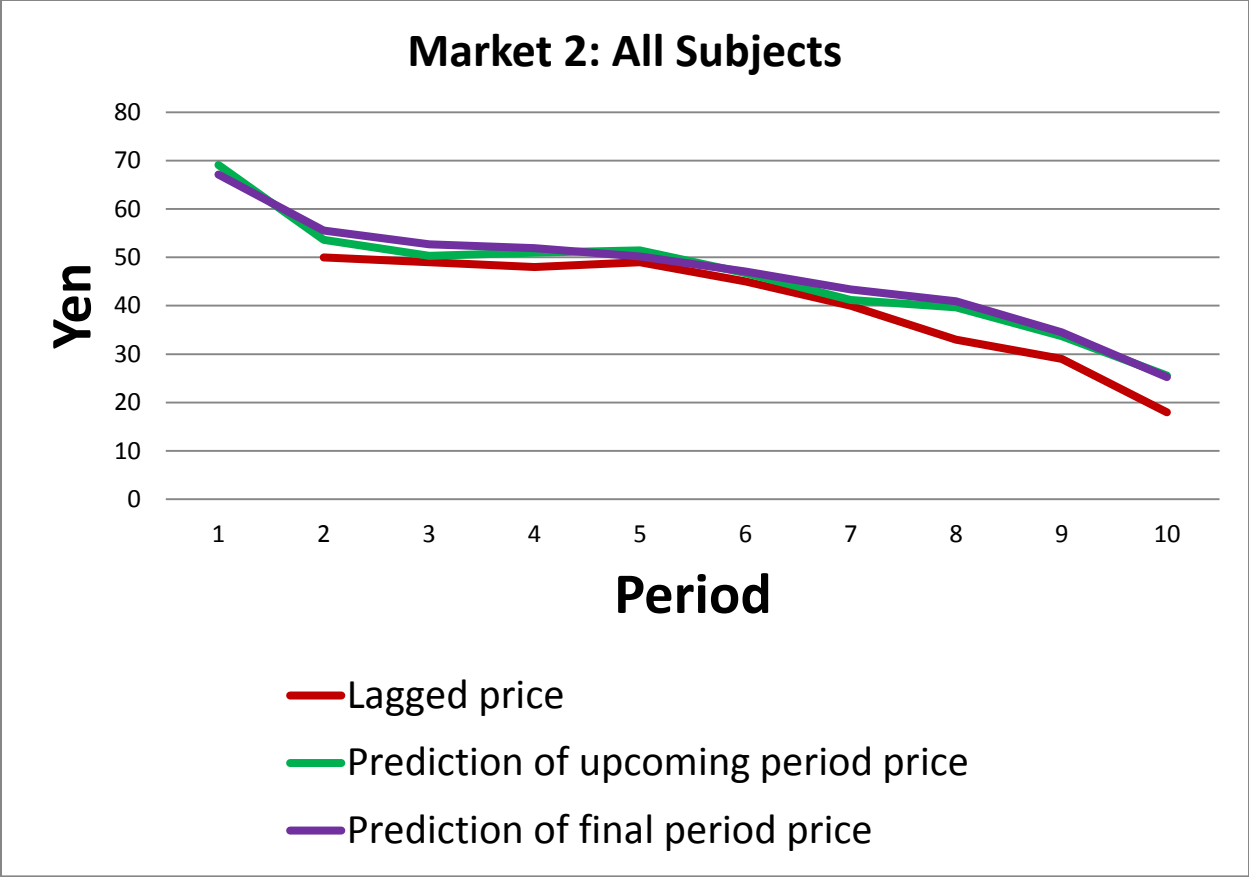


Fig. 7b: Price Predictions vs. Lagged Prices, Market 2, All Subjects

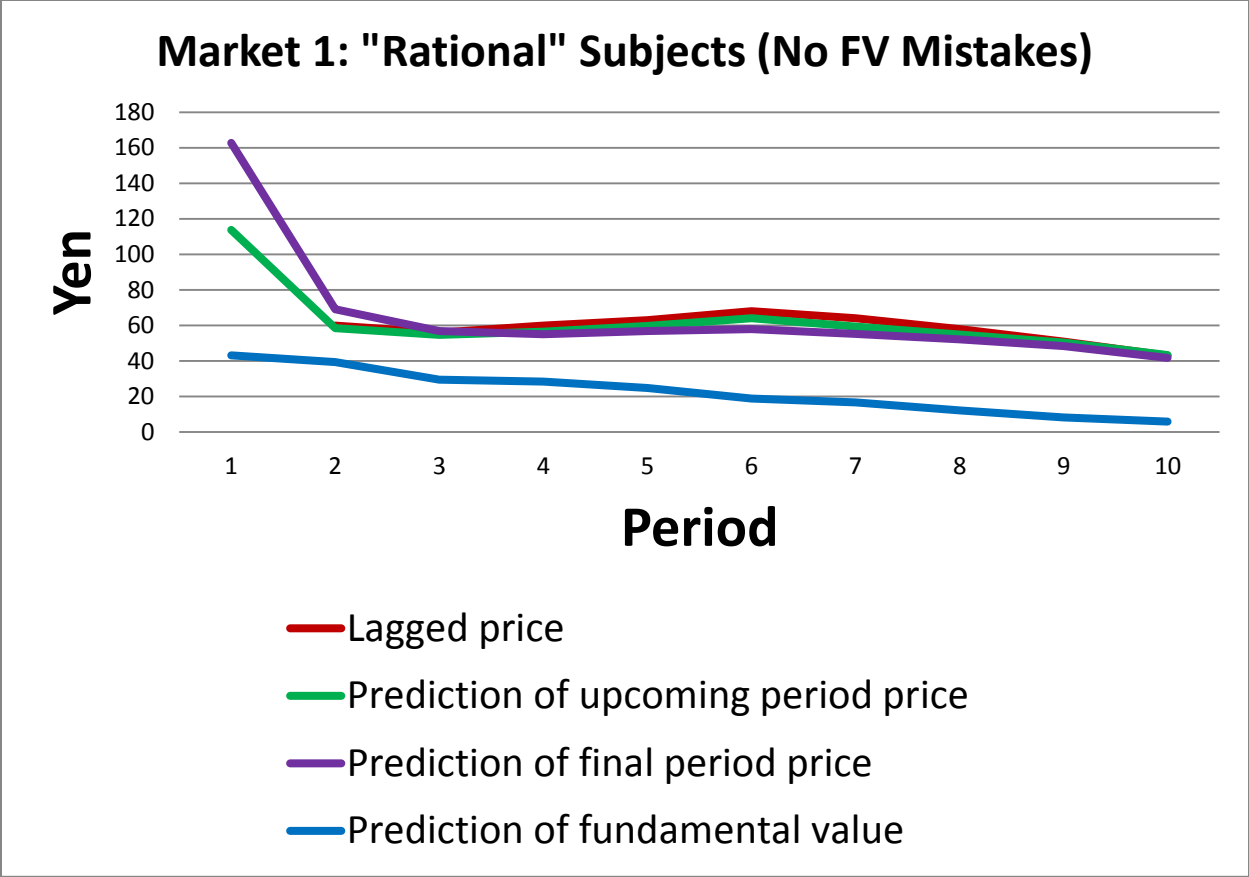


Fig. 8a: Price Predictions vs. Lagged Prices, Market 1, "Rational" Subjects

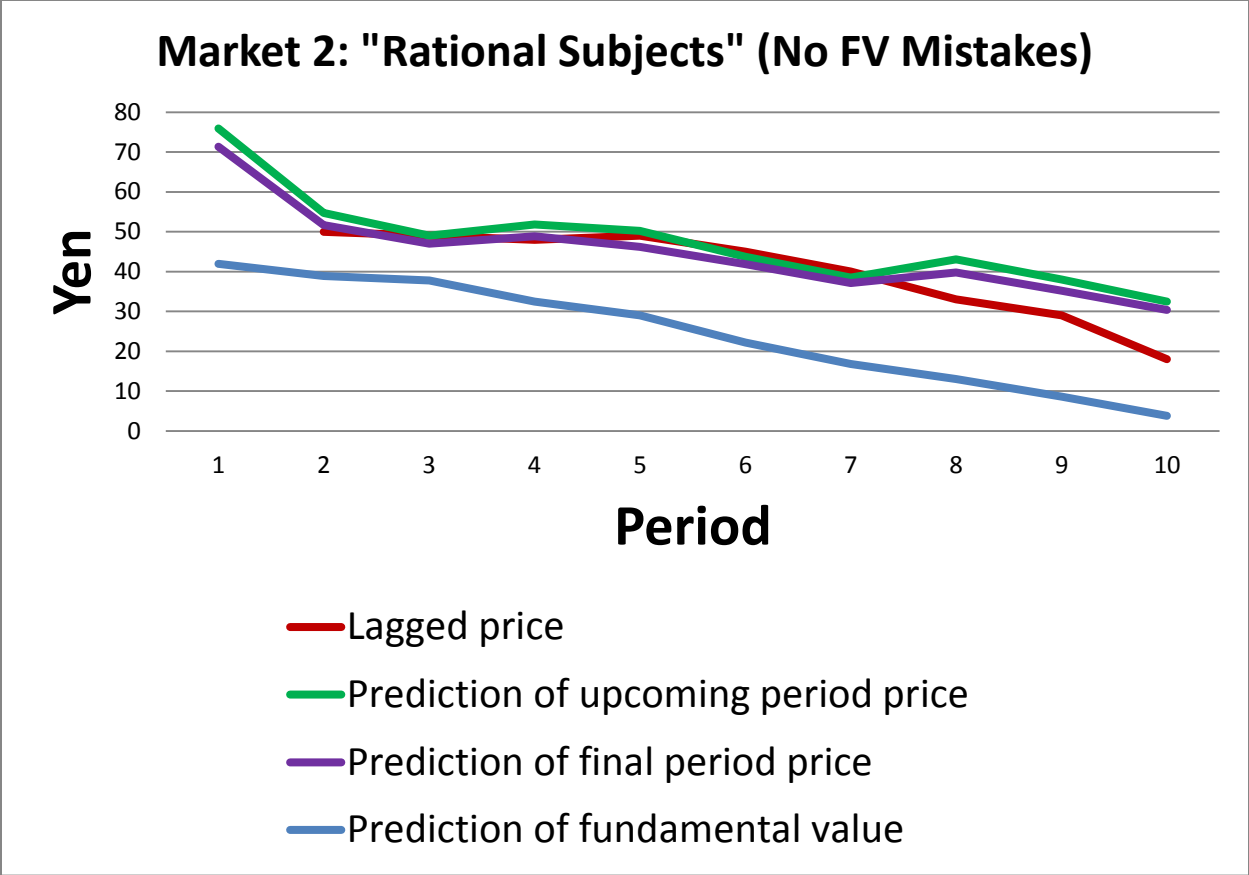


Fig. 8b: Price Predictions vs. Lagged Prices, Market 2, "Rational" Subjects

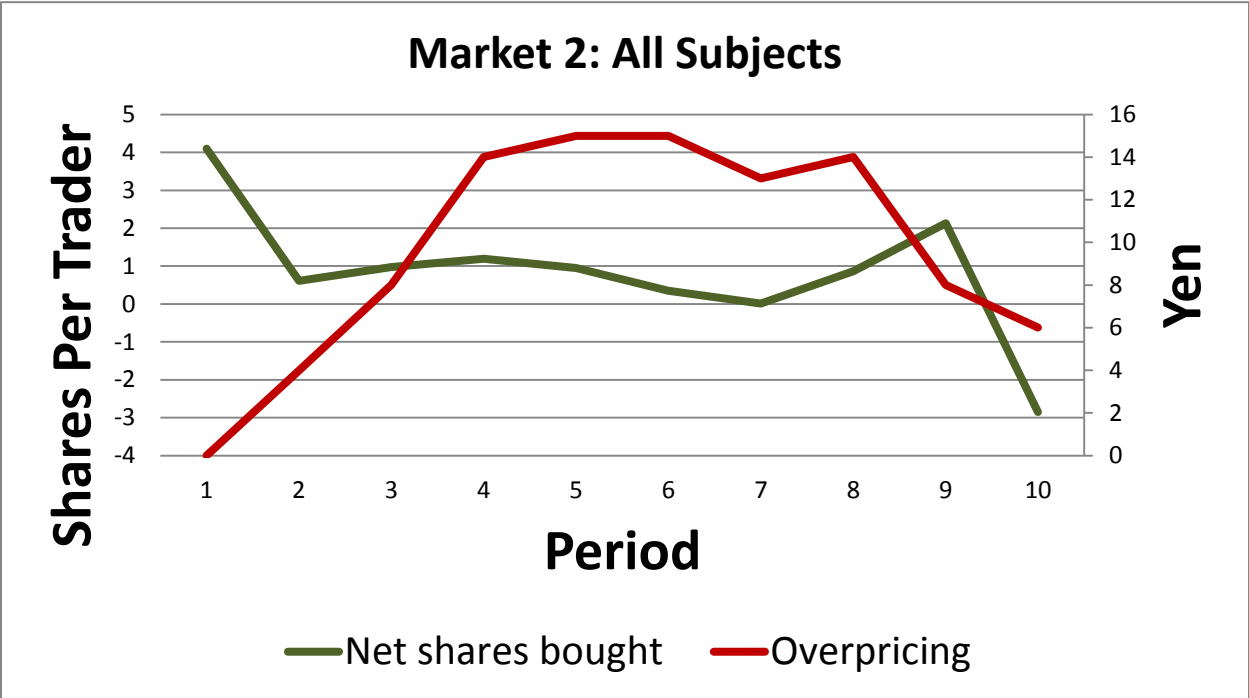
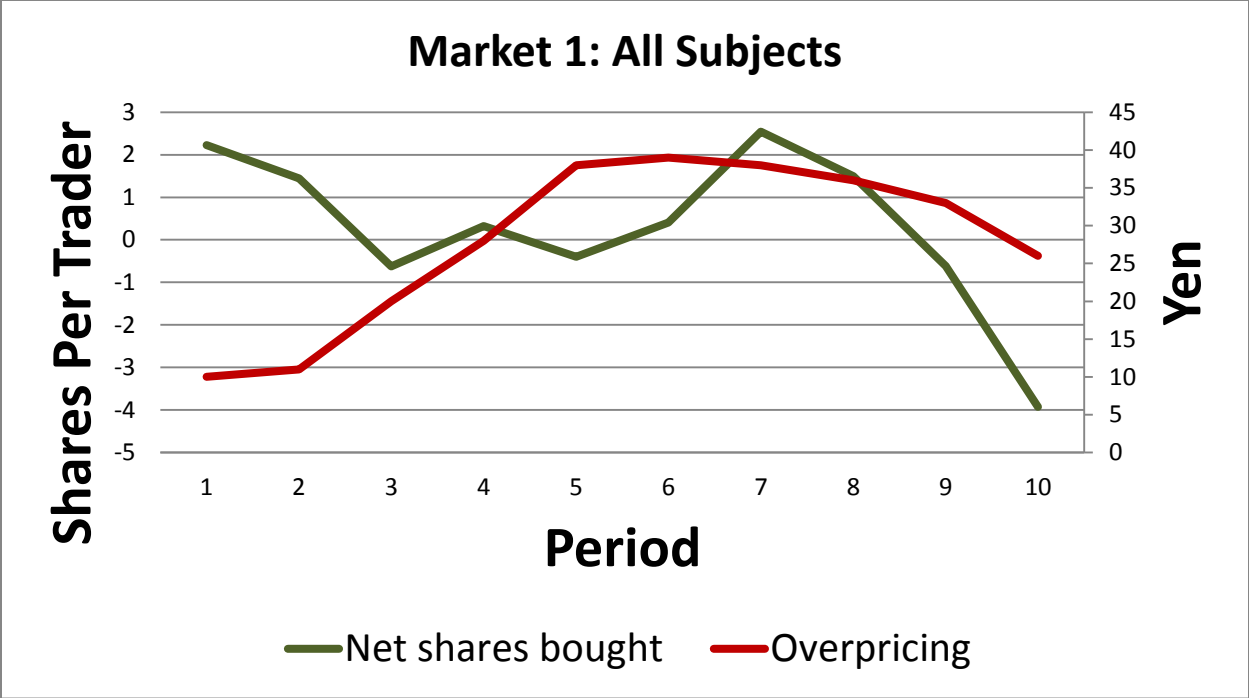


Fig. 9: Trading Decisions vs. Prices, All Subjects

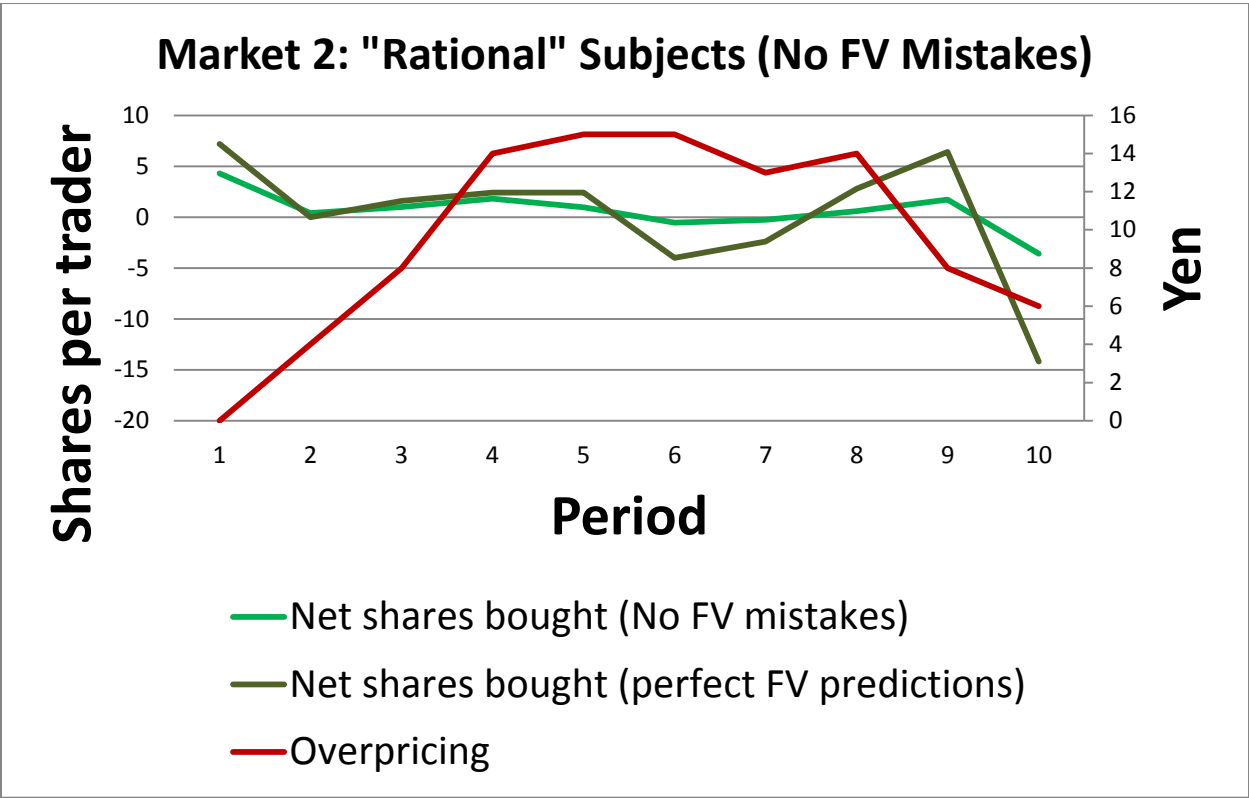
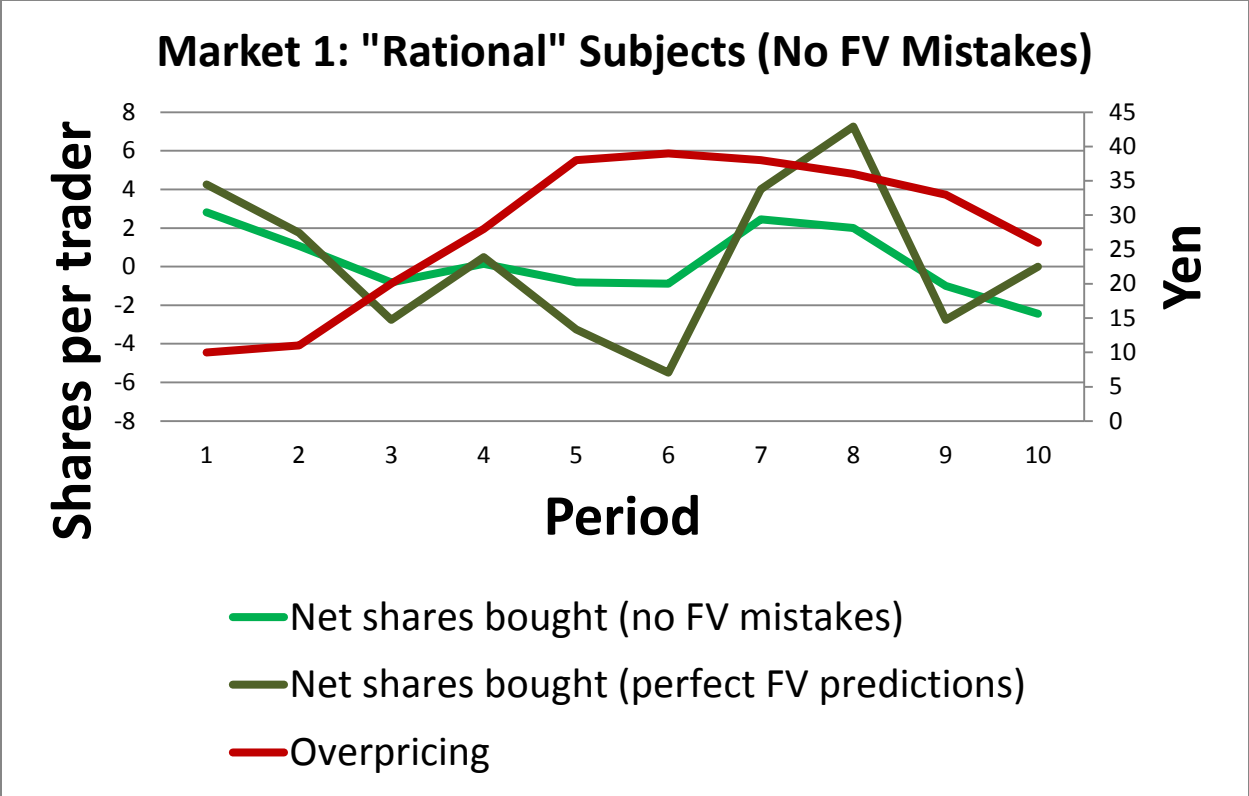


Fig. 10: Trading Decisions vs. Prices, "Rational" Subjects

**Table 1: Treatments**

Day	# of Subjects	Treatment
1	26	Basic
2	3	Basic
3	20	Uncertain
4	19	Pictures
5	15	Basic

**Table 2: Correct Fundamental Beliefs as a Function of Lagged Overpricing - Fixed Effects Logit Model**

Outcome Variable	Market	Restriction	Coefficient on OVERP <sub>t-1</sub>	p-value
NOMIS <sub>it</sub>	1	none	-.0651 (.0145)	0.000
NOTOFF <sub>it</sub>	1	none	-.0341 (.0112)	0.002
COR <sub>it</sub>	1	none	.0156 (.0108)	0.146
NOMIS <sub>it</sub>	1	NOMIS <sub>1</sub> = 1 and E2[FV2]< E1[FV1]	-.0656 (.0319)	0.040
NOTOFF <sub>it</sub>	1	NOMIS <sub>1</sub> = 1 and E2[FV2]< E1[FV1]	-.0595 (.0190)	0.002
NOMIS <sub>it</sub>	1	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> =1	-.1320 (.0384)	0.001
NOTOFF <sub>it</sub>	1	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> =1	-.1695 (.0365)	0.000
NOMIS <sub>it</sub>	2	none	-.1219 (.0352)	0.001
NOTOFF <sub>it</sub>	2	none	-.0824 (.0268)	0.002
COR <sub>it</sub>	2	none	-.0026 (.0236)	0.912
NOMIS <sub>it</sub>	2	NOMIS <sub>1</sub> = 1 and E2[FV2]< E1[FV1]	-.1946 (.0792)	0.014
NOTOFF <sub>it</sub>	2	NOMIS <sub>1</sub> = 1 and E2[FV2]< E1[FV1]	-.0849 (.0440)	0.054
NOMIS <sub>it</sub>	2	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> =1	-.1727 (.0744)	0.020
NOTOFF <sub>it</sub>	2	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> =1	-.3237 (.0901)	0.000

**Table 3: Trade-Weighted Fundamental Mistakes - Adaptive Model**

$$TWM_{it} = \alpha + c_i + \beta P_t + (1 - \beta) TWM_{i,t-1} + \varepsilon_{it}$$

Market	Restriction	$\beta$	p-value	R-squared (within-panel)
1	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> = 1	.7042 (.0936)	0.000	0.208
1	NOMIS <sub>1</sub> = 1 and E2[FV2] < E1[FV1]	.5682 (.0993)	0.000	0.152
2	NOTOFF <sub>1</sub> = NOTOFF <sub>2</sub> = 1	.3193 (.0478)	0.000	0.177
2	NOMIS <sub>1</sub> = 1 and E2[FV2] < E1[FV1]	.2963 (.1974)	0.136	0.016

**Table 4a: Adaptive Expectations Model of Next Period Price Predictions**

$$PRN_{it} = \alpha + c_i + \gamma P_t + (1 - \gamma) PRN_{i,t-1} + \varepsilon_{it}$$

Market	Restriction	$\gamma$	p-value	R-squared (within-panel)
1	none	.9516 (.0136)	0.000	0.880
1	NOMIS <sub>it</sub> = 1 for all t	.9897 (.0071)	0.000	0.989
2	none	.6220 (.0356)	0.000	0.319
2	NOMIS <sub>it</sub> = 1 for all t	.5848 (.0600)	0.000	0.284

**Table 4b: Adaptive Expectations Model of Final Period Price Predictions**

$$PR10_{it} = \alpha + c_i + \delta P_t + (1 - \delta) PR10_{i,t-1} + \varepsilon_{it}$$

Market	Restriction	$\delta$	p-value	R-squared (within-panel)
1	none	.8791 (.0085)	0.000	0.942
1	NOMIS <sub>it</sub> = 1 for all t	.9111 (.0100)	0.000	0.975
2	none	.6523 (.0292)	0.000	0.432
2	NOMIS <sub>it</sub> = 1 for all t	.6490 (.0487)	0.000	0.426

**Table 5: Net Buying as a Function of Believed Overpricing (Mistaken Traders)**

$$\text{NETBUY}_{it} = \alpha + c_i + \beta \text{DM}_{it} + \varepsilon_{it}$$

Market	Restriction	$\beta$	p-value
1	$\sum_t \text{NOMIS}_{it} < 2$	-0.0001 (.0030)	0.976
2	$\sum_t \text{NOMIS}_{it} < 2$	0.0104 (.0040)	0.011

**Table 6: Net Buying as a Function of Beliefs (Well-Calibrated Traders)**

$$\text{NETBUY}_{it} = \alpha + c_i + \beta_f \text{PRBUB}_{it} + \beta_s \text{PRSTRISE}_{it} + \beta_l \text{PRLTRISE}_{it} + \varepsilon_{it}$$

Market	Restriction	$\beta_f$	$\beta_s$	$\beta_l$	p-value ( $\beta_f$ )	p-value ( $\beta_s$ )	p-value ( $\beta_l$ )
1	$\sum_t \text{NOMIS}_{it} > 8$	-0.0346 (.0137)	.1211 (.0409)	.0086 (.0183)	0.012	0.003	0.639
2	$\sum_t \text{NOMIS}_{it} > 8$	-0.0166 (.0166)	.0071 (.0063)	.0133 (.0218)	0.315	0.260	0.543

**Table 7: Net Buying as a Function of Momentum**

$$\text{NETBUY}_{it} = \alpha + c_i + \beta_1 (\text{Pt} - \text{Pt-1}) + \beta_2 (\text{Pt-1} - \text{Pt-2}) + \beta_3 (\text{Pt-2} - \text{Pt-3}) + \beta_4 (\text{Pt-3} - \text{Pt-4}) + \varepsilon_{it}$$

Market	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	p-value ( $\beta_1$ )	p-value ( $\beta_2$ )	p-value ( $\beta_3$ )	p-value ( $\beta_4$ )
1	.2035 (.0908)	-.2884 (.0935)	.1842 (.0958)	.3715 (.0710)	0.026	0.002	0.055	0.000
2	.0079 (.2215)	.3750 (.1461)	-.3061 (.2238)	.0261 (.2069)	0.972	0.011	0.172	0.900

**Table 8: Prediction Volatility as a Function of Uncertain Treatment Dummy**

Outcome Variable	Market	Regression Coefficient	p-value
VOLFi	1	30.6 (36.7)	0.406
VOLNi	1	-5.99 (16.2)	0.714
VOL10i	1	-34.7 (44.5)	0.438
VOLFi	2	72.0 (28.4)	0.013
VOLNi	2	-3.79 (4.71)	0.42
VOL10i	2	-5.74 (5.36)	0.288

**Table 9: Fundamental Mistakes as a Function of Uncertain Treatment Dummy**

Outcome Variable	Market	Regression Coefficient	p-value
NOMISi	1	-.1067 (.1084)	0.328
CORi	1	-.0961 (.0852)	0.263
NOMISi	2	-.1095 (.0412)	0.008
CORi	2	-.1811 (.0363)	0.000

**Table 10: Fundamental Mistakes as a Function of Pictures Treatment Dummy**

Outcome Variable	Market	Regression Coefficient	p-value
NOMISi	1	.1901 (.1090)	0.085
CORi	1	.1453 (.0859)	0.095
NOMISi	2	.2394 (.1158)	0.041
CORi	2	.2779 (.0831)	0.001

# Appendix A: Experimental Instructions

This is an experiment about decision-making in financial markets. In this experiment, you will participate in a computerized market, in which you will buy and sell a financial asset, and make predictions about the asset. The better investment decisions and predictions you make, the more money you take home, so invest wisely!

## The Asset

The asset that you will be buying and selling is computer-generated. It is divided into “shares.” You can buy and sell these shares individually.

The asset market is divided into 10 “periods.” At the end of each period, each share of the asset pays an amount of money called a “dividend.” This dividend is the amount of yen that you get for owning the share. The dividend is random, and is determined each period by a computerized random number generator. The dividends are the same for all shares, but different from period to period.

Here are the possible dividends, and the percentage chance of each:

<u>Dividend per share</u>	<u>Percentage chance</u>
0	50%
10	50%

So if you own 3 shares at the end of Period 6, there is a 50% chance that you will get 30 yen in dividend payments at the end of Period 6, and a 50% that you will get 0 yen.

## Buying and Selling

You will have a computerized cash account and asset portfolio. The cash account contains your cash. You can use this cash to buy and sell shares of the asset. The asset portfolio contains your shares of the asset.

Each period, you will see the market price of the asset. You can buy as many shares as you like at this market price, as long as you have enough cash in your account. For example, if you have 1000 yen in your account and the market price is 100, you can buy up to 10 shares. Alternatively, you can sell shares at the market price. You can sell as many shares as you have in your account. Buying and selling shares does not change the price. In each period, you can buy or sell shares, but not both.

The market price comes from an earlier experiment. In that experiment, groups of 5 or 6 people (experimental subjects like yourself) traded the asset among themselves. The average price they paid for the asset in each period became the “market price” that you see.

In addition to the market price, you will see the “high” and “low”. These are the highest and lowest prices that were paid for the asset when the market price was determined. You cannot buy and sell at these prices, only at the market price. However, looking at the high and low may help you decide how much to buy or sell.

The amount of cash in your account after at the end of each period:

Your cash at the beginning of the period – (# of shares you bought) x (market price) + (# of shares you sold) x (market price) + (this period’s dividend) x (the number of shares in your portfolio)

At the end of the market, you get to take home all the cash in your account.

## Predictions

Before each period, you will be asked to predict three things:

### 1. The market price in the upcoming period

This is your prediction of what you think the market price will be in the period that is about to start.

### 2. The market price in the final period (period 10)

This is your prediction of what you think the market price will be in the FINAL period of the market.

### 3. The Total Dividend Yield Per Share

The Total Dividend Yield Per Share is the TOTAL amount of dividends that you think someone would receive from ONE share of the asset, if they bought the share in the upcoming period and held it until the end of the market. So if you think that someone who bought 3 shares this period and held them until the end of the market would receive a total of 300 yen in dividends from those 3 shares, then the Total Dividend Yield Per Share is 100.

## The Trading Software

The trading software you will be using is called z-Tree. We will show you how it works.

You will always see the following information at the top of the screen

- Period** ← This is the current trading period. If it is between periods, this is the number of the next period.
- Time Remaining** ← This is the time left for you to make your decision.

You will always see the following information in a column on the right-hand side of the screen:

- Cash** ← This shows how much cash you currently have in your account. Cash is denominated in yen.
- Shares** ← This shows how many shares of the asset you currently own. This is called your “portfolio”.

You will also see the following information in a column on the left of the screen:

**Market Price**

← This is the price of the asset. You can buy and sell at this price.

**High**

← This is the highest price paid for a share of the asset (by the people in the market where the price was determined).

**Low**

← This is the lowest price paid for a share of the asset (by the people in the market where the price was determined).

On the left hand side of the screen, you will also see two charts:

**Price History**

← This shows the market price in each of the previous periods

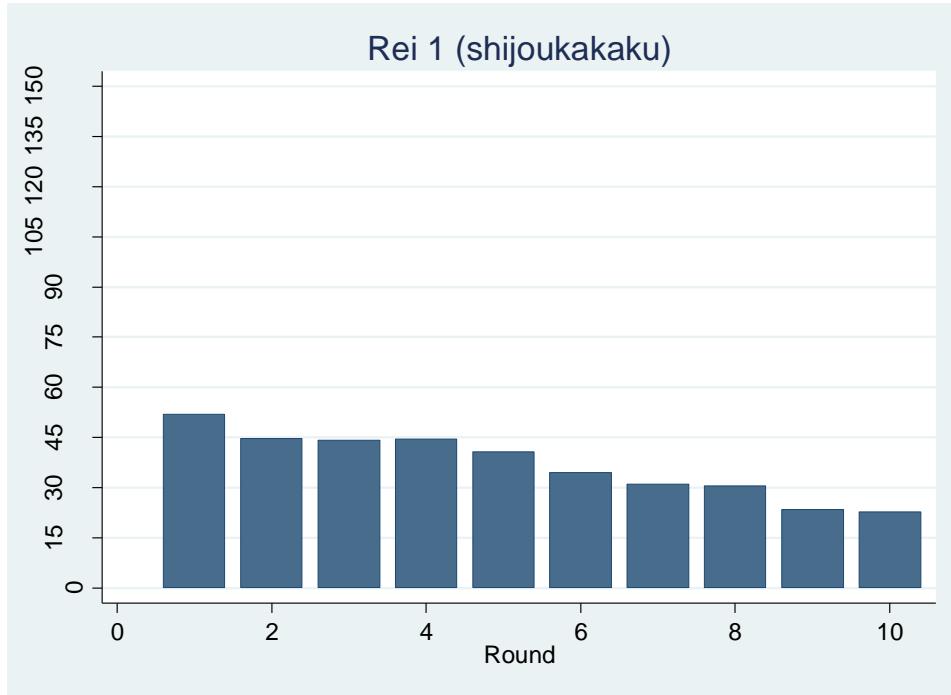
**Dividend History**

← This shows the dividend (per share) paid to holders of the asset in each of the previous periods

Finally, you will see **input boxes**. These are the boxes where you make your predictions and your buying/selling decisions.

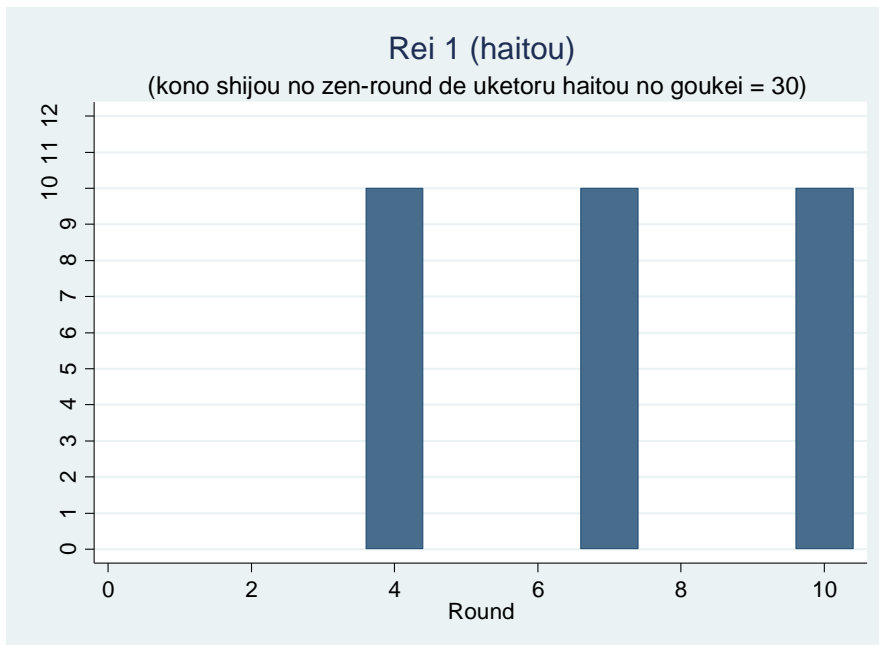
# **Examples of Market Prices and Dividends**

### Example 1 (market price)

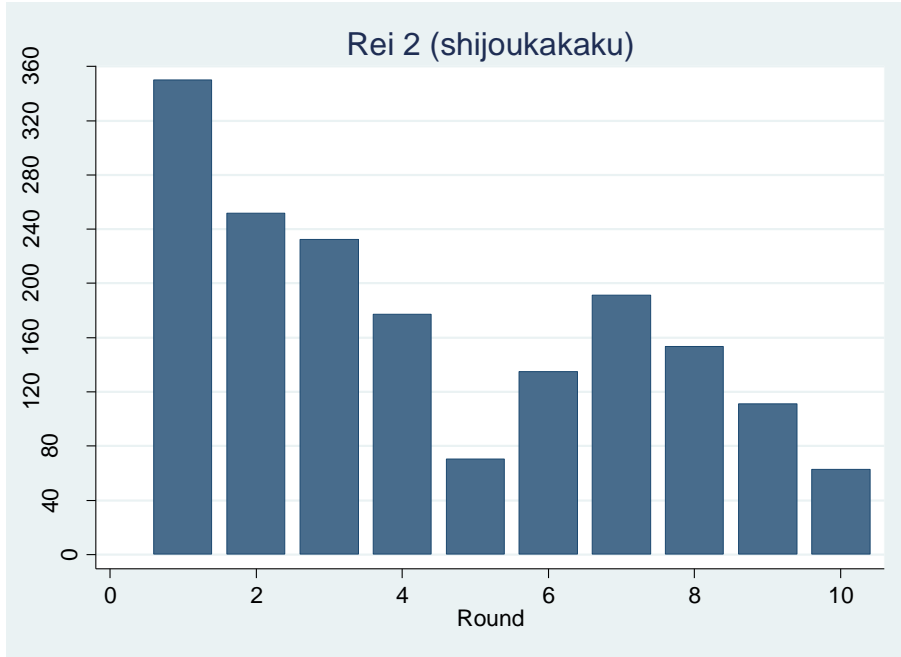


### Example 1 (dividends)

(total dividend per share received in this market = 30)

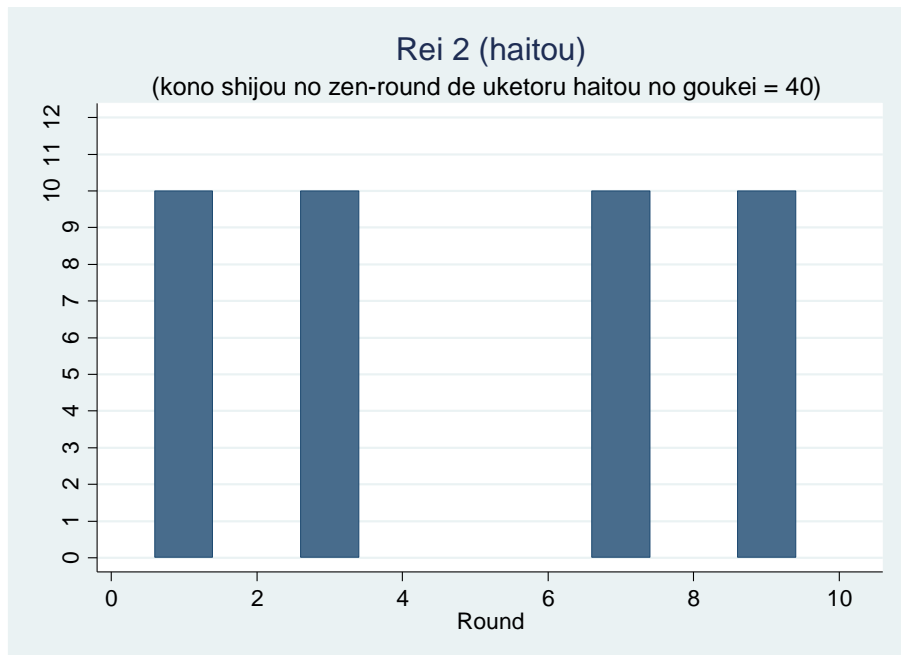


### Example 2 (market price)

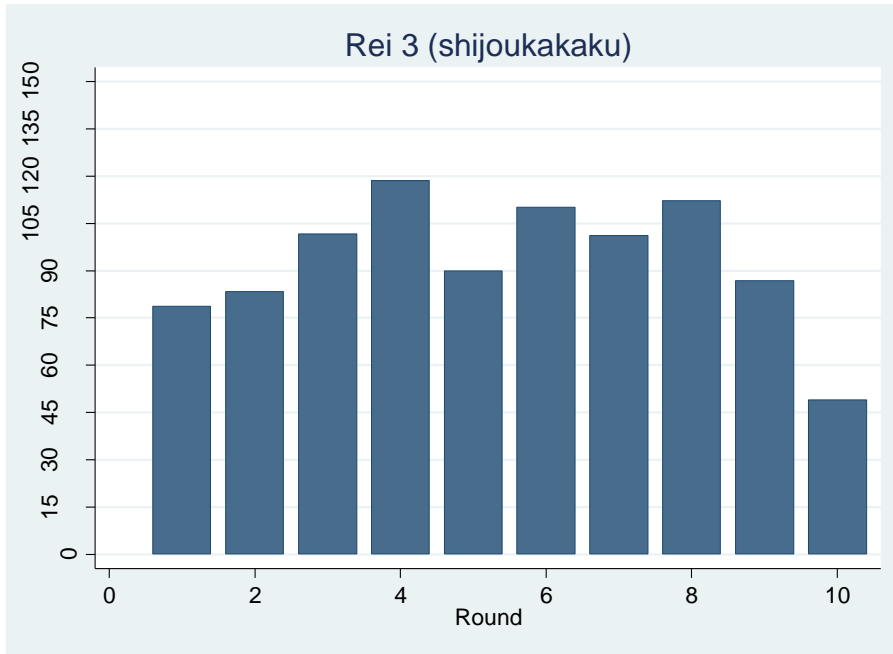


### Example 2 (dividends)

(total dividend per share received in this market = 40)

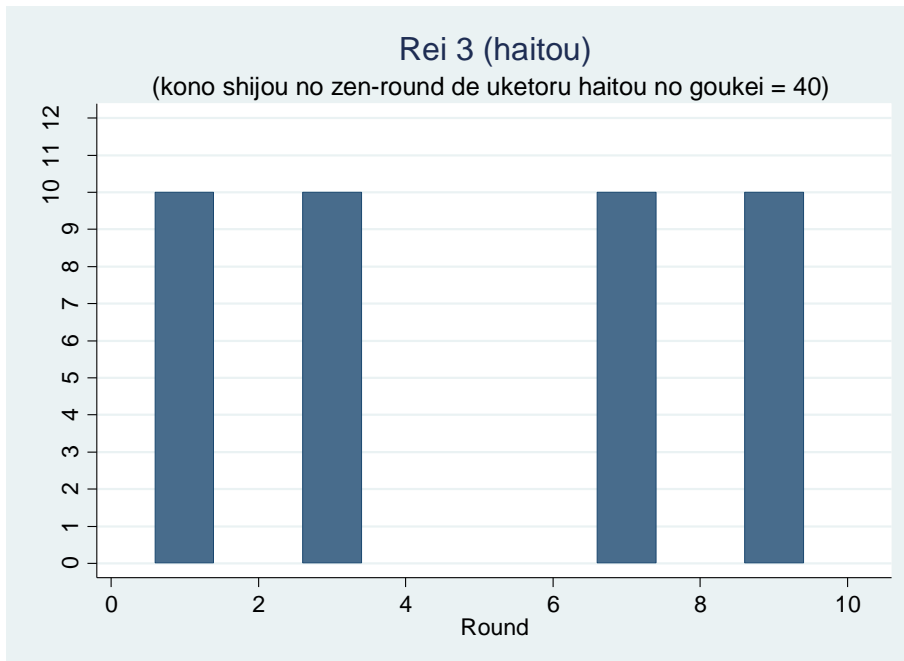


### Example 3 (market price)

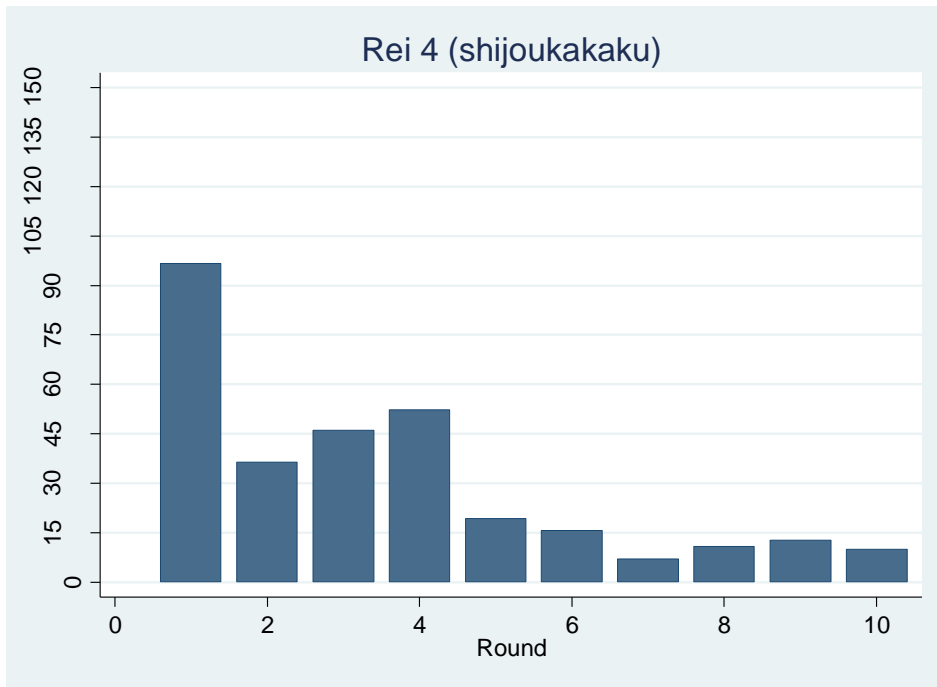


### Example 3 (dividends)

(total dividend per share received in this market = 40)

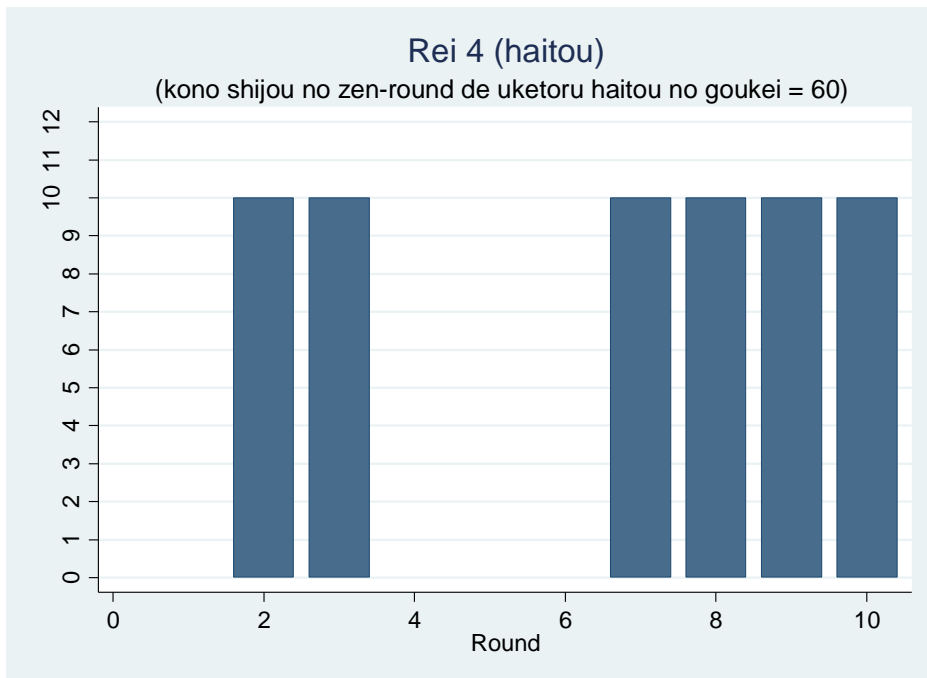


### Example 4 (market price)



### Example 4 (dividends)

(total dividend per share received in this market = 60)



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