Individual Trader Behavior in Experimental Asset Markets

Noah Smith

July 2, 2012

Abstract

I investigate the behavior of individual investors in an experimental asset market that features a bubble. Subjects trade a risky asset at prices that do not change in response to their trades. The prices are taken from the outcome of a previous asset market experiment. This unique setup makes it possible to identify behavioral differences between subjects who understand asset fundamentals and those who do not, and also to isolate the factors driving asset demand. I find broad similarity between the behaviors of subjects with different levels of understanding. Even subjects who demonstrate good understanding of fundamentals tend to buy at prices that they know to exceed those fundamentals, thus giving up chances for certain gains. These subjects' trading decisions are influenced by their predictions of short-term price movements, showing that speculation exists in this market. I also find that lagged asset prices are a strong predictor of trading behavior, indicating a possible role for a type of herd behavior, in which subjects erroneously use the price as a signal of asset value. These results shed light on why bubbles may persist despite the presence of rational traders in the market.

1 Introduction

Many severe and protracted recessions begin just after the occurrence of large and rapid rises and crashes in asset prices, commonly known as asset-price "bubbles." In particular, the U.S. financial crisis of 2008 and the deep recession that followed were immediately preceded by a large rise and crash in U.S. housing prices. This begs the question: Do the asset price movements actually *cause* the slumps in real output? That possibility makes the "bubble" phenomenon an important target for research.

Disagreement exists as to whether these rises and crashes are rational responses to information about asset fundamentals, or whether they represent large-scale mispricings. In fact, some economists use the term "bubble" to refer only to episodes in which prices exceed fundamentals. Thus, the literature contains (at least) two alternative definitions for bubbles, one phenomenological and the other theoretical:

1. Definition 1 (phenomenological): A "bubble" is an "upward [asset] price movement over an extended range that then implodes" (Kindleberger 1978).

2. Definition 2 (theoretical): A "bubble" is a sustained episode in which assets trade at prices substantially different from fundamental values.

It is difficult to determine empirically whether bubbles in the sense of Definition 1 are also bubbles in the sense of Definition 2, since real-world fundamentals are rarely known. Laboratory experiments are thus an attractive technique for studying bubbles, since the experimenter knows fundamental values with certainty. Importantly, this represents a rare instance in which lab experiments may have direct relevance for understanding macroeconomic phenomena.

The classic "bubble experiments" of Smith, Suchanek, and Williams (1988) found dramatic mispricings that resembled real-world bubbles. However, the validity of these "lab bubbles" has been questioned by subsequent research. Many researchers suggest that the mispricing in these experiments is purely due to subject confusion about fundamental values - when subjects correctly understand fundamentals, these researchers say, "lab bubbles" invariably disappear. This critique is closely related to a common theoretical argument against the existence of bubbles, i.e. the idea that well-informed traders will "pop" bubbles by selling when prices are above fundamentals (Abreu and Brunnermeier 2003). The question of whether large, sustained asset mispricings can exist, in the lab or in the real world, hinges on the question of *whether traders with good information about fundamentals tend to "join" bubbles.*

Theories exist as to why they might. One idea is that well-informed traders may engage in *speculation*, ignoring their understanding of fundamentals in order to bet on price movements and reap a capital gain[1]. A second idea is *herd behavior*, in which traders choose to ignore their own information about fundamentals in order to "follow the market". Herding might apply to sophisticated traders directly, or could provide a coordination mechanism for irrational "noise" traders whose collective

---

[1]Indeed, some economists consider speculation to be so central an explanation of bubbles that they define a "bubble" only as a mispricing caused by speculation; see, for example, Brunnermeier (2007).

action overwhelms the ability of sophisticated traders to arbitrage against them.[2] In order to determine which phenomena (if any) causes sophisticated traders to ride bubbles, economists must *identify the factors that drive the asset demands of individual traders during bubble periods.*

The present study thus addresses two important unanswered questions in the bubble experiment literature:

1. Are subjects who understand fundamentals in asset market experiments willing to pay prices in excess of those fundamentals?

2. What are the factors driving subjects' asset demands during these bubbles?

To answer these questions, I study individual investor behavior in a new type of experimental asset market that has not previously been used in this literature[3]. Using prices and dividends taken from a previous laboratory market in the style of Smith, Suchanek, and Williams (1988), I confront subjects with these time series and give them the opportunity to trade the same asset at the given market prices; I call this a *partial-equilibrium* setup. This unique setup confers at least two advantages in answering the two questions listed above. First, because the subjects in the present experiment do not interact with one another, the decisions of subjects who correctly understand asset fundamentals can be analyzed independently from the decisions of subjects who may be confused or mistaken about fundamentals. Thus, the setup can determine whether sophisticated traders in a laboratory setting regularly "buy into" bubbles. Second, the partial-equilibrium setup also allows me to study the factors influencing individual traders' asset demands. This is in contrast to the group market setup normally used in the literature, in which feedback effects exist between prices and expectations. These advantages make the partial-equilibrium setup an important addition to the toolkit of experimental economists who study bubbles.

Using this setup, I find that:

1. "Smart traders" do buy into bubbles. Subjects who demonstrate clear understanding of the risky asset's fundamental value nevertheless tend to buy the asset at prices that they know to be well in excess of that value, thus passing up an opportunity for certain gains. This buying is concentrated just after the peak of the price bubble.

---

[2]In general, this can happen when traders either are risk-averse or have constraints on short selling.

[3]At least, to the author's knowledge.

2. "Smart traders" engage in speculation. There is a significant positive correlation between a subject's trading decisions and her predictions of short-term price movements. This correlation is stronger for subjects who demonstrate understanding of fundamentals than for those who do not.

3. There is a large and significant positive correlation between lagged average asset prices and subjects' decisions to buy the asset, independently of their price predictions.

These results imply that the "bubble" result common to many asset-pricing experiments need not be purely due to subject confusion about fundamentals, and probably has more external validity than many now suppose. they also show that speculation by relatively sophisticated subjects is present in laboratory asset bubbles. The third result indicates the presence of a second source of asset mispricing, potentially related to herd behavior, that merits further study.

Section 2 describes related literature and discusses how the present study relates to that literature. Section 3 details the experimental setup and methodology. Section 4 presents and discusses the results of the experiment. Section 5 concludes.

2 Related Literature

2.1 Bubbles in experimental asset markets

In a laboratory market, fundamental values are known to the experimenter, so mispricings can be identified with certainty. The best-known instance in which this has occurred is in the classic "bubble experiments" by Smith, Suchanek, and Williams (1988) (henceforth SSW). In that study, small groups of subjects traded a single short-lived risky asset against cash using a continuous double auction market. The asset paid a dividend after every trading period, and the i.i.d. stochastic process governing the per-period dividend was told to all traders before the experiment. The outcome 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 next two decades, this fascinating bubble result was replicated by many other studies, and proved robust to many changes in market institutions and asset fundamentals.[4]

---

[4]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.

However, many have questioned the external validity of this result. Although fundamentals in these studies are known to the experimenter, and are *told* to subjects, subjects may be confused and fail to understand the dividend process. Laboratory "bubbles" may therefore simply reflect subjects' mistakes, rather than some more interesting phenomenon like speculation. This was proposed by Fisher (1998), who wrote: "[Experimental asset market] bubbles arise for two reasons. First, subjects take time to learn about the dividends, not trusting initially the experiment's instructions. Second, agents have heterogeneous prior beliefs." Hirota and Sunder (2007) go even further, calling the SSW result "a laboratory artifact."

In the 2000s, a number of studies emerged that appeared to support this conclusion. Lei, Noussair, and Plott (2001) showed that SSW-type bubbles can occur even when resale of the asset (and, hence, speculation) is not allowed. That implies that subjects simply fail to understand the experimental parameters. Lei and Vesely (2009) find that when subjects are allowed to experience the dividend process before the experiment, they generate no bubbles. Dufwenberg, Lindqvist, and Moore (2005) find that even when only two out of a group of six subjects have recently participated in a similar experimental asset market (and thus presumably understand the dividend process), bubbles do not occur. And Kirchler, Huber, and Stockl (2010) find that simply giving the asset a different name dramatically reduces bubbles.[5]

These results[6] suggest an emerging consensus that laboratory bubbles only occur when most or all of a subject group fails to understand asset fundamentals. If true, that would make the classic SSW result fairly uninteresting for the study of real financial markets, since most professional investors presumably at least understand the basics of valuation of the asset classes in which they invest.

However, this emerging consensus has not yet been tested conclusively. This is because the type of asset market used in all of the aforementioned studies has inherent limitations that make it difficult to systematically characterize the behavior of traders with different levels of understanding. Because most markets involve a mix of subjects who understand asset fundamentals and those who do not, the decisions of "smart" traders can both influence and be influenced by the decisions of "confused" traders. It is therefore difficult to tell if bubbles in laboratory asset markets are

---

[5]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.

[6]A few studies, however, hint that the SSW bubble result may not simply be an artifact. Haruvy, Lahav, and Noussair (2007) elicit predictions of future prices from traders in a bubble experiment. They find that after having once observed a price runup and crash, subjects predict price peaks and attempt (unsuccessfully) to sell their holdings before the predicted peak.

occurring *in spite* of the actions of "smart" traders, or *because* of them.

This is why the partial-equilibrium setup used in the present study has the potential to shed new light on the by-now somewhat byzantine bubble experiment literature. By independently observing the behavior of "smart" and "confused" traders, the setup can test the notion that bubbles are merely the (uninteresting) result of confusion about fundamentals.

2.2   Theories of bubbles

Theories exist in which bubbles can form without the participation of traders who understand fundamentals. "Heterogeneous belief" models obtain the result that if short selling is constrained, prices are determined by the valuations of the most optimistic investors (Harrison and Kreps 1978, Morris 1996). These models occupy a middle ground between the view that bubbles reflect the best available forecast of fundamentals and the view that bubbles are large-scale mispricings (Barsky 2009). However, bubbles in these models are not particularly robust to the presence of substantial percentages of traders who know true fundamentals, or to the relaxation of constraints on short-selling.

Other models have been developed to show how well-informed traders may choose to "buy into" bubbles rather than trade against what they know to be mispricings. These include the "noise trader" models of DeLong, et. al. (1990a and 1990b), and Abreu and Brunnermeier (2003). In noise trader models, rational arbitrageurs interact with fundamentally irrational "noise traders"; when the coordinated actions of the latter produce bubbles, arbitrageurs may only be able to trade against the bubbles by accepting large amounts of risk, including the risk inherent in the asset itself (fundamental risk), the risk that noise trader demand for the asset will increase even further (noise trader risk), and the risk that other arbitrageurs will choose to "ride" the bubble instead (coordination risk).

A third class of models exists. In models of "herd behavior," rational investors ignore their private information about fundamentals, because market imperfections force them to over-rely on the actions of other traders as a source of information about fundamentals (Avery and Zemsky 1998). Because of the loss of information due to incomplete markets, prices in these models do not reflect the best possible forecast of fundamentals given the total information present in the market. Models of herd behavior are typically highly stylized and sensitive to market institutions; hence, they have received comparatively little attention as an explanation for bubbles.

Each of these theories relies on a different factor that governs asset demands: beliefs about fundamentals in the case of heterogeneous-prior models, price predic-

tions in the case of speculation models, and market prices and trades in the case of herding models. The existing bubble experiment literature therefore has difficulty testing these theories, since the factors listed above will in general be both endogenous to trading decisions and subject to interaction effects between traders. Thus, identifying the factors governing asset demand is another task at which the partial-equilibrium approach is a useful addition to what has been used in the past.

3 Experimental Setup

The asset market in this study differs substantially from that found in most asset-market experiments. The main difference is that in this experiment, subjects trade in a partial-equilibrium market; i.e., prices are not affected by the actions of subjects. Because of this, subjects do not interact, asset supply is not fixed, and markets do not clear. This setup is similar to that used by Schmalensee (1976) and Dwyer (1993) to study expectation formation. It has the advantage of being able to isolate the effects of prices on beliefs and behavior, since prices are pre-determined. It also has the advantage of being able to differentiate between the behavior of different types of subjects. Finally the effects of experimental treatments on individual-level variables can be measured by cross-sectional statistical analysis, without the presence of between-subject interaction effects. However, these advantages come at a cost; because markets do not clear, equilibrium outcomes cannot be observed. Thus, the partial-equilibrium setup is a complement to the typical setup, not a substitute.

In addition, the setup in this experiment introduces a new way to measure understanding of fundamentals. Understanding is verified dynamically by asking subjects to predict, *each period*, the future dividend income stream associated with one share of the asset. This approach has the advantage that it measures understanding of fundamentals at the time that trading occurs, so that subjects who seem to understand fundamentals at the experiment's outset but who later question their understanding will not be mis-classified as understanding fundamentals. Also, asking about dividend income as merely one prediction among many reduces the possibility of leading subjects by emphasizing dividends as the sole measure of fundamental value.

3.1 Source of the parameters

In order to maximize this study's relevance to the existing literature, I use prices and dividends that correspond as closely as possible to what is seen in a typical "bubble experiment." Before the experiment, I obtained a series of prices and dividends from a previous asset market experiment, conducted on June 6, 2011 at the University

of Michigan. That experiment was a "group bubble experiment," extremely similar in nature to the original SSW setup. For the details of that previous study, see Smith (2011).[7] The market from which the present study's prices were taken will henceforth be referred to as the "Source Market." The Source Market prices and dividends (each corresponding to one share of the asset) can be seen in Figure 1, along with the fundamental value of the asset. It is clear that Market 1 produced a bubble, both in the sense of a rise and fall in prices, and also in the sense of a mispricing. Market 2 produced what might or might not be called a bubble; prices are flat, but are above fundamentals for most of the market.[8] Both price series follow the classic patterns for the first and second repetitions[9] of a SSW-type asset market.

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.[10] 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 (~$33) was paid as a "show-up fee," and the rest, averaging 1823 yen (~$24.30) per subject, as experimental incentives.

---

[7]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.

[8]The subjects who produced the prices for Market 2 were the same group as for Market 1. Thus, the experience level of the subjects in the source experiment roughly matched the experience level of the subjects in the present experiment.

[9]That is, the first and second times within the experiment that the subjects participate in an asset market of this type.

[10]One possible advantage of using Japanese subjects is that, at the time the experiment was conducted, most asset prices in Japan had been trending down for over two decades. The possibility that American or European subjects might have a tacit belief that "asset prices always go up in the long run" is therefore not present here.

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.

Subjects participated in two experimental "markets," each of which lasted 10 periods.[11] 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. 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.[12]

This partial-equilibrium 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' actions 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.

After trading in each period, 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.[13] The dividends differed from period to period, but were the

---

[11]The term "market" is a bit of a misnomer, since the subjects did not interact with one another, but only with a computer.

[12]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.

[13]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

same for each share and each subject 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. Therefore the asset's risk-neutral fundamental value per share in period t, assuming zero discounting, is given by:

$$FV_t = 55 - 5t \tag{1}$$

Subjects were repeatedly told that the prices and dividends they were observing were taken from a previous group experiment at the University of Michigan, as described above.

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 for the period, 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.

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

- $\{P_1, P_2, ..., P_n\}$, where P_j is the market price of one share of the asset in Period j,

- $\{H_1, H_2, ..., H_n\}$, where H_j is the "high" in Period j,

- $\{L_1, L_2, ..., L_n\}$, where L_j is the "high" in Period j, and

- $\{D_1, D_2, ..., D_{n-1}\}$, 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 period in which to make three predictions (180 seconds for each of the first two periods of Market 1). Each was asked to predict:

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

---

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.

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

3. 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.

P3 is the expected value of one share of the asset, i.e. the fundamental value.
An explanation of the flow of the experiment can be seen in Figure 2.

Subjects were incentivized to make accurate predictions about price and fundamentals. For each of the three predictions made in each period, subjects were paid according to the following formula:

$$\text{Payment} = 25¥ - 2¥ \times |\text{prediction - realized value}|$$

The total maximum prediction incentive per period was slightly more than that paid 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.[14] The theoretical maximum prediction incentive received a subject who made 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.

3.4   Market 2

Subjects in this experiment participated in a repetition of the asset market. This was done in order to ascertain what behavioral changes, if any, would be caused by "design experience."[15] After a subject finished the first market (Market 1), she was allowed to begin Market 2 immediately[16]. Market 2 was identical to Market 1 in all

---

[14]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.

[15]"Design experience" simply means "experience with a particular market setup."

[16]This somewhat ameliorates the "active participation effect" proposed by Lei, Noussair, and Plott (2001). Those authors suggested that sophisticated traders join bubbles in these experiments because otherwise they would have nothing to do during the experiment and would hence become bored. In the present study, subjects were able to rapidly click through to the end of a market and collect dividends rapidly without trading, if they so chose.

respects, except that the prices and dividends were different (subjects were told this). Subjects were not told that the traders in the Source Market for Market 2 were the same individuals as the traders in the Source Market for Market 1 (in fact, they were the same). Henceforth, I sometimes refer to Market 2 traders as "design-experienced" traders, and Market 1 traders as "design-inexperienced" traders.

3.5 Experimental Treatments

The above description completely describes the experimental setup for Treatment 1, the "Basic" treatment. 44 of the subjects participated in this treatment. In addition, there were two other experimental treatment conditions, the "Uncertain" treatment and the "Pictures" treatment, which encompassed 20 and 19 subjects, respectively.

Treatment 2 is called the "Uncertain" treatment. In this treatment, 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 that the probabilities were constant every period and between both markets; however, they did not know the values of the probabilities. This treatment was included in order to test for the existence of a particular form of herding: namely, whether or not subjects update their beliefs about fundamental values to reflect observed market prices. This type of herding, however, was not observed.

Treatment 3 is called the "Pictures" treatment. In this treatment, subjects were shown images of price and dividend series from several other markets in the same experiment as the Source Market.[17] The idea was to give these subjects a general idea of what kind of price movements to expect in these markets, coupled with a (slightly) better understanding of the dividend process; in general, it was thought that seeing the "pictures" would provide these 19 subjects with a sort of market experience. The pictures shown to the subjects can be seen in Appendix B. Three out of the four price series in these pictures included mispricings, two included a rise-and-crash pattern, and one was close to rational pricing; the pictures were thus fairly representative of the typical mix of results in a bubble experiment. One hypothesis was that subjects in this treatment, knowing that prices often tended to rise and then fall, would speculate more than subjects in other treatments; this would be consistent with the

---

[17]Actually, these series were not perfectly 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 (2011). In addition, one of the pictures came from a market whose participants had already participated in one experimental market. However, subjects in the current experiment were not told either of these things, as the idea behind the Pictures treatment was merely to give these subjects a general idea of what they might encounter in the market.

results of Haruvy, Lahav, and Noussair (2007). An alternative hypothesis was that seeing examples of dividends might make these subjects understand fundamentals better, and that they would therefore avoid buying during bubbles, consistent with the result in Lei and Vesely (2009). In fact, both of these hypotheses are formally rejected by the data.

4   Results

In this section I first describe some general features of the experimental data, and then present the paper's three key results:

Result 1: *Even subjects who understand fundamentals well tend to buy at prices that are well above fundamental value.*

Result 2: *Subjects who understand fundamentals well tend to trade based on their predictions of short-term price movements.*

Result 3: *Lagged average prices are a significant predictor of trading decisions.*

Throughout the rest of the paper, I use the terms "traders" and "subjects" interchangeably. I use the term "smart traders" to refer to subjects who understand fundamentals, and the term "confused traders" to refer to subjects who do not demonstrate understanding of fundamentals[18].

Standard errors in all regressions are clustered at the individual (subject) level.

4.1   Description of the Data

Four kinds of data were collected in this experiment: predictions about asset fundamentals, predictions about next-period prices, predictions of final-period prices, and trading decisions. The following subsections describe some general features and interesting properties of these variables.

---

[18]This terminology is not meant to indicate that traders who understand fundamentals necessarily trade in a "smart" way. The term "smart traders" is meant to indicate that subjects who understand the experimental parameters are "smart" relative to this experiment, while not necessarily being smarter in some more general sense (higher I.Q., etc.).

4.1.1 Beliefs about fundamentals

Each period, subjects predict the expected future dividend income per share (fundamental value). This makes it possible to identify subjects who understand the fundamental value well. To quantify how well a subject understands fundamentals, I define subject i's "mistake" about fundamentals at time t as the difference between her prediction of the fundamental in period t and the correct value:

$$M_{it} \equiv E_{it}[FV_t] - FV_t \qquad (2)$$

Since one primary purpose of this study is to analyze the behavior of subjects who understand fundamentals "well," it is necessary to specify what size and frequency of mistakes disqualify a subject from this category. First, I introduce three categorizations of the size of M_{it}, in increasing order of stringency:

1. "Small" mistake: $abs(M_{it}) \leq FV_t$

2. "Smaller" mistake: $abs(M_{it}) \leq \sigma FV_t$, where σ is an arbitrary parameter between 0 and 1, set to 0.5 for simplicity[19]

3. "Smallest" mistake: $abs(M_{it}) \leq 5$

A "small" mistake indicates that the subject predicted a value for the fundamental that was possible at time t (since the maximum possible value of the per-share dividend is just twice the expected value, and the minimum is zero). A "smaller" mistake indicates that the subject's prediction was reasonably close to the correct expected value; this makes allowances for Bayesian updating of dividend probabilities.[20] A "smallest" mistake indicates that the subject's prediction precisely equaled the correct expected value, with allowance for convex preferences over prediction accuracy (i.e., a desire to guess the "exact right" dividend value; in odd-numbered periods, the mathematical expected value of the total remaining dividend is not actually a possible realization).

I then introduce two specifications for whether a subject "understands fundamentals or not" at time t:

---

[19]All results in this paper continue to hold if the parameter σ is set at 0.2 instead of 0.5. Thus, setting $\sigma = 0.5$ is done only for simplicity, not because the results for "smart traders" depend on using a lax criterion for understanding of fundamentals.

[20]In the Uncertain treatment, Bayesian updating is appropriate. In the other treatments, it is not, but I consider it to be only a small departure from rationality.

1. A subject is "correct" at time t if her mistake about fundamentals at time t is smaller than a certain size, and "incorrect" otherwise.

2. A subject is "smart" at time t if her mistakes about fundamentals are smaller than a certain size for all times earlier than or equal to t, and "confused" otherwise.

In other words, "correct"/"incorrect" measures whether a subject is *currently* mistaken about fundamentals, and "smart"/"confused" measures whether a subject has *ever* been mistaken about fundamentals during the current market. "Smart"/"confused" is therefore a much more stringent criterion for understanding.

Crossing the three mistake size categories by the two specifications of mistakenness yields six dummy variables for understanding of fundamentals. These six dummies, which I will henceforth call "smartness dummies," are listed in Table 2, along with the number of traders who meet each criterion in each period. For the rest of the analysis in this paper, I generally use the smartness dummies $D\_MORECORRECT_{it}$ and $D\_SMARTER_{it}$ when analyzing the data:

$$D\_MORECORRECT_{it} \equiv \begin{cases} 0 & |M_t| > 0.5(55 - 5t) \\ 1 & |M_t| \le 0.5(55 - 5t) \end{cases} \tag{3}$$

$$D\_SMARTER_{it} \equiv \begin{cases} 0 & |M_\tau| > 0.5(55 - 5\tau) \\ 1 & |M\tau| \le 0.5(55 - 5\tau) \end{cases} \forall \tau \le t \tag{4}$$

These dummies, which use the middle category of mistake size, represent a compromise between strictness and statistical power.

Although this study is focused on the behavior of subjects who understand fundamentals well, it is also interesting to ask whether or not subjects who are confused about the experimental parameters tend to become less confused over time. Figure 3 plots average mistakes vs. time in Market 1 for subjects for whom $D\_SMARTER_{i,10} = 0$ (that is, subjects who get the fundamentals wrong at least once). The average mistake falls over time. A fixed-effects regression of mistakes on time for this subgroup confirms that mistakes trend downward over the course of the market. This indicates that subjects learn about fundamentals over time.[21]

---

[21] An alternate interpretation is that some of the "confused" subjects are simply reporting the expected total dividend income for their portfolio, rather than the per-share dividend income. Such subjects, while confused about the question being asked of them, would actually be less confused about the experimental parameters than their predictions would suggest.

4.1.2 Beliefs about prices

Denote a subject's period-t predictions of prices in period t and prices in period 10 by:

$$E\_PNEXT_{it} \equiv E_{i,t+1}[P_{t+1}] \tag{5}$$

$$E\_PFINAL_{it} \equiv E_{i,t+1}[P_{10}] \tag{6}$$

Here, P_t denotes the price at time t, and the expectation operator indicates a subject's stated prediction.

Note that the expectations at time t are defined using predictions given at the beginning of period $t+1$. Because predictions are made before trading, but market prices are observed only during trading, there exists the possibility that a trader updates his/her price predictions *after* seeing the market price but *before* making his/her trading decision. In other words, subjects' true beliefs about future prices at the time they trade are not observed. It is therefore necessary to proxy for beliefs during the trading stage of period t with the predictions made at the beginning of period $t+1$. In the time between when trading occurs and when this proxy is observed, the period t dividend is realized; also, subjects may revise their beliefs for unobservable reasons. This will result in an errors-in-variables problem for regression estimates using these price predictions as explanatory variables:

$$E_{i,t+1}[P_{t+1}] = E\_PNEXT_{it}^* + f(D_t) + \mu_{it} \tag{7}$$

$$E_{i,t+1}[P_{10}] = E\_PFINAL_{it}^* + g(D_t) + \nu_{it} \tag{8}$$

Here, $E\_PNEXT_{it}^*$ is the "true" prediction of one-period-ahead price appreciation at the time that period t trading decisions are made, $f(D_t)$ is some function of the realized period-t dividend D_t, and μ_{it} is a mean-zero error term; the terms in Equation 8 are defined analogously. The presence of errors in variables will result in attenuation bias of the estimates of the beta coefficients on E_PNEXT_{it} and E_PFINAL_{it} when these variables are used as regressors; the true values of the coefficients will be larger than the estimated values. However, there is reason to believe that the systematic error from the observation of period-t dividends is negligible, since regressions of $E_{i,t+1}[P_{t+1}]$ and $E_{i,t+1}[P_{10}]$ on D_t do not find effects of dividends on subsequent price predictions that are significantly different from zero.

How do expectations evolve? Figure 4 shows plots average values of E_PNEXT_{it} and E_PFINAL_{it} over time for Market 1, along with lagged prices (i.e. the most

16

recently observed price when the prediction was made). The figure suggests that next-period price predictions are adaptive, i.e. that they track recently observed prices. That is the finding of Haruvy, Lahav, and Noussair (2007). Those authors also find that price predictions are extrapolative, i.e. that they incorporate the expectation that recent price movements will be continued. To test for adaptive and extrapolative expectations, I regress upcoming period price predictions on lagged prices and lagged price momentum, interacting momentum with a dummy for whether subjects are "smart" about fundamentals:

$$
\begin{aligned}
E\_PNEXT_{it} \; = \; & \alpha_i + \beta_P P_{t-1} + \beta_M (P_{t-1} - P_{t-2}) \\
& + \beta_S D\_SMARTER_{it} \\
& + \beta_{SM} D\_SMARTER_{it}(P_{t-1} - P_{t-2}) + \varepsilon_{it}
\end{aligned}
\tag{9}
$$

The results of this regression can be seen in Table 3. The coefficient on the lagged price is highly significant (p-value 0.000) and has a value of around 0.7, indicating that price expectations have an adaptive component. The coefficient on lagged momentum is not significantly different from zero, but the coefficient on the interaction term is positive and significant at the 5% level, indicating that traders who understand fundamentals tend to form extrapolative price expectations, but that traders who misunderstand fundamentals do not. These results are highly robust to alternative regression specifications, and to the use of an Arellano-Bond panel GMM estimator. These findings broadly confirm the findings of Haruvy, Lahav, and Noussair (2007).

However, there is substantial cross-sectional variation in price predictions. To illustrate this fact, Table 4 shows the cross-sectional standard deviation of E_PNEXT_{it} divided by the price P_t for each period in Market 1.

4.1.3 Trading Decisions

I use three measures of subjects' trading decisions. The first, $NETBUY_{it}$, is simply the number of shares bought or sold by trader i in period t. The second measure, $ACTION$, is a dummy variable that measures whether a trader bought, sold, or held in period t:

$$
ACTION_{it} \equiv \begin{cases} -1 & NETBUY_{it} < 0 \\ 0 & NETBUY_{it} = 0 \\ 1 & NETBUY_{it} > 0 \end{cases}
\tag{10}
$$

Since $NETBUY$ is just demand for the asset at the given price, it measures

17

whether a trader's actions would tend to inflate or deflate a bubble in a given period. However, $NETBUY$ is not a perfect measure of a subject's desire to hold the asset, because it depends on past trading decisions in a complex way. A subject who already has a large number of shares, but who perceives an increase in risk, may choose to hold or even to sell a few shares even if she believes the asset's return is greater than its price. Thus, it is desirable to have a measure of asset holdings that is not constrained by past decisions. Define $ASSETSHARE$ as:

$$ASSETSHARE_{it} \equiv \frac{SHARES_{it} * P_{it}}{SHARES_{it} * P_{it} + CASH_{it}} \qquad (11)$$

$SHARES_{it}$ and $CASH_{it}$ are defined after a subject's trading decision has been made, but before dividend income is received. Hence, $ASSETSHARE_{it}$ is the fraction of a subject's beginning-of-period wealth that she chooses to hold in the risky asset. Although psychological status quo bias may be present,[22] subjects are formally free to choose any $ASSETSHARE$ they like in each period. I also define $\widetilde{ASSETSHARE}_{it}$ as the deviation of a subject's asset share at time t from her average asset share in the entire market:

$$\widetilde{ASSETSHARE}_{it} \equiv ASSETSHARE_{it} - \frac{1}{10} \sum_{\tau=1}^{10} ASSETSHARE_{i\tau} \qquad (12)$$

Figure 5 plots the average values of $NETBUY$ and $ASSETSHARE$ across subjects for each period in Market 1, along with the asset price. Net asset demand is positive at the start of the bubble, near zero at the bubble peak, then strongly positive again directly after the peak, before turning negative in the final period; average asset holdings follow a similar path.

One interesting question is whether the price path imposed on the subjects in this experiment would represent a market equilibrium if the subjects were allowed to trade with one another. If net asset demand is zero (and assuming that asset demand doesn't depend on the trading process itself), then the given price would be an equilibrium[23]. For each period in Market 1, I test the null hypothesis that net

---

[22]Indeed, a rational risk-neutral trader will always set $ASSETSHARE$ equal to 0 or 1, depending on whether she predicts a negative or positive return for the risky asset. In actuality, subjects in this experiment often choose values of $ASSETSHARE$ between 0 and 1, which may reflect status quo bias, non risk-neutrality over small gambles, or both.

[23]This is, of course, not sufficient to guarantee that a bubble would emerge if these subjects were allowed to trade with each other. But if total asset demand among these subjects had been significantly negative for this subject pool over the entire bubble, it would have indicated that the

18

asset demand across all subjects is equal to zero, using Wilcoxon signed-rank tests. The results of these tests can be seen in Table 5. For periods 3, 4, 5, 6, and 9, the null of zero net asset demand cannot be rejected at the 10% level. For all periods when the null is rejected, asset demand was positive, except in period 10, in which it was negative. Thus, the decisions of subjects in this experiment are consistent with the formation of a bubble of approximately the size of the bubble that emerged in the market from which the prices were taken.

4.1.4 Similarities and differences between subject types

From Figure 5, it is apparent that the aggregate behavior of smart traders and confused traders is broadly similar. In Figure 6, I confirm the similarity, by plotting the average values of $NETBUY$ and $ASSETSHARE$ in Market 1 for two very different groups of traders: the "smartest" traders (who got the fundamental within 5 of the correct value in every period) and the "most confused" traders" (who never predicted a feasible value for the fundamental). The broad similarity is still evident. This is itself an intriguing result. It suggests that much of traders' behavior in this type of market represents a reaction to factors that are common across subjects - prices, dividends, and time - rather than to individual beliefs. That is not a result that would emerge from a "heterogeneous prior" model, in which heterogeneity of actions is driven by heterogeneity of beliefs. A partial explanation for the similarity will be given in Section 4.4.

Actually, the behavior of the two groups is measurably different. For any definition of "smart" and "confused," a test will reject the null that smart traders and confused traders buy the same amount (or hold the same amount) of the asset over the course of the market. This is due primarily to the difference in behavior at the peak of the bubble, during periods 3-6. In these periods, smart traders sell on average, while confused traders on average hold or buy. Because of this difference in buying behavior, a gap opens up between the two groups' $ASSETSHARE$ that persists until the end of the market (see Figure 5 and Figure 6). In fact, during period 6, at the peak of the bubble, the "smartest" trader group actually sells out completely (Figure 6b). The difference indicates that fundamental-based buying does indeed exist; smart traders arbitrage against the bubble while the bubble is inflating. After the peak, however, the arbtrage no longer persists, as will be shown in the following section.

I now turn to the key results of the experiment.

---

subjects in the present study were less bubble-prone than the subjects in the Source Market.

4.2 Bubble buying by smart traders

Result 1: *Even subjects who understand fundamentals well tend to buy at prices that are well above fundamental value.*

The first question asked by this study is whether traders will buy into bubbles even when they understand fundamentals well. In the present experiment, it is known which subjects understand fundamentals at the time they make their trading decisions. Since the asset's price exceeds its fundamental value in all periods in Market 1, any nonzero holdings of the risky asset by "smart" traders can technically be viewed as buying into the bubble. The null hypothesis that subjects who understand fundamentals in every period do not buy into the bubble can therefore be formally stated as: $D\_SMARTER_{it} = 1 \ \forall t \Rightarrow SHARES_{it} = 0 \ \forall t$. This hypothesis is easily rejected (Wilcoxon signed-rank test, p-value=0.000). A far less restrictive version of the null is that subjects who understand fundamentals in all periods never hold more than 1 share of the risky asset: $D\_SMARTER_{it} = 1 \ \forall t \Rightarrow SHARES_{it} = 1$ $\forall t$. This hypothesis is also easily rejected (two-sided Wilcoxon signed-rank test, p-value=0.000).[24] Smart traders are indeed willing to hold the asset at prices that they know exceed fundamentals.

However, this null hypothesis may be viewed as too restrictive. A more dramatic demonstration of the significant degree to which "smart" traders buy into the bubble is provided by examining these traders' behavior directly after the bubble peak in Market 1, in periods 7 and 8. As Figures 5 and 6 show, smart traders' asset demands appear to explode upward in these periods. Table 6 shows the percentages of smart and confused traders who bought, sold, and held in periods 7 and 8; the after-peak buying appears to persist across all levels of smartness.

To formally test that this is the case, I define two different versions of the null hypothesis that asset demand by smart traders does not increase in a given period:

1. $H0_1$: $NETBUY_{it} = 0$

2. $H0_2$: $ACTION_{it} = 0$

I then test these hypotheses for periods 7 and 8, for two different groups of "smart" traders: A) "more correct" traders ($D\_MORECORRECT_{it} = 1$), and B)

---

[24]The result is the same if smart traders are allowed a few periods to verify that their understanding of fundamentals is indeed correct. The hypothesis that $D\_SMARTER_{it} = 1$ $\forall t \Rightarrow SHARES_{it} = 1 \ \forall t > t_0$ is rejected for any t_0 less than 8; in other words, only in the last two periods are smart traders unwilling to hold more than one share of the risky asset.

"smarter" traders ($D\_SMARTER_{it} = 1$). All tests are two-sided Wilcoxon signed-rank tests. The results of these tests can be seen in Table 7. In period 7, the null $H0_1$ of no net buying is rejected both for "more correct" traders (p-value=0.000) and for "smarter" traders (p-value=0.021), while the null $H0_2$ of no net buyers is rejected both for "more correct" traders (p-value=0.001) and for "smarter" traders (p-value=0.007). In period 8, neither null can be rejected at the 5% level for either group; however, a third null hypothesis, that $NETBUY_{i7} + NETBUY_{i8} = 0$, is rejected for both groups (p-value=0.003 and p-value=0.046 for "more correct" and "smarter" traders, respectively).

Why focus on periods 7 and 8? There are four reasons. The first is that Result 1 is an *existence* result; if traders who understand fundamentals *ever* buy at prices in excess of fundamentals, it means that arbitrage by smart traders is not guaranteed to prevent lab bubbles, even if smart traders are present - and, in fact, that smart traders can be a source of positive net asset demand during these bubbles. Second, in these periods the price is not only above the fundamental value, but also above the *maximum* possible value of future dividends, meaning that smart traders' decision to buy represents a decision to *forego certain gains.* Third, although periods 7 and 8 are not the only periods in which smart traders buy into the bubble - periods 1 and 2 yield similar results - periods 7 and 8 come late in Market 1. This means that, by period 7, smart traders have had time to A) rebalance their portfolios from their initial allocations, B) observe several periods of market prices, C) observe dividend series and verify that they are, in fact, smart, and D) familiarize themselves completely with the trading system. This makes it very difficult to interpret the result as a laboratory artifact. Finally, periods 7 and 8 come just after the price has begun to fall from its peak; the fact that this is when both smart and confused traders tend to go on a buying spree is itself a phenomenon worthy of investigation.

Buying in periods 7 and 8 was generally a poor decision in Market 1. The asset's realized return was negative in all subsequent periods. Nevertheless, the decision was consistent with smart traders' predictions. Define the one-period-ahead and final-period total asset returns predicted by a smart trader[25] as:

$$E\_RETURN\_1_{it} \equiv E\_PNEXT_{it} + 5 - P_t \tag{13}$$

$$E\_RETURN\_10_{it} \equiv E\_PFINAL_{it} + E_t[FV_t] - 5 - P_t \tag{14}$$

---

[25]Note that this is only an approximation of the true predicted return, which is unobserved. These values assume that the subject predicts a dividend of 5 in the upcoming period and 5 in the final period. But because these quantities are defined only for smart traders, these approximations are reasonable.

Almost all smart traders (all but one or two subjects) predicted positive values for both of these asset returns in periods 7 and 8.

The result that smart traders buy into bubbles contradicts the conclusion of Lei and Vesely (2009), Kirchler, Huber, and Stockl (2010), Fisher (1998), and others who argue that laboratory asset bubbles are purely the result of subjects' misunderstanding of fundamentals. It means that we must look elsewhere for an explanation for these bubbles. The next result offers one such explanation.

4.3   Speculation by smart traders

Result 2: *Subjects who understand fundamentals well tend to trade based on their predictions of short-term price movements.*

"Speculation" can be defined in a number of ways. For the purposes of this study, I define it as "buying an asset at a price exceeding what one believes to be the asset's fundamental value, or selling at a price below what one believes to be the asset's fundamental value, in the hopes of reaping a capital gain." If subjects in an experimental asset market are speculating, then their predictions of future price movements should be a significant predictor of their trading behavior, even when their beliefs about fundamental values are taken into account.

To determine if this is the case, I regress trading behavior on various factors. As measures of trading behavior, I use $NETBUY$ and $\widetilde{ASSETSHARE}$.[26] I will refer to these measures as "buying behavior" and "asset holding behavior," respectively. As explanatory variables, I use three measures of the income that traders expect to be able to receive from the risky asset:

$$E\_BUYANDHOLD_{it} = E_{it}[FV_t] - P_{it} \tag{15}$$

$$E\_APPRECIATION\_1_{it} = E\_PNEXT_{it} - P_t \tag{16}$$

$$E\_APPRECIATION\_F_{it} = E\_PFINAL_{it} - E\_PNEXT_{it} \tag{17}$$

---

[26]I use the deviation from individual mean asset shares, $\widetilde{ASSETSHARE}$, rather than the raw asset share, $ASSETSHARE$, in order to allow for individual fixed effects in subjects' desired levels of risk. However, I do not account for fixed effects in net buying, because net buying is a flow measure rather than a stock measure, and individual fixed effects in $NETBUY$ do not have a clear interpretation. As a side note, all results obtained in the regressions using $NETBUY$ as the dependent variable also hold when fixed effects are taken into account.

The first of these is the expected buy-and-hold income, which is the difference between the expected remaining dividend income per share and the current price, i.e. the income a trader expects to be able to receive from buying a share of the asset in period t and holding it through the end of the market. The second factor is the expected one-period appreciation, i.e. the amount of capital gain a trader expects to be able to receive from buying a share of the asset in period t and selling it in the following period. The third factor is the expected further appreciation, i.e. the additional expected capital gain a trader expects to be able to receive from holding a share of the asset in period $t+1$ and selling it in period 10.[27]

With more price prediction data, a finer partition of predicted income variables would be possible; subjects could, for example, expect to buy in period 4 and sell in period 8. However, with only two price predictions and one fundamental prediction made in each period, the above partition of expected potential income uses all the available information.

The variable of interest is $E\_APPRECIATION\_1$. If this variable predicts the trading behavior of smart traders, it means that smart traders speculate. Thus, I regress trading behavior on expected one-period price appreciation, interacted with a smartness dummy. For each of the two measures of trading behavior (buying behavior and asset holding behavior), I first perform a simple baseline regression without covariates, followed by a regression with covariates included.

The equations of the regressions explaining buying behavior are:

$$
\begin{aligned}
NETBUY_{it} \; = \; & \alpha + \beta E\_APPRECIATION\_1_{it} \\
& + \rho D\_SMARTER_{it} \\
& + \gamma (E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}) \\
& + \varepsilon_{it}
\end{aligned} \tag{18}
$$

$$
\begin{aligned}
NETBUY_{it} \; = \; & \alpha + \beta E\_APPRECIATION\_1_{it} \\
& + \rho D\_SMARTER_{it} \\
& + \gamma (E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}) \\
& + \delta Z_{it} + \varepsilon_{it}
\end{aligned} \tag{19}
$$

Where Z_{it} is a vector of covariates that includes:

---

[27]An alternative to using the expected further appreciation would be to simply use the expected capital gain from buying now and selling in the final period. However, in practice this turns out to be highly collinear with the expected one-period capital gain.

- $CASH_{i,t-1}$, the cash in the subject's account at the beginning of period t,

- $SHARES_{it}$, the subject's shares of the risky asset at the beginning of period t,

- $E\_BUYANDHOLD_{it}$, the predicted profit from buying in period t and holding through the end of the market,

- $E\_APPRECIATION\_F_{it}$, the predicted further price appreciation (i.e., the predicted capital gain from holding in period $t+1$ and selling in the final period,

- $E\_BUYANDHOLD_{it} \times D\_SMARTER_{it}$, the smartness dummy interacted with the predicted buy-and-hold value,

- $E\_APPRECIATION\_F_{it} \times D\_SMARTER_{it}$, the smartness dummy interacted with the predicted further price appreciation,

- $\overline{P}_{t-1}$, the lagged average of past asset prices,

- D_{t-1}, the one-period lagged dividend, and

- t, a linear time trend.

I also run analogous regressions using $D\_MORECORRECT$ as the smartness dummy instead of $D\_SMARTER$.

Analogously, the equations of the regressions explaining asset holding behavior are:

$$
\begin{aligned}
\widetilde{ASSETSHARE}_{it} \;=\; & \alpha + \beta \widetilde{E\_APPRECIATION\_1}_{it} && (20) \\
& + \rho D\_SMARTER_{it} \\
& + \gamma (\widetilde{E\_APPRECIATION\_1}_{it} \times D\_SMARTER_{it}) \\
& + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
\widetilde{ASSETSHARE}_{it} \;=\; & \alpha + \beta \widetilde{E\_APPRECIATION\_1}_{it} && (21) \\
& + \rho D\_SMARTER_{it} \\
& + \gamma (\widetilde{E\_APPRECIATION\_1}_{it} \times D\_SMARTER_{it}) \\
& + \delta Z_{it} + \varepsilon_{it}
\end{aligned}
$$

Where Z_{it} is a vector of covariates that includes:

- $\widetilde{ASSETSHARE}_{i,t-1}$

- $\widetilde{ASSETSHARE}_{i,t-2}$

- $\widetilde{E\_BUYANDHOLD}_{it}$

- $\widetilde{E\_APPRECIATION\_F}_{it}$

- $\widetilde{E\_BUYANDHOLD}_{it} \times D\_SMARTER_{it}$, the smartness dummy interacted with the predicted buy-and-hold value,

- $\widetilde{E\_APPRECIATION\_F}_{it} \times D\_SMARTER_{it}$, the smartness dummy interacted with the predicted further price appreciation,

- $\overline{P}_{t-1}$,

- D_{t-1}, and

- t.

Again I run analogous regressions using $D\_MORECORRECT$ as the smartness dummy in place of $D\_SMARTER$.

The coefficients that measure short-term price speculation are β and γ. A positive value for the sum of these coefficients indicates speculation by smart traders.

Table 8 shows the results for Equations 18 and 19, and Table 9 shows the results for Equations 20 and 21. The coefficients β and γ are positive and significant in all specifications[28]. γ, the interaction-term coefficient, is about one order of magnitude larger than β in all specifications. The economic interpretation of the coefficients is as follows: a trader who understood fundamentals well in all previous periods (including the current period), if she predicted the price to go up by 20 more yen in the next period, bought about 1-4 more shares of the asset, or held another 10-25% of her wealth in the risky asset. In contrast, a trader who did not understand fundamentals bought approximately 0.1-0.4 more shares, or held another 1-2% of her

---

[28]The coefficients β and γ are larger when the covariates are included. This is partly because $E\_APPRECIATION\_F_{it}$, the expected further appreciation, is negatively correlated with $E\_APPRECIATION\_1_{it}$. If $E\_APPRECIATION\_F_{it}$ is omitted as a covariate, β and γ are still larger in the regression with covariates, but the difference is not as large.

wealth in the risky asset, for a similar increase in predicted one-period appreciation.[29] Not only does a speculative motive exist, it is substantially *stronger* for traders who understand fundamentals than for those who don't. This may be because smart traders have more confidence in their price predictions.

The result for β and γ is robust to a large set of alternative specifications, including the omission of either or both of the other predicted income regressors, the use of lagged or leading values of smartness dummies, more lags of dividends, lagged values of net buying, quadratic time trends, and the use of an Arellano-Bond panel GMM estimator instead of OLS.

Thus, short-term speculation is a substantial motive for traders who understand fundamentals. Like Result 1, this is an *existence* result; the coefficients β and γ are not meant to measure the total speculation motive, but to provide a lower bound (subjects may also speculate on their predictions of more long-term price appreciation). The result does not contradict the finding in Lei, Noussair, and Plott (2001) that laboratory bubbles do not *require* speculation, but it shows that speculation nevertheless exists and is significant. Importantly, speculation will tend to prevent smart traders from exerting deflating pressure on bubbles.

4.4   Effect of past prices on trading behavior

Result 3: *Lagged average prices are a significant predictor of trading decisions.*

Although subjects in this market do speculate, their predictions of future asset returns do not explain all of their trading behavior. In the regression results in Tables 8 and 9, lagged average prices emerge as a significant regressor with a coefficient several times as large as the coefficient on expected one-period price appreciation. This result persists in all of the alternative regression specifications listed above. This result is consistent with the broad features of observed trading behavior. Subjects tend to hold or sell the asset in periods 3-6, when the price is higher than its recent values. They then tend to buy in periods 7 and 8, after prices have begun to decline.

An interesting question is whether smart traders differ from other traders in their use of lagged prices. To assess whether they do, I run the regression in Equation

---

[29]Actually, the difference is not quite as large if we take into account the larger variance of price predictions among traders who do not understand fundamentals. A predicted 20 yen appreciation is about two unconditional standard deviations of $E\_APPRECIATION\_1$ for smart traders, but only about 2/3 of a standard deviation for confused traders. Thus, the speculation motive is only about three times as strong for smart traders, not ten times.

19 for subsamples of smart traders only, using several definitions of "smart". The results can be seen in Table 10. For the stricter definitions of "smartness" used in most of this paper ($D\_MORECORRECT_{it} = 1$ and $D\_SMARTER_{it} = 1$), significance cannot be established; however, for looser definitions of "smartness" ($D\_MORECORRECT_{it} = 1$ and $D\_SMARTER_{it} = 1$), lagged prices emerge as significant. This is perhaps not surprising; because prices do not vary across subjects, the relatively small numbers of subjects who meet the stricter "smartness" criteria result in this regression having low power. But if smart traders do indeed trade based on lagged prices, it would explain much of the result in Section 4.1.4; a broad similarity between trader types would be exactly what one would observe if the price history itself was a significant factor influencing the asset demands of all subjects. So although the data are insufficient to conclude that the very smartest traders trade on lagged prices, they indicate that there is a strong possibility that this is happening.

However, even if smart traders do not trade based on lagged prices, the phenomenon remains interesting and important, because it provides another mechanism by which *price-to-price feedback* can cause bubble-shaped asset mispricings. If traders who observe higher prices in the past are willing to accept higher prices in the future, temporary overpricings due to mistakes about fundamentals will grow larger over time. Instead of being corrected by a learning process, bubbles will be self-sustaining.

Why should average past asset prices predict traders' decision to buy? Because this experiment used the same price path for all subjects, it is only possible to conjecture. One possible explanation might seem to be *loss aversion*. If prices fall, loss-averse subjects whose wealth has declined may become risk-loving, buying in the hope that prices will rise and they will recoup their losses. However, given that most smart traders (as well as most traders in general) expect *positive* asset returns in periods 7 and 8, loss aversion seems like an incomplete explanation. Additionally, loss aversion is unable to explain the substantial nonzero asset holdings of many smart traders even at the bubble peak.

A second possible explanation is that a trader's predictions of future prices may depend on the prices she has observed in the past. Subjects may thus be engaging in a simple form of *technical analysis*, in which they try to gauge "support levels." If the market has demonstrated that it is willing to pay a price of 60 for the asset, and the price falls to 55, the asset may look "cheap." In fact, lagged average prices are positively correlated with predictions of future prices, as one would expect if subjects were forming their beliefs in this way. However, this explanation too seems incomplete; even when expectations of final-period prices are included as regressors, lagged average prices still emerge as significant. If subjects believed in "support

levels," this belief should reflect itself in their final-period price predictions. Nor does error in the measurement of price predictions seem likely to explain all of the result, since the coefficient on lagged prices is an order of magnitude larger than the coefficients on price predictions.

There is a third possible reason for the "lagged price effect": *herd behavior.* Avery and Zemsky (1998) define herd behavior in financial markets as occurring when a trader reverses her trading decision (e.g. buys instead of sells) based on her observation of the trading decisions of others[30]. In the present experiment, subjects do not directly observe the actions of the others, only prices. However, note that observing a market price of 60 yen conveys the information that there existed subjects in the Source Market who purchased the asset for 60 or more yen in the given period[31]. If this observation affects the behavior of traders in the present study, then herd behavior is present.

Why would traders "imitate" the traders in the Source Market? This would happen if subjects *do not equate the asset's fundamental value with the dividend income that it provides.* Subjects may feel instinctively that if traders in the Source Market were willing to pay 60 yen for the asset, the asset must be worth somewhere in the neighborhood of 60 yen, while not explicitly forming beliefs about *why* it would have this value. "Smart" traders may understand all of the experimental parameters, yet fail to intuitively grasp that dividend income and resale value are the asset's only sources of value (alternatively, they may understand that dividends equal fundamentals, but not have complete confidence in this knowledge). While this type of herding would not fit the typical description of rational information-based herding (see Hirshleifer and Teoh 2001), it would constitute "behavioral" or "instinctual" herding.

Such behavior is irrational, but it closely matches a very plausible strategy for real-world investing. A trader first assumes that the market is basically efficient, and that market prices are close to "right." She then looks for information that indicates small differences between the current price and the asset's true fundamental value or future resale value. When she is reasonably confident that such a difference exists, she makes a trade. This type of behavior is entirely consistent with the actions of the individual investors in the present experiment. However, though this strategy

---

[30]This is similar to the definition of herding given in Bikhchandani, Hirshleifer, and Welch (1992). It is unrelated to the notion of "managerial herding" in Scharfstein and Stein (1990). Note that the Avery and Zemsky (1998) also includes the kind of "technical analysis" postulated above; however, since in Avery and Zemsky's (1998) highly stylized model, traders are not allowed to resell the asset, I consider "support levels" and "herding" to be separate notions.

[31]And, additionally, that the traders who bought at 60 were in some sense "average".

may sound reasonable, it represents herd behavior. If market prices deviate from fundamentals due to heterogeneous beliefs or mistakes, lagged asset prices no longer represent a good baseline for valuing an asset.

4.5   Design-experienced traders

Figure 7 displays average net buying and average asset holdings for Market 2, along with market prices. The pattern of net buying appears similar to that in Market 1, with strong initial asset demand, reduced demand in middle periods when prices are most different from fundamentals, and then a positive spike in demand when prices begin to fall steeply. However, unlike in Market 1, $ASSETSHARE$ falls steeply as prices fall; this happens because the fall in prices overwhelms subjects' after-peak buying.

Repeating the regressions from Equations 18-21 yields results that differ from the results in Market 1. Beliefs about future prices no longer emerge as a significant predictor of trader behavior (see Table 11). The impact of lagged prices in this market is difficult to assess, since prices in Market 2 are highly collinear with time. When time is omitted from the regressions, lagged prices become an important explanatory variable (Table 11);[32] however, it is impossible to tell whether this is due to an effect like that seen in Market 1, or due to a time trend in asset demand.

These results indicate that design-experienced subjects rely *less* on their price predictions than do design-inexperienced subjects; speculation is not obviously in evidence. This is consistent with the smaller incidence of bubbles seen in market repetitions in most asset pricing experiments.

4.6   Effects of experimental treatments

Table 12 shows that the number of smart traders ($D\_SMARTER_{i,10} = 1$) was significantly higher (p-value=0.004) in the Pictures treatment, and insignificantly lower (p-value=0.134) in the Uncertain treatment (Wilcoxon rank-sum tests).[33] Showing subjects examples of feasible price and dividend series does increase their understanding of fundamentals, a result similar to that found by Lei and Vesely (2009).

However, $NETBUY$ and $ASSETSHARE$ are not significantly different across the three treatment groups in period 7 or period 8 of Market 1 (see Table 13).

---

[32]This is true even when the sample is restricted to smart traders.

[33]This result also holds for $D\_SMART_{i,10}$. A similar result obtains for the null hypothesis that cumulative mistakes $\sum_t M_{it}$ are the same across treatment groups; mistakes are insignificantly higher in the Uncertain treatment and significantly lower in the Pictures treatment.

The greater understanding of fundamentals induced by the Pictures treatment does not stop traders from buying into the bubble after the peak. When the sample is restricted to only smart traders ($D\_SMARTER_{it} = 1$), smart traders in Treatment 3 are found to buy significantly fewer shares in period 7 (p-value=0.045). Thus, there is some evidence that the Pictures treatment prevented smart traders from joining the bubble.

To ascertain whether subjects in the different treatments speculated to different degrees, I use the following regressions:

$$
\begin{aligned}
NETBUY_{it} \quad = \quad & \alpha + \beta \times E\_APPRECIATION\_1_{it} \qquad\qquad (22) \\
& + \rho D\_PICTURES_i \\
& + \gamma \times (E\_APPRECIATION\_1_{it} \times D\_PICTURES_i) \\
& + Z_{it} + \varepsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
\widetilde{ASSETSHARE}_{it} \quad = \quad & \alpha + \beta \times \widetilde{E\_APPRECIATION}\_1_{it} \qquad\qquad (23) \\
& + \rho D\_PICTURES_i \\
& + \gamma \times (\widetilde{E\_APPRECIATION}\_1_{it} \times D\_PICTURES_i) \\
& + Z_{it} + \varepsilon_{it}
\end{aligned}
$$

Here, $D\_PICTURES_i$ is a dummy for the Pictures treatment, and Z_{it} is a vector of covariates[34]. Analogous regressions were run with $D\_UNCERTAIN_i$, a dummy for the Uncertain treatment, in its place. The Uncertain treatment is found to have no measurable effect on the degree of speculation. The results of the estimations for the Pictures treatment appear in Table 14.. Subjects in the Pictures treatment were found to trade significantly less in accordance with their predictions of one-period price appreciation, and significantly more in accordance with their predictions of further price appreciation.

This result is perhaps surprising, since subjects who had seen examples of market price paths had more information with which to speculate. In particular, they could see that prices tended to display significant momentum, and that prices in bubble markets tended to peak and decline in the middle of the market. However, these traders chose to speculate less (at least in the short term) than traders who had no such information. This is contrary to the result of Haruvy, Lahav, and Noussair (2007), who find that traders who have witnessed bubbles try to "time the market," buying into a bubble and attempting to sell out just before the peak.

---

[34]The covariates are the same as in Equations (*****) and (*****), except with treatment dummies instead of smartness dummies.

I conjecture that the reason for the decreased speculation in the Pictures treatment is greater attention to risk. Seeing a large array of *different* price paths informs subjects of the potentially large variance of prices, and discourages speculative behavior. This could also explain the decreased degree of speculation exhibited by all subjects in Market 2; after having witnessed a rise and crash in prices, and after having traded on their own incorrect price predictions, traders are more hesitant to trust their own judgment. This explanation has the flavor of the "overconfidence" literature (e.g. Barber and Odean 2000, Scheinkman and Xiong 2003), in which individual investors overestimate the precision of their own forecasts.

5   Conclusion

What can bubble experiments tell us about real-world bubbles? If bubble-shaped mispricings in real-world asset markets are caused primarily by feedback effects between non-financial sectors and asset markets, then the answer is "little." But if bubbles are caused by "price-to-price feedback," in which price movements themselves cause later price movements, then it may be possible to increase our understanding of the bubble phenomenon by studying simple, isolated financial markets like the one presented in this paper. The focus of "bubble experiments" should therefore be on identifying the behavioral and institutional sources of price-to-price feedback.

The first main contribution of this paper is to show that price-to-price feedback in simple experimental asset markets is not purely a function of subject confusion. The tendency of traders who understand fundamentals to buy just after the peak of a bubble shows that the movement of prices alone is sufficient to make these "smart" traders knowingly overpay for a risky asset - behavior that, in equilibrium, will have an effect on the price. This is the first study to show conclusively that this is the case.

This paper's second main contribution is to identify one source of price-to-price feedback, and to present evidence that a second source exists. "Smart" traders tend to trade based on their predictions of short-term price appreciation, irrespective of their understanding of fundamentals. This form of speculation may not be necessary for bubbles to appear (as in Lei, Noussair, & Plott 2001), but it clearly has the potential to contribute to bubbles. If smart traders predict that an already overpriced asset will continue to increase in price (as they do in Market 1 of this experiment), short-term speculation will tend to reduce the degree to which these smart traders pop bubbles through arbitrage.

The second source of price-to-price feedback in this experiment is unknown. In this experiment, subjects were more likely to demand a risky asset at a given price

when past prices had been higher. This indicates the possibility that a form of herd behavior is at work, in which subjects believe that the market price is "close to right." If further research shows this to be the case, it will have profound implications for our understanding of how asset markets function. Generally, we think of markets as aggregating information. But if price bubbles - initiated, perhaps, due to heterogeneous beliefs or a burst of overconfident speculation - cause traders to believe that the market price is the "right" price, it means that financial markets have the capacity to aggregate *mis*information. That is clearly a phenomenon deserving of more study.

The third contribution of this paper is to identify a phenomenon of "after-peak buying." In this experiment, a group of traders whose net demand was approximately zero at the peak of a bubble began to buy strongly when the price began to fall. In a market equilibrium, this positive net demand would cause the price to rise, and thus sustain or reinflate the bubble. Although many studies focus on the *initial causes* of mispricings, another interesting question is why those mispricings are *sustained*. This question, too, is a goal for future research.

Finally, this paper makes a methodological contribution to the asset-pricing experiment literature. Whereas most asset market experiments use small markets as their unit of analysis, this study uses non-interacting individual traders facing market prices that they are too "small" to affect. Although this partial-equilibrium approach is not as useful as the typical setup for studying the effects of institutions on market outcomes, it is potentially more useful for studying the determinants of individual behavior, since it removes price endogeneity, group fixed effects, and coordination effects from the analysis. In one regard, this approach actually has more external validity than the traditional small-market general-equilibrium setup, since real-world investors are often individually too "small" to affect prices. Another way of saying this is that in a traditional asset-pricing experiment individual behavior is aggregated by a small, illiquid market, while a partial-equilibrium experiment provides insight into the individual behavior patterns that will be aggregated by large, liquid markets in the real world.

There are three fairly obvious extensions of this experiment that should be pursued in order to better understand and extend the results. The first is to vary the price path, using price series from a number of experimental "source" markets. This will allow a clearer determination of the effect of past prices on expectations of future prices, as well as on trading behavior. The second extension is to assess subjects' *willingness to pay* for the asset, using a call market setup. Such a setup would allow a determination of the size of the mispricing that the most bullish traders would be willing to support for a given history of prices and dividends. It would also allow

computation of the hypothetical equilibrium price that would emerge from an aggregation of individual trader demands, and allow the experimenter to compare this price with the pre-determined market price, in order to ascertain whether traders on average would tend to pop or further inflate a given bubble. The third extension is to relax constraints on short selling and margin buying, as has been done in some "group" bubble experiments.

The methodology in this study also has applicability beyond the bubble experiment literature. The partial-equilibrium approach used here represents an important complement to traditional market-clearing experimental techniques, since it has the capability to isolate the determinants of individual behavior and expectations. There are any number of observed market phenomena that might be caused by a number of different types of behavior at the individual level - excess volatility, under-saving, and large equity premia, to name just a few. Additionally, although the process of individual expectation formation was not a major focus of this paper, expectation formation under uncertainty is obviously another area where a partial-equilibrium approach can be of use. These applications should be considered not only in terms of their relevance to financial economics, but to macroeconomics in general. In the words of Randall Kroszner (2010):

> "Building a greater understanding of the interaction of the formation and change of expectations at the individual level and the implications for market-wide and economy-wide behavior by perhaps drawing on experimental methods...is a great challenge for economics but one with potentially high pay-offs."

This study, and the methodology explored here, is a (small) step toward the advancement of such a research program.

References

Abreu, Dilip and Markus Brunnermeier. 2003. Bubbles and Crashes. *Econometrica* 71(1): 173-204.

Ackert, Luck and Bryan K. Church. 1998. The Effects of Subject Pool and Design Experience on Rationality in Experimental Asset Markets. Working paper.

Ackert, Lucy F., Narat Charupat, Bryan K. Church, Richard Deaves. 2006. Margin, short sell, and lotteries in experimental asset markets. *Southern Economic Journal* 73(2): 419–436.

Ackert, Lucy F., Richard Deaves, and Brian D. Kluger. 2006. The origins of bubbles in laboratory asset markets. Working paper.

Avery, Christopher and Peter Zemsky. 1998. Multidimensional uncertainty and herd behavior in financial markets. *American Economic Review* 88: 724—748.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55: 773-806.

Barsky, Robert, 2009. The Japanese bubble: a 'heterogeneous' approach. NBER Working Paper No. 15052.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch. 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy* 100(5): 992-1026.

Brunnermeier, Markus and Stefan Nagel. 2004. Hedge funds and the technology bubble. *Journal of Finance* 59(5): 2013-2040.

Cagan, Philip. The monetary dynamics of hyperinflation. In *Studies in the Quantity Theory of Money*, ed. by M. Friedman. Chicago: University of Chicago Press, 1956.

Caginalp, Gunduz, David Porter, Vernon Smith. 1998. Initial cash/asset ratio and asset prices: An experimental study. PNAS USA 95 756–161.

Caginalp, Gunduz, David Porter, Vernon Smith. 2000. Momentum and overreaction in experimental asset markets. *International Journal of Industrial Organization* 18: 187–204.

Caginalp, Gunduz, David Porter, Vernon Smith. 2001. Financial bubbles: Excess cash, momentum and incomplete information. *The Journal of Psychology and Financial Markets* 2(2): 80–99.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, Robert J. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98(4): 703-738.

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, Robert J. Waldmann. 1990. Positive feedback investment strategies and destabilizing rational speculation. *The Journal of Finance* 45 (2): 379-395.

Dufwenberg, Martin, Tobias Lindqvist, Evan Moore. 2005. Bubbles and experience: An experiment. *The American Economic Review* 95(5): 1731–1737.

Dwyer, Gerald P. Jr., Arlington W. Williams, Raymond C. Battalio, Timothy I. Mason. 1993. Tests of rational expectations in a stark setting. *The Economic Journal* 103: 586-601.

Fischbacher, Urs. 2007. z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* 10(2) 171–178.

Fisher, Eric. 1998. Explaining bubbles in experimental asset markets. Working paper.

Harrison, J.Michael and David M. Kreps. 1978. Speculative investor behavior in a model with heterogeneous expectations. *The Quarterly Journal of Economics* 92(2): 322-336.

Haruvy, Ernan, Yaron Lahav, Charles Noussair. 2007. Traders' expectations in asset markets: Experimental evidence. *American Economic Review* 97(5): 1901–1920.

Hirshleifer, David and Siew Hong Teoh. 2001. Herd behavior and cascading in capital markets: A review and synthesis. Working paper.

Hussam, Reshmaan N., David Porter, Vernon L. Smith. 2008. Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review* 98(3): 924–937.

Kindleberger, Charles. *Manias, Panics, and Crashes: A History of Financial Crises*, New York: Basic Books, 1978.

King, Ronald R., Vernon L. Smith, Arlington Williams, Mark V. van Boening, Mark V. The robustness of bubbles and crashes in experimental stock markets. In R. H. Day and P. Chen, *Nonlinear Dynamics and Evolutionary Economics*. Oxford, England: Oxford University Press, 1993.

Kirchler, Michael, Jurgen Huber, Thomas Stockl. 2010. Thar she bursts – a critical investigation of bubble experiments. Working paper.

Kroszner, Randall. 2010. Implications of the financial crisis. *American Economic Association, Ten Years and Beyond: Economists Answer NSF's Call for Long-Term Research Agendas*. Available at SSRN: http://ssrn.com/abstract=1889315

Lei, Vivian, Charles N. Noussair, Charles R. Plott. 2001. Nonspeculative bubbles in experimental asset markets: lack of common knowledge of rationality vs. actual irrationality. *Econometrica* 69(4): 831–859.

Lei, Vivian, F. Vesely. 2009. Market efficiency: evidence from a no-bubble asset market experiment. *Pacific Economic Review* 14(2): 246–258.

Malkiel, Burton. 2010. Bubbles in asset prices. CEPR Working Paper #200.

Morris, Stephen. 1996. Speculative investor behavior and learning. *The Quarterly Journal of Economics* 111(4): 1111-1133.

Noussair, Charles N., Stephane Robin, Bernard Ruffieux. 2001. Price bubbles in laboratory asset markets with constant fundamental values. *Experimental Economics* 4: 87–105.

Noussair, Charles N., Steven Tucker. 2006. Futures markets and bubble formation in experimental asset markets. *Pacific Economic Review* 11(2): 167–184.

Oechssler, Jorg, Carsten Schmidt, Wendelin Schnedler. 2007. On the ingredients for bubble formation: informed traders and communication. Working paper.

Porter, David P., Vernon L. Smith. 1995. Futures contracting and dividend uncertainty in experimental asset markets. *The Journal of Business* 68(4): 509–541.

Scharfstein, David S. and Jeremy C. Stein. 1990. Herd behavior and investment. *The American Economic Review* 80(3): 465-479.

Scheinkman, Jose A., Wei Xiong. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111(6): 1183-1219.

Schmalensee, Richard. 1976. An experimental study of expectation formation. *Econometrica* 44(1): 17-41

Shiller, Robert, 2003. From efficient markets to behavioral finance. *Journal of Economic Perspectives*, 17(1): 83-104.

Smith, Vernon, Gerry Suchanek, and Arlington Williams. 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5): 1119–1151.

Smith, Vernon, Mark van Boening, Charissa P. Wellford. 2000. Dividend timing and behavior in laboratory asset markets. *Economic Theory* 16: 567–583.

Van Boening, Mark, Arlington W. Williams, Shawn LaMaster. 1993. Price bubbles and crashes in experimental call markets. *Economic Letters* 41(2): 179–185.

Appendix A: Experimental Instructions

(Note: Instructions that appear in normal type were given in all treatments. Instructions that appear in <mark>highlighted font</mark> were omitted from the Uncertain treatment. Instructions that appear in *italics* were included only in the Uncertain treatment.)

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.

<mark>Here are the possible dividends, and the percentage chance of each:</mark>
Here are the possible dividends. The dividend probabilities are the same in all periods, but we will not reveal these probabilities:

Dividend per share	Percentage chance
0	<mark>50%</mark> *??*
10	<mark>50%</mark> *??*

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

Appendix B: Examples of Market Prices and Dividends (Pictures Treatment)

Note: Translations appear in text outside pictures.

Example 1 (market price)
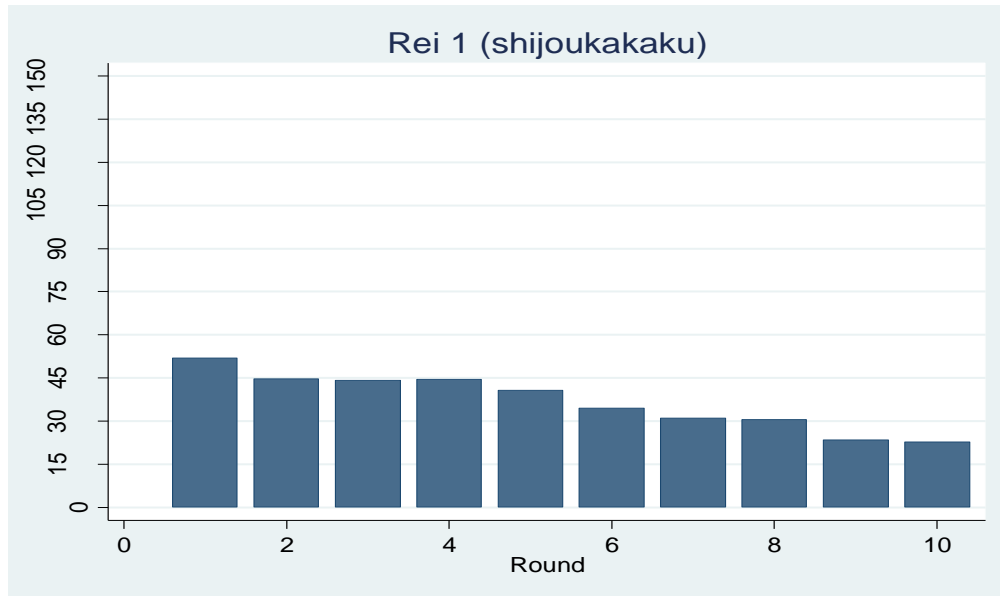
Example 1 (dividends)
(total dividend per share received in this market = 30)
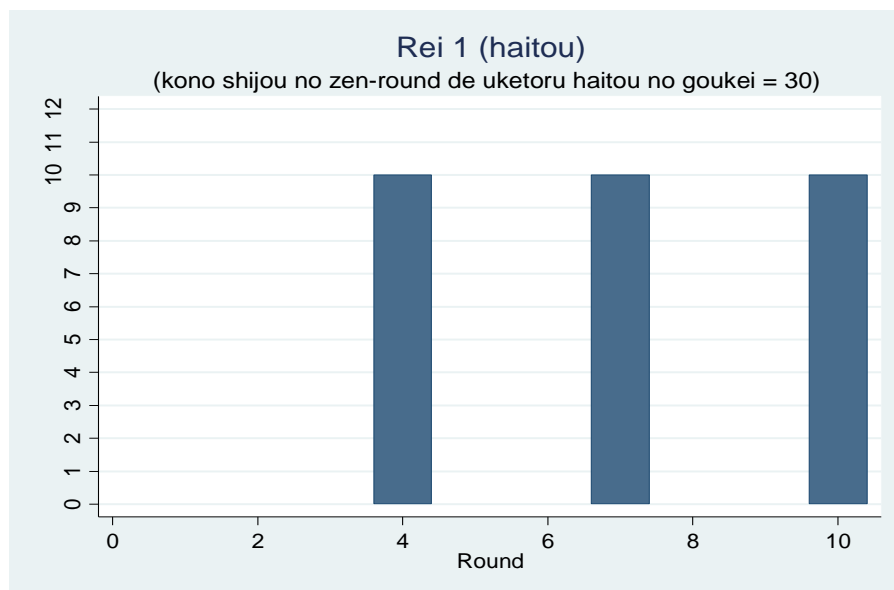
Example 2 (market price)

Rei 2 (shijoukakaku)
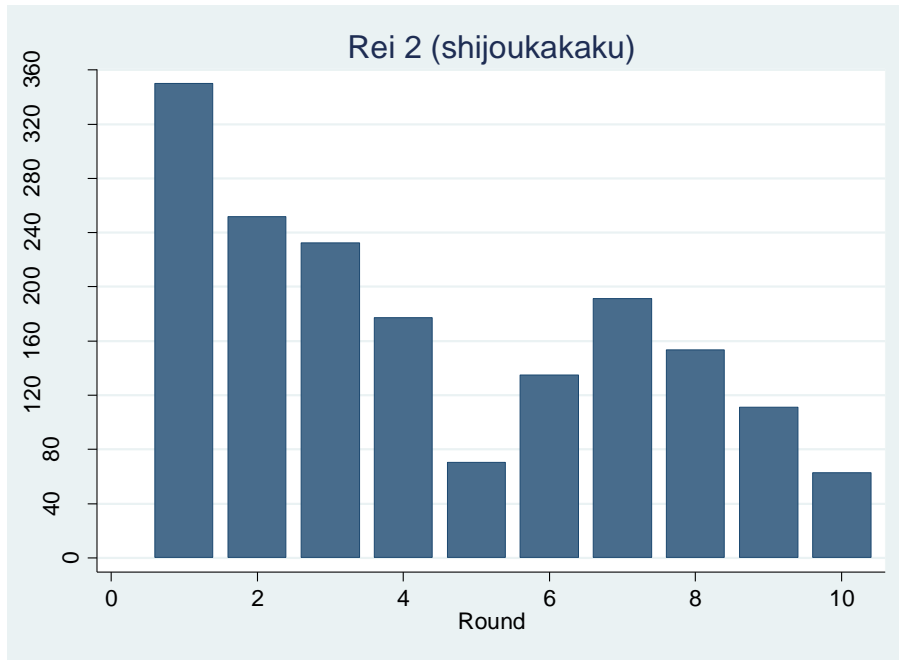
Example 2 (dividends)
(total dividend per share received in this market = 40)

Rei 2 (haitou)
(kono shijou no zen-round de uketoru haitou no goukei = 40)
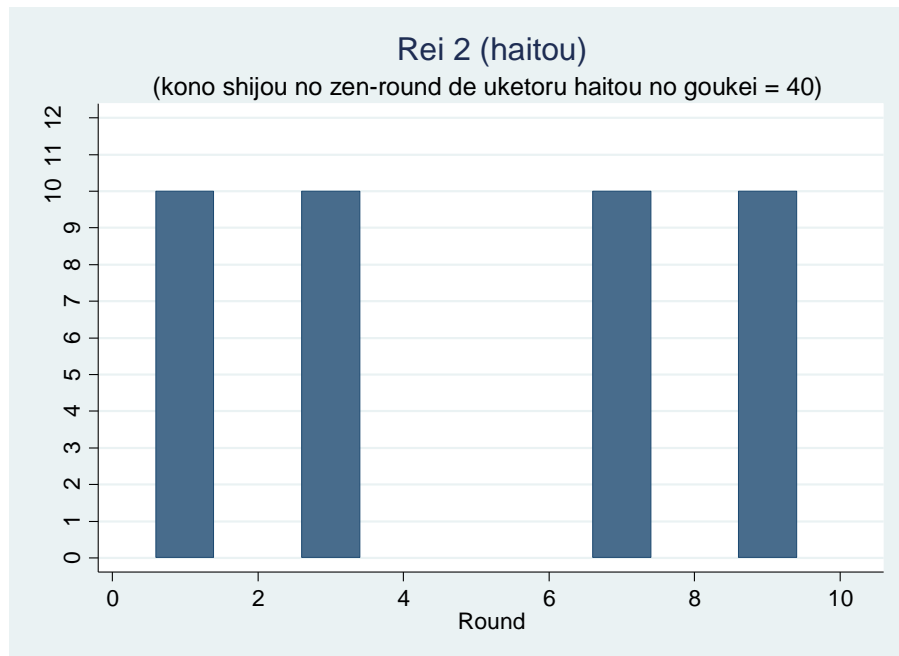
Example 3 (market price)

Rei 3 (shijoukakaku)
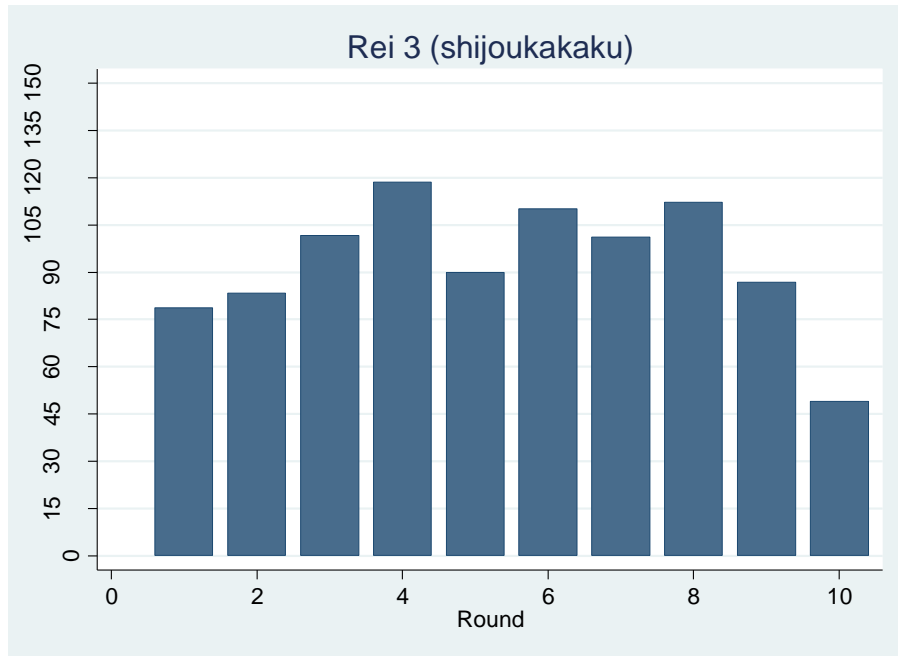
Example 3 (dividends)
(total dividend per share received in this market = 40)

Rei 3 (haitou)
(kono shijou no zen-round de uketoru haitou no goukei = 40)

Example 4 (market price)

Rei 4 (shijoukakaku)

Round
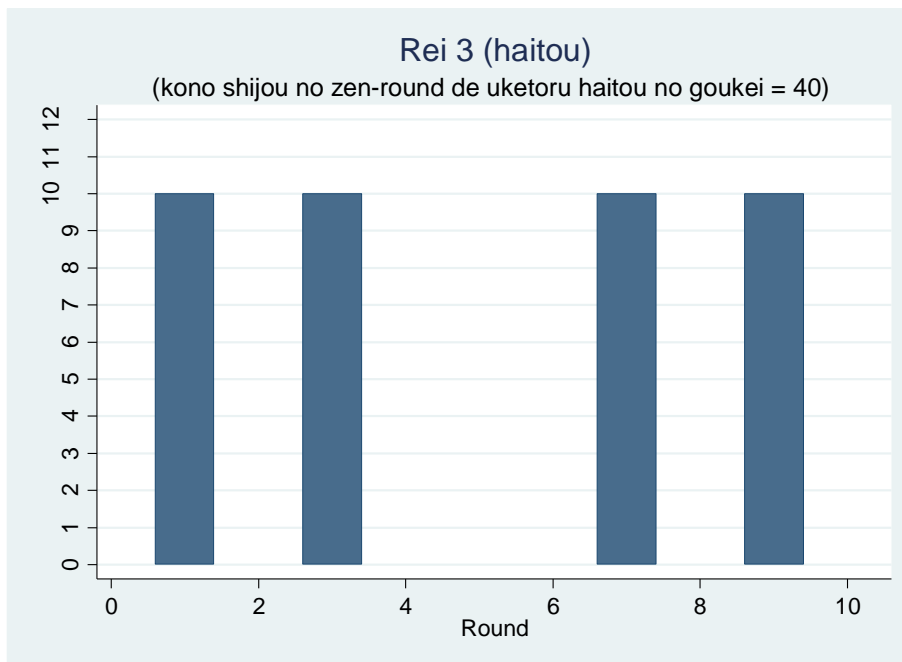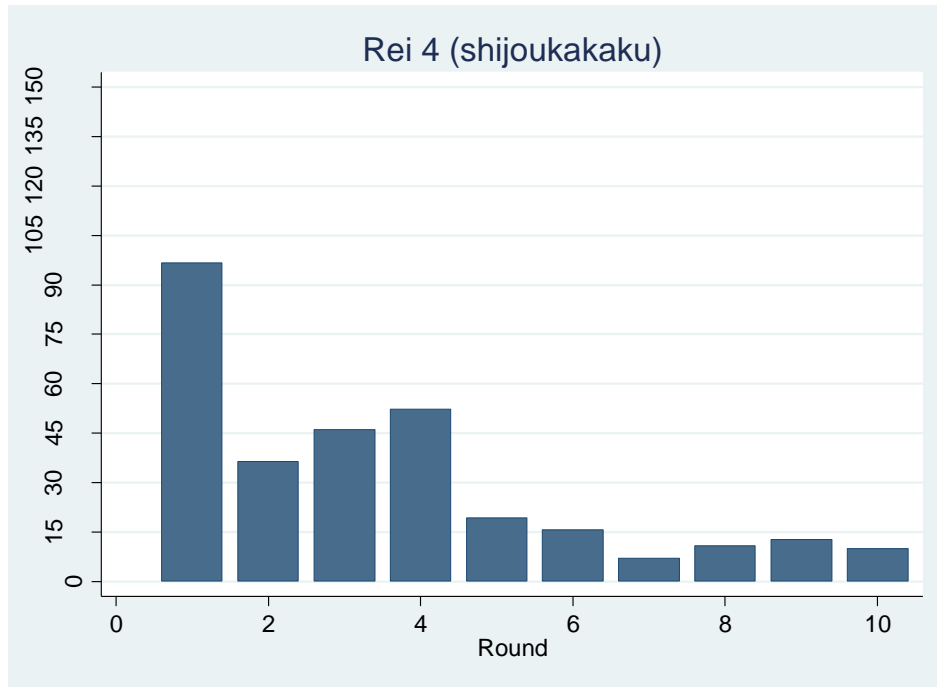
Example 4 (dividends)
(total dividend per share received in this market = 60)

Rei 4 (haitou)
(kono shijou no zen-round de uketoru haitou no goukei = 60)

Round
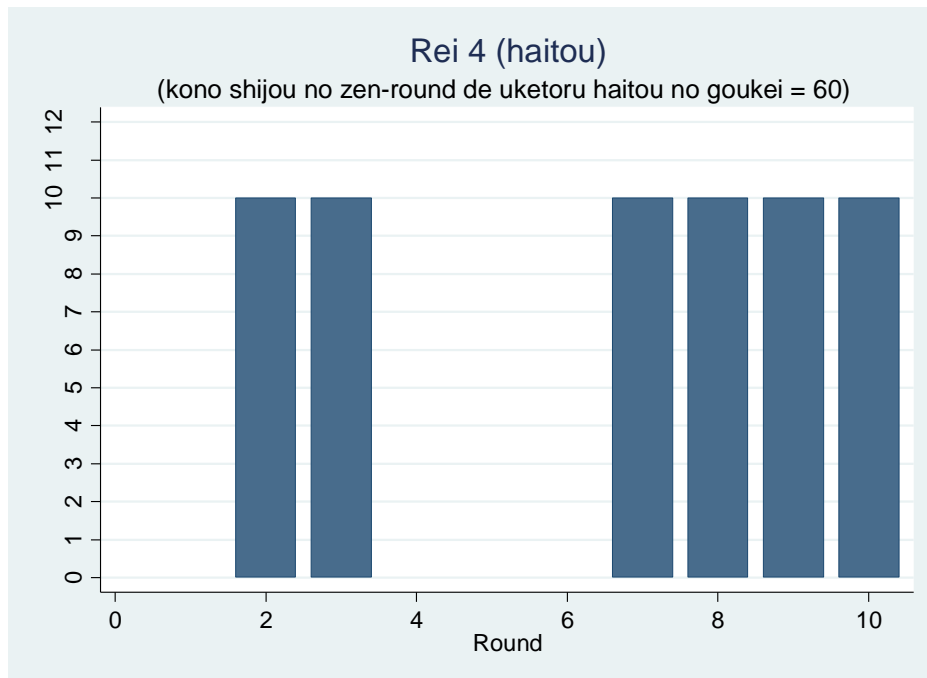
Table 1: Treatments

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

Table 2: Smartness Dummies

Smartness Dummy	Definition	# of Traders in Period									
		1	2	3	4	5	6	7	8	9	10
D_CORRECT	Prediction of fundamental is feasible	57	48	45	42	41	42	36	35	36	39
D_MORECORRECT	Prediction of fundamental is less than 50% from true value	36	36	33	30	25	23	27	28	26	39
D_MOSTCORRECT	Prediction of fundamental is less than 5 yen from true value	18	29	15	22	20	20	17	26	26	39
D_SMART	Prediction of fundamental is feasible in all previous and current periods	57	45	41	38	35	33	31	29	29	28
D_SMARTEST	Prediction of fundamental is less than 50% from true value in all previous and current periods	36	27	24	23	17	15	14	14	13	13
D_SMARTEST	Prediction of fundamental is less than 5 yen from true value in all previous and current periods	18	13	8	8	6	6	4	4	4	4

Table 3: Price Predictions

Regressor	Coefficient	p-value
P_{t-1}	0.681***	0.000
$P_{t-1} - P_{t-2}$	-0.547	0.112
$D\_MORECORRECT_{it}$	0.425	0.777
$D\_MORECORRECT_{it} \times (P_{t-1} - P_{t-2})$	0.874*	0.059
LHS: E_PNEXT_{it}		R-squared: 0.382

Regressor	Coefficient	p-value
P_{t-1}	0.729***	0.000
$P_{t-1} - P_{t-2}$	-0.439	0.130
$D\_SMARTER_{it}$	0.914	0.665
$D\_SMARTER_{it} \times (P_{t-1} - P_{t-2})$	0.758**	0.041
LHS: E_PNEXT_{it}		R-squared: 0.349

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 4: Variation of Price Predictions

Period	Standard deviation of upcoming-period price prediction as a percentage of market price
1	3.319
2	0.423
3	0.914
4	0.225
5	0.221
6	0.226
7	0.228
8	0.564
9	0.736
10	0.758

Table 5: Net Asset Demand by Period

Period	Price	Price-FV	(Price-FV)/FV	Total net buying	Total net buying / shares outstanding (%)	p-value for H0: $NETBUY_{it} = 0$
1	60	10	1.2	184.9	44.56	0.000
2	56	11	1.2	120.0	20.00	0.000
3	60	20	1.5	-52.0	-7.22	0.191
4	63	28	1.8	27.0	4.04	0.679
5	68	38	2.3	-33.0	-4.75	0.933
6	64	39	2.6	34.0	5.14	0.252
7	58	38	2.9	211.0	30.31	0.000
8	51	36	3.4	124.0	13.67	0.001
9	43	33	4.3	51.0	4.95	0.696
10	31	26	6.2	-326.0	-33.27	0.000

Table 6: Trading Behavior in Periods 7 and 8

Period	Price - FV	(Price-FV)/FV	Trader Category	# of Traders	% who bought	% who held	Average net buying	Average asset share
7	38	1.9	All	83	71	23	2.54	0.54
7	38	1.9	$D\_MORECORRECT_{it} = 1$	27	70	19	1.96	0.42
7	38	1.9	$D\_SMARTER_{it} = 1$	14	71	21	1.93	0.36
8	36	2.4	All	83	48	34	1.43	0.59
8	36	2.4	$D\_MORECORRECT_{it} = 1$	26	50	35	1.86	0.47
8	36	2.4	$D\_SMARTER_{it} = 1$	14	50	29	2.64	0.45

Table 7: Net Buying in Periods 7 and 8

Period	Price - FV	(Price-FV)/FV	Trader Category	# of Traders	p-value for H0: $NETBUY_{it} = 0$	p-value for H0: $ACTION_{it} = 0$
7	38	1.9	All	83	0.000	0.000
7	38	1.9	$D\_MORECORRECT_{it} = 1$	27	0.000	0.001
7	38	1.9	$D\_SMARTER_{it} = 1$	14	0.011	0.004
8	36	2.4	All	83	0.001	0.001
8	36	2.4	$D\_MORECORRECT_{it} = 1$	26	0.029	0.054
8	36	2.4	$D\_SMARTER_{it} = 1$	14	0.071	0.103

Period	Price - FV	(Price-FV)/FV	Trader Category	# of Traders	p-value for H0: $ASSETSHARE_{it} = 0$	p-value for H0: $SHARES_{i,8} - SHARES_{i,6} = 0$
7	38	1.9	All	83	0.008	
7	38	1.9	$D\_MORECORRECT_{it} = 1$	27	0.360	
7	38	1.9	$D\_SMARTER_{it} = 1$	14	0.488	
8	36	2.4	All	83	0.000	0.000
8	36	2.4	$D\_MORECORRECT_{it} = 1$	26	0.240	0.001
8	36	2.4	$D\_SMARTER_{it} = 1$	14	0.267	0.023

Table 8a: Determinants of Net Buying

Regressor	Simple Regression		Covariates Included	
	Coefficient	p-value	Coefficient	p-value
$E\_APPRECIATION\_1_{it}$	0.010***	0.008	0.010**	0.017
$D\_MORECORRECT_{it}$	-0.262	0.284	0.824	0.207
$E\_APPRECIATION\_1_{it} \times$ $D\_MORECORRECT_{it}$	0.108***	0.005	0.099**	0.046
$E\_BUYANDHOLD_{it}$			0.001**	0.013
$E\_APPRECIATION\_F_{it}$			0.003	0.516
$E\_BUYANDHOLD_{it} \times$ $D\_MORECORRECT_{it}$			0.034	0.147
$E\_APPRECIATION\_F_{it} \times$ $D\_MORECORRECT_{it}$			0.04***	0.000
$CASH_{i,\,t-1}$			0.007**	0.011
D_{t-1}			0.016	0.653
$SHARES_{i,\,t-1}$			0.102	0.333
t			-0.375***	0.007
$\bar{P}_{t-1}$			0.771***	0.000
LHS: $NETBUY_{it}$	R-squared: .024		R-squared: .162	

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 8b: Determinants of Net Buying

Regressor	Simple Regression		Covariates Included	
	Coefficient	p-value	Coefficient	p-value
$E\_APPRECIATION\_1_{it}$	0.010**	0.010	0.012***	0.005
$D\_SMARTER_{it}$	-0.389*	0.086	1.549	0.100
$E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}$	0.138***	0.003	0.227**	0.010
$E\_BUYANDHOLD_{it}$			0.001**	0.014
$E\_APPRECIATION\_F_{it}$			0.004	0.326
$E\_BUYANDHOLD_{it} \times D\_SMARTER_{it}$			0.075**	0.024
$E\_APPRECIATION\_F_{it} \times D\_SMARTER_{it}$			0.034***	0.002
$CASH_{i,t-1}$			0.007***	0.005
D_{t-1}			0.004	0.900
$SHARES_{i,t-1}$			0.123	0.231
t			-0.398***	0.003
$\bar{P}_{t-1}$			0.722***	0.000
LHS: $NETBUY_{it}$	R-squared: .030		R-squared: .282	

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 9a: Determinants of Asset Holding

Regressor	Simple Regression		Covariates Included	
	Coefficient	p-value	Coefficient	p-value
$E\_APPRECIATION\_1_{it}$	0.000	0.562	0.001***	0.002
$E\_APPRECIATION\_1_{it} \times D\_MORECORRECT_{it}$	0.009***	0.000	0.007***	0.004
$E\_BUYANDHOLD_{it}$			0.000	0.943
$E\_APPRECIATION\_F_{it}$			0.000	0.559
$E\_BUYANDHOLD_{it} \times D\_MORECORRECT_{it}$			-0.001**	0.029
$E\_APPRECIATION\_F_{it} \times D\_MORECORRECT_{it}$			-0.001	0.52
$ASSETSHARE_{i,t-1}$			0.479***	0
$ASSETSHARE_{i,t-2}$			-0.201**	0.025
D_{t-1}			-0.002	0.165
t			-0.018***	0.005
$\bar{P}_{t-1}$			0.027**	0.015
LHS: $ASSETSHARE_{it}$	R-squared: .032			R-squared: .232

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 9b: Determinants of Asset Holding

Regressor	Simple Regression		Covariates Included	
	Coefficient	p-value	Coefficient	p-value
$E\_APPRECIATION\_1_{it}$	0.000	0.516	0.001***	0.001
$E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}$	0.011***	0.000	0.013***	0.006
$E\_BUYANDHOLD_{it}$			0.000	0.93
$E\_APPRECIATION\_F_{it}$			0.000	0.522
$E\_BUYANDHOLD_{it} \times D\_SMARTER_{it}$			0.009**	0.042
$E\_APPRECIATION\_F_{it} \times D\_SMARTER_{it}$			0.000	0.959
$ASSETSHARE_{i,t-1}$			0.46***	0
$ASSETSHARE_{i,t-2}$			-0.212**	0.017
D_{t-1}			-0.003	0.112
t			-0.016**	0.012
$\bar{P}_{t-1}$			0.029***	0.005
LHS: $ASSETSHARE_{it}$	R-squared: .037		R-squared: .247	

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 10: Significance of Lagged Prices in Subgroup Regressions

Subgroup	Coefficient on Lagged Prices	p-value
$D\_MORECORRECT_{it} = 1$	.592	0.118
$D\_SMARTER_{it} = 1$	.473	0.401
$D\_CORRECT_{it} = 1$	.711**	0.034
$D\_SMART_{it} = 1$	.686*	0.064

LHS: $NETBUY_{it}$

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 11a: Net Buying in Market 2

Regressor	Coefficient	p-value
$E\_BUYANDHOLD_{it}$	0.001*	0.088
$E\_APPRECIATION\_1_{it}$	0.003	0.323
$E\_APPRECIATION\_F_{it}$	0.006	0.721
$D\_SMARTER_{it}$	0.444	0.256
$E\_BUYANDHOLD_{it} \times D\_SMARTER_{it}$	0.0289	0.271
$E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}$	0.0168	0.558
$E\_APPRECIATION\_F_{it} \times D\_SMARTER_{it}$	0.00339	0.923
$CASH_{i, t-1}$	0.0160***	0.000
D_{t-1}	-0.007	0.815
$SHARES_{i, t-1}$	0.518***	0.000
$\bar{P}_{t-1}$	0.586***	0.000

LHS: $NETBUY_{it}$ R-squared: .104

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 11b: Asset Holding in Market 2

Regressor	Coefficient	p-value
$E\_BUYANDHOLD_{it}$	0.000	0.339
$E\_APPRECIATION\_1_{it}$	0.000	0.581
$E\_APPRECIATION\_F_{it}$	0.001	0.350
$E\_BUYANDHOLD_{it} \times D\_SMARTER_{it}$	-0.003**	0.043
$E\_APPRECIATION\_1_{it} \times D\_SMARTER_{it}$	-0.000	0.857
$E\_APPRECIATION\_F_{it} \times D\_SMARTER_{it}$	-0.010***	0.002
$ASSETSHARE_{i,t-1}$	0.586***	0.000
$ASSETSHARE_{i,t-2}$	-0.160***	0.001
D_{t-1}	-0.005***	0.000
$\bar{P}_{t-1}$	0.027***	0.000

LHS: $ASSETSHARE_{it}$	R-squared: .491

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 12: Effect of Experimental Treatments on Fundamental Mistakes

Hypothesis	z-score	p-value
$D\_SMARTER_{i,10}(UNCERTAIN) = D\_SMARTER_{i,10}(OTHER)$	1.497	0.1344
$D\_SMARTER_{i,10}(PICTURES) = D\_SMARTER_{i,10}(OTHER)$	-2.875	0.004

Table 13a: Differences in Period 7 and 8 Trading, Uncertain Treatment

Trader Category	#obs	Period 7	
		H0: $NETBUY(UNCERTAIN)$ $= NETBUY(OTHER)$	H0: $ASSETSHARE(UNCERTAIN)$ $= ASSETSHARE(OTHER)$
All	83	0.569	0.655
$D\_SMARTER_{it} = 1$	14	0.706	0.533
		Period 8	
		H0: $NETBUY(UNCERTAIN)$ $= NETBUY(OTHER)$	H0: $ASSETSHARE(UNCERTAIN)$ $= ASSETSHARE(OTHER)$
All	83	0.740	0.915
$D\_SMARTER_{it} = 1$	14	0.705	0.535

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 13b: Differences in Period 7 and 8 Trading, Pictures Treatment

Trader Category	#obs	Period 7	
		H0: $NETBUY(PICTURES)$ $= NETBUY(OTHER)$	H0: $ASSETSHARE(PICTURES)$ $= ASSETSHARE(OTHER)$
All	83	0.208	0.324
$D\_SMARTER_{it} = 1$	14	0.045**	0.275
		Period 8	
		H0: $NETBUY(PICTURES)$ $= NETBUY(OTHER)$	H0: $ASSETSHARE(PICTURES)$ $= ASSETSHARE(OTHER)$
All	83	0.678	0.172
$D\_SMARTER_{it} = 1$	14	0.217	0.064*

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Table 14a: Net Buying, Pictures Treatment

Regressor	Coefficient	p-value
$E\_BUYANDHOLD_{it}$	0.001*	0.091
$E\_APPRECIATION\_1_{it}$	0.039**	0.046
$E\_APPRECIATION\_F_{it}$	0.003	0.798
$D\_PICTURES_i$	-0.789**	0.033
$E\_BUYANDHOLD_{it} \times D\_PICTURES_i$	0.002	0.171
$E\_APPRECIATION\_1_{it} \times D\_PICTURES_i$	-0.025	0.193
$E\_APPRECIATION\_F_{it} \times D\_PICTURES_i$	0.008	0.545
LHS: $NETBUY_{it}$	R-squared: .127	

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Note: Other covariates not shown.

Table 14b: Asset Holding, Pictures Treatment

Regressor	Coefficient	p-value
$E\_BUYANDHOLD_{it}$	-0.000	0.608
$E\_APPRECIATION\_1_{it}$	0.004***	0.005
$E\_APPRECIATION\_F_{it}$	-0.001**	0.015
$E\_BUYANDHOLD_{it} \times D\_PICTURES_i$	0.0004***	0.001
$E\_APPRECIATION\_1_{it} \times D\_PICTURES_i$	-0.003**	0.024
$E\_APPRECIATION\_F_{it} \times D\_PICTURES_i$	0.001***	0.003
LHS: $ASSETSHARE_{it}$	R-squared: .227	

Note: *** = significant at the 1% level, ** = significant at the 5% level, * = significant at the 10% level

Note: Other covariates not shown.

Figure 1a: Prices and Fundamentals in Market 1
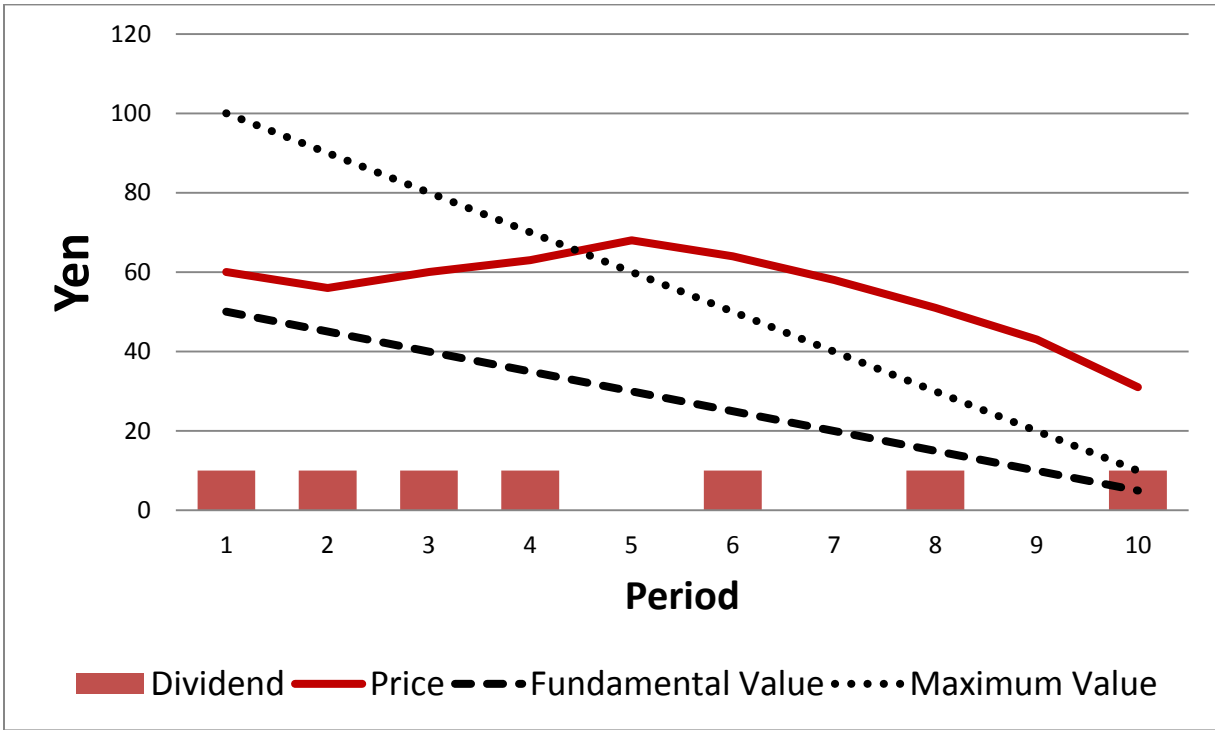
Figure 1b: Prices and Fundamentals in Market 2
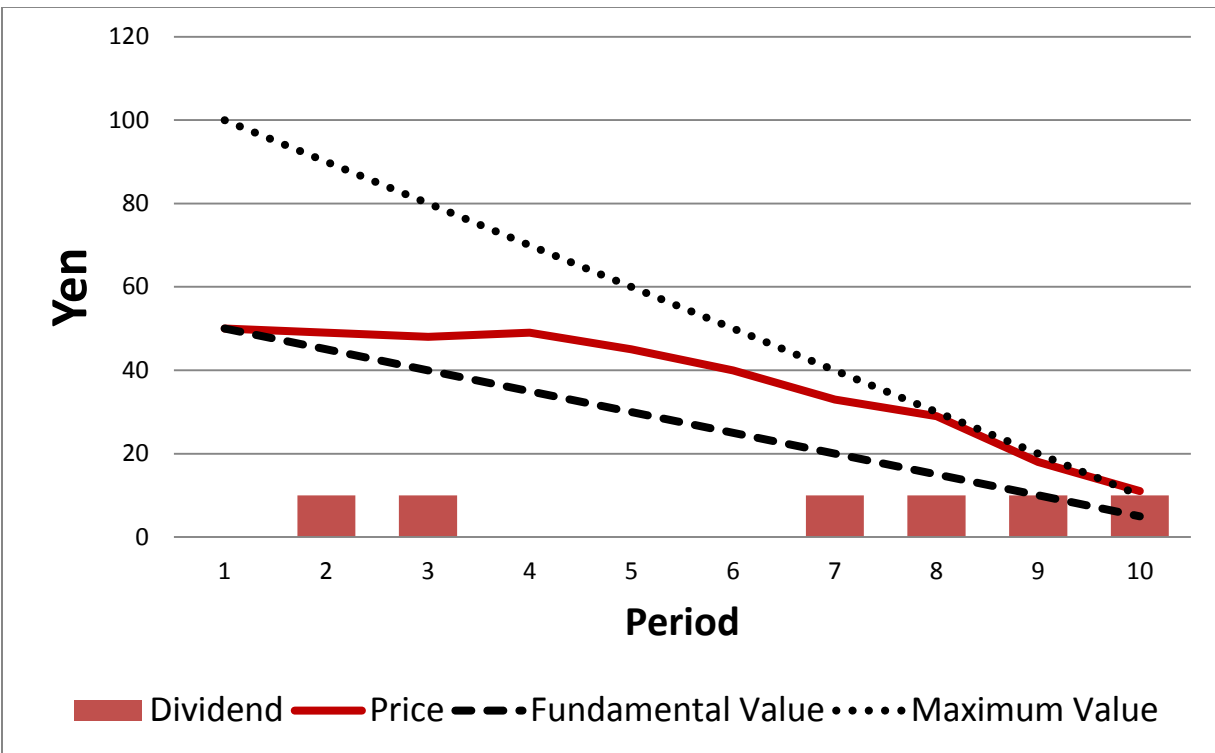
Figure 2: Diagram of the Experimental Procedure

Market prices known

Instructions → Period 1 predictions → Period 1 trading → Period 1 dividends

→ Period 2 predictions → Period 2 trading → Period 2 dividends

··· → Period 10 predictions → Period 10 trading → Period 10 dividends (end)

Figure 3: Confused Traders' Mistakes About FV in Market 1
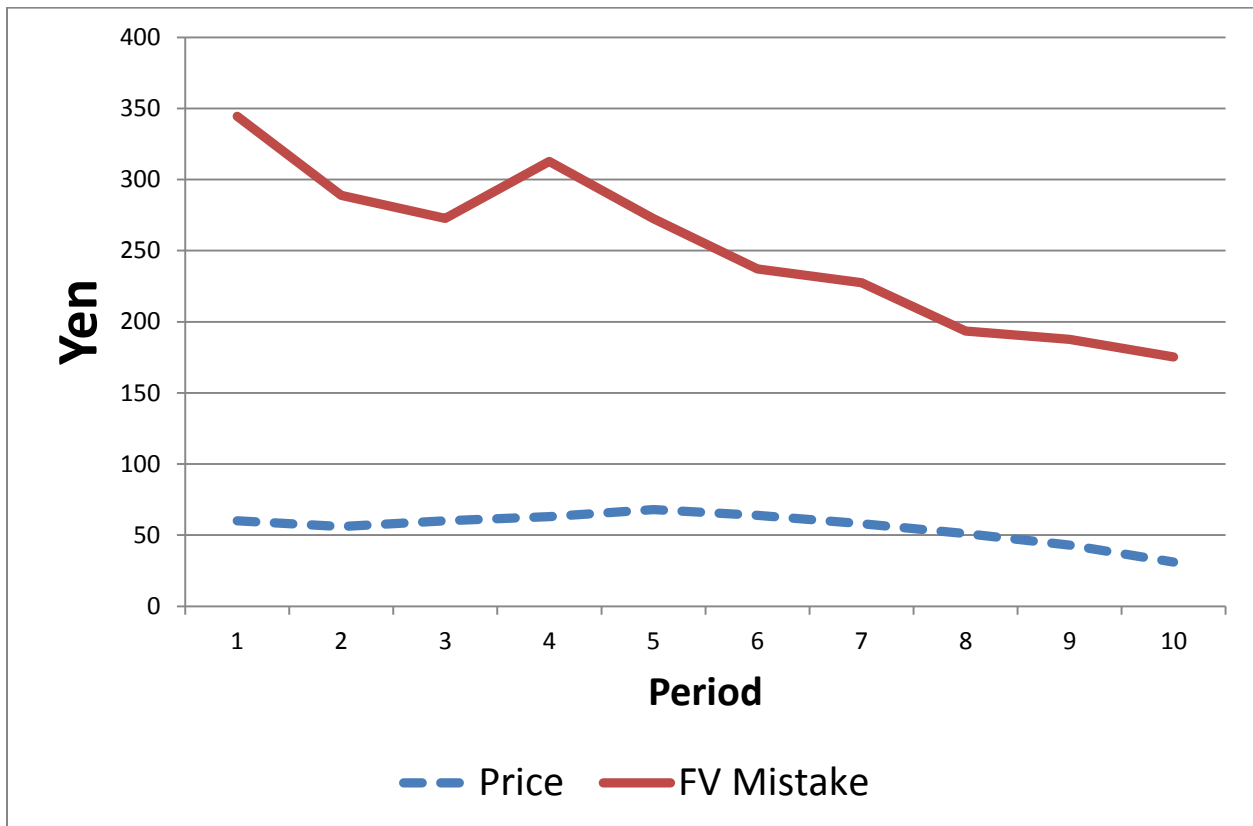
Fig. 4a: Price Predictions vs. Lagged Prices, Market 1, All Subjects

······ Lagged price

- - - Prediction of upcoming period price

—— Prediction of final period price
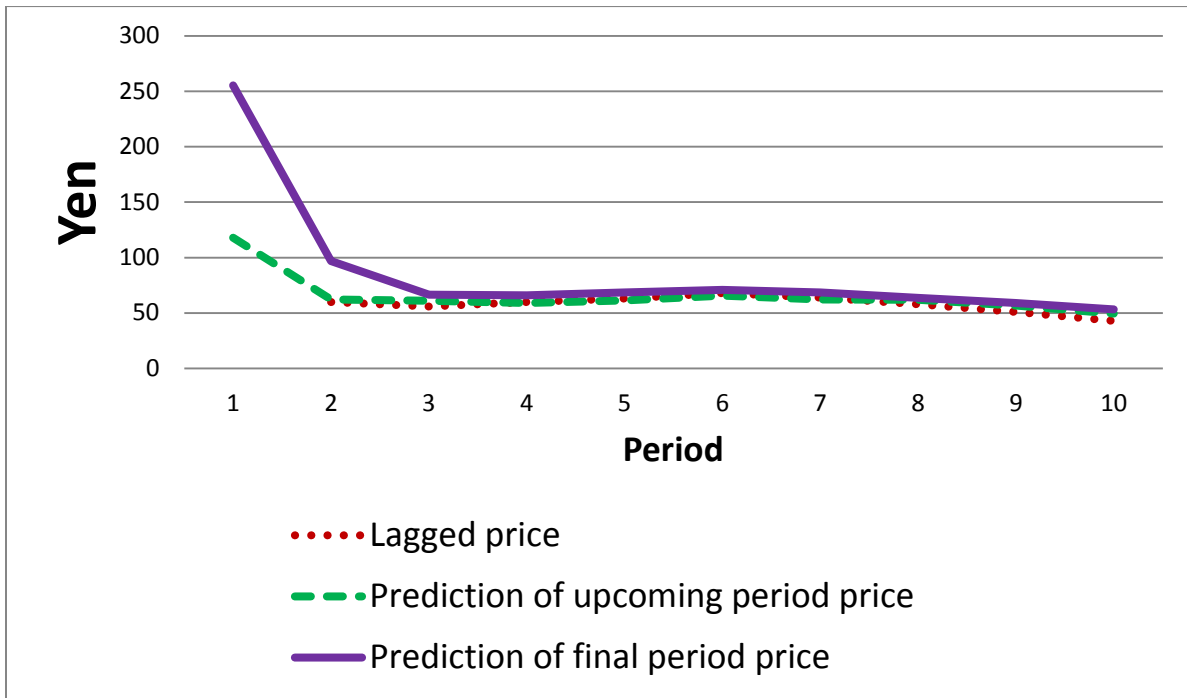
Fig. 4b: Price Predictions vs. Lagged Prices, Market 1, Smart Traders

- - - Lagged price

- - - Prediction of upcoming period price

—— Prediction of final period price

······ Prediction of fundamental value
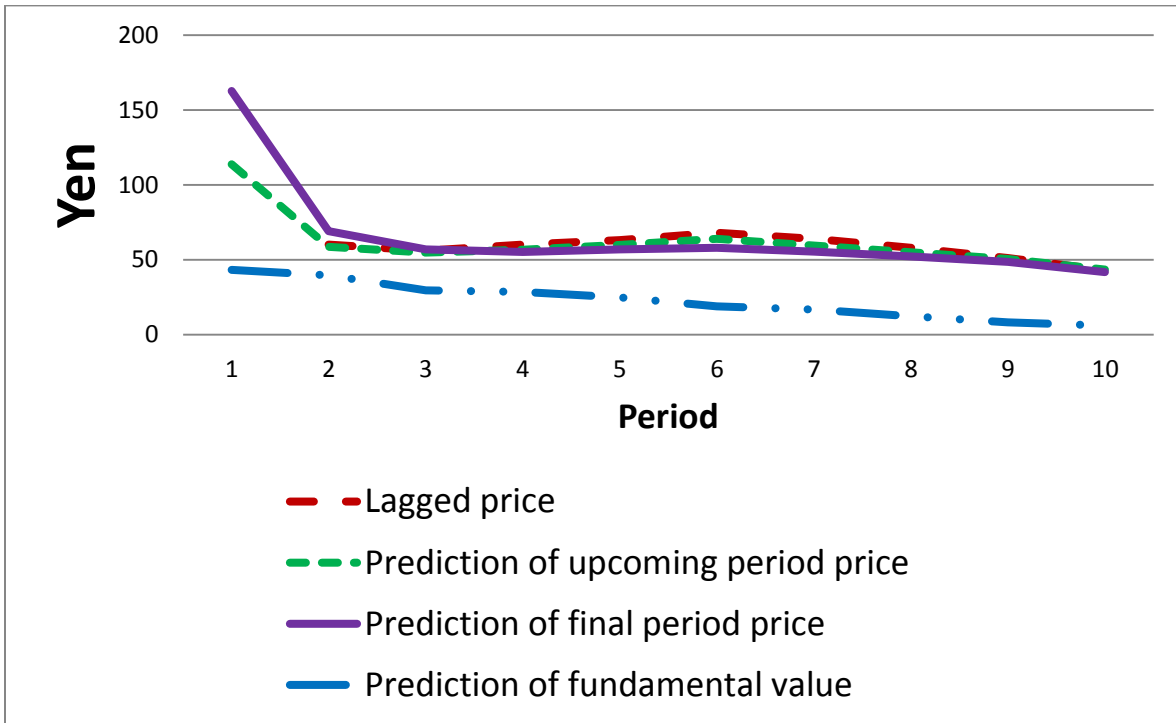
Figure 5a: Average Net Buying in Market 1
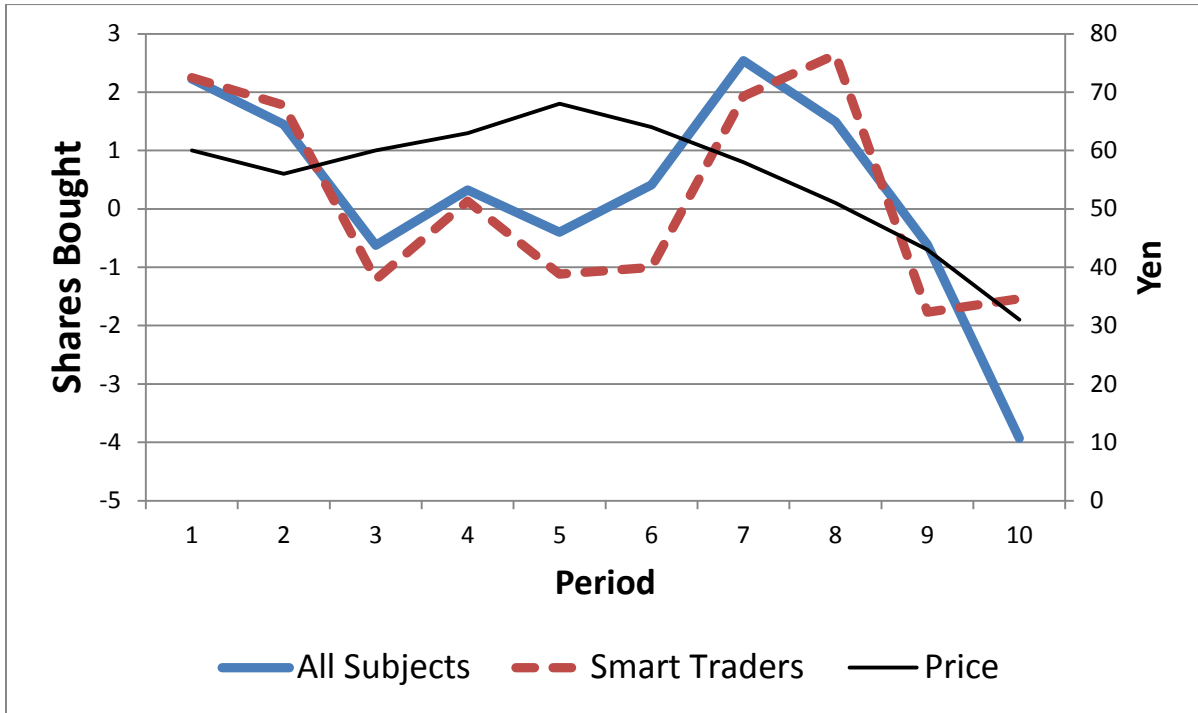
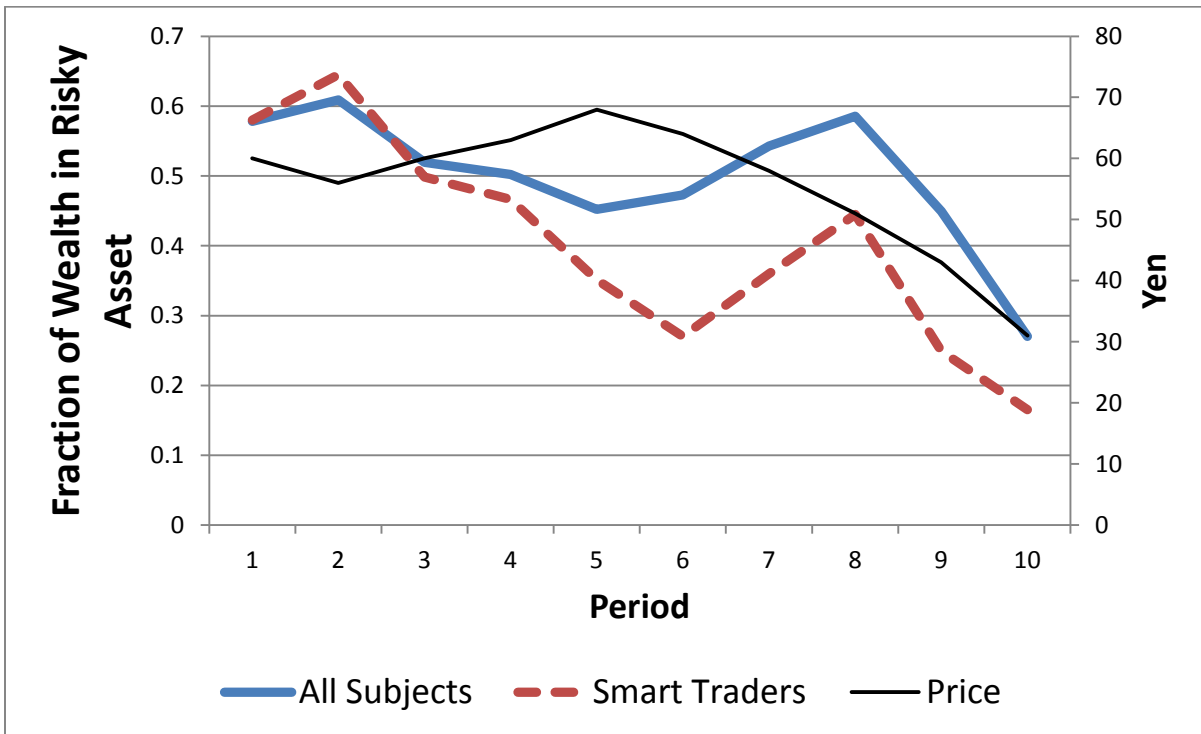# Figure 5b: Average Asset Shares in Market 1

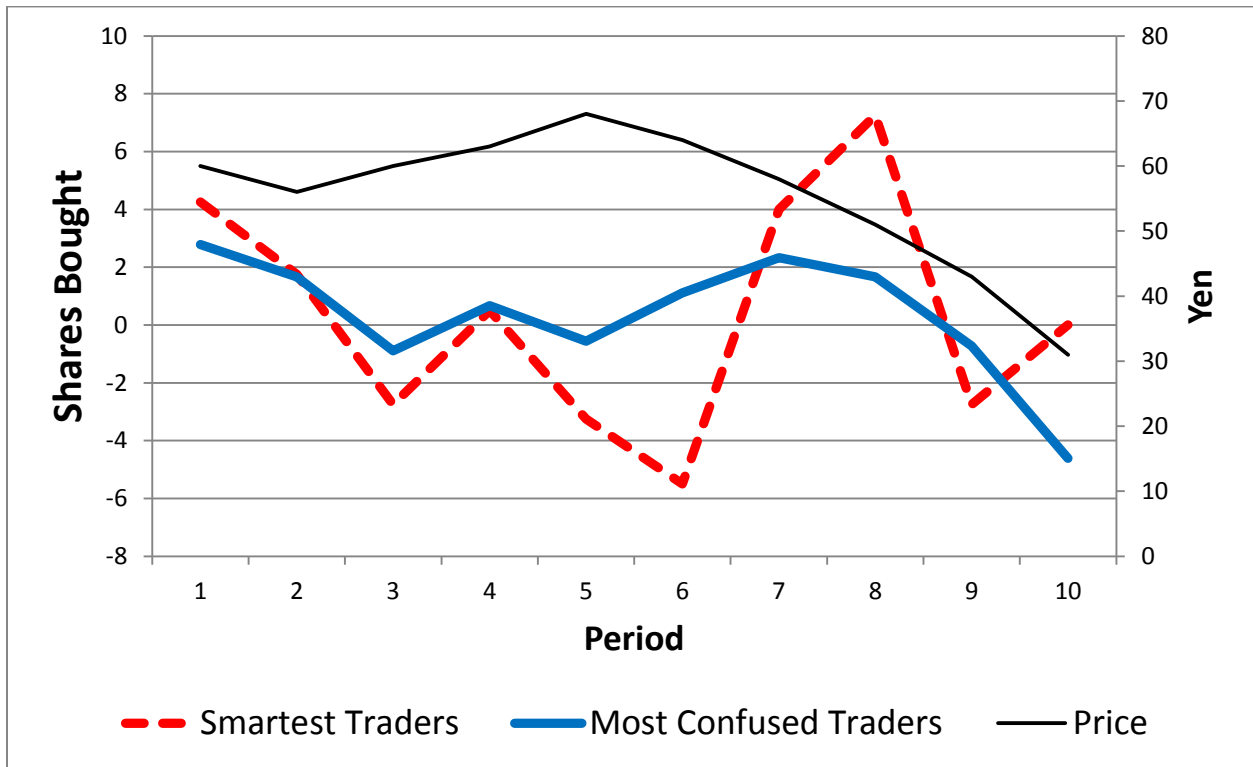# Figure 5a: Average Net Buying in Market 1 (Extreme Groups)

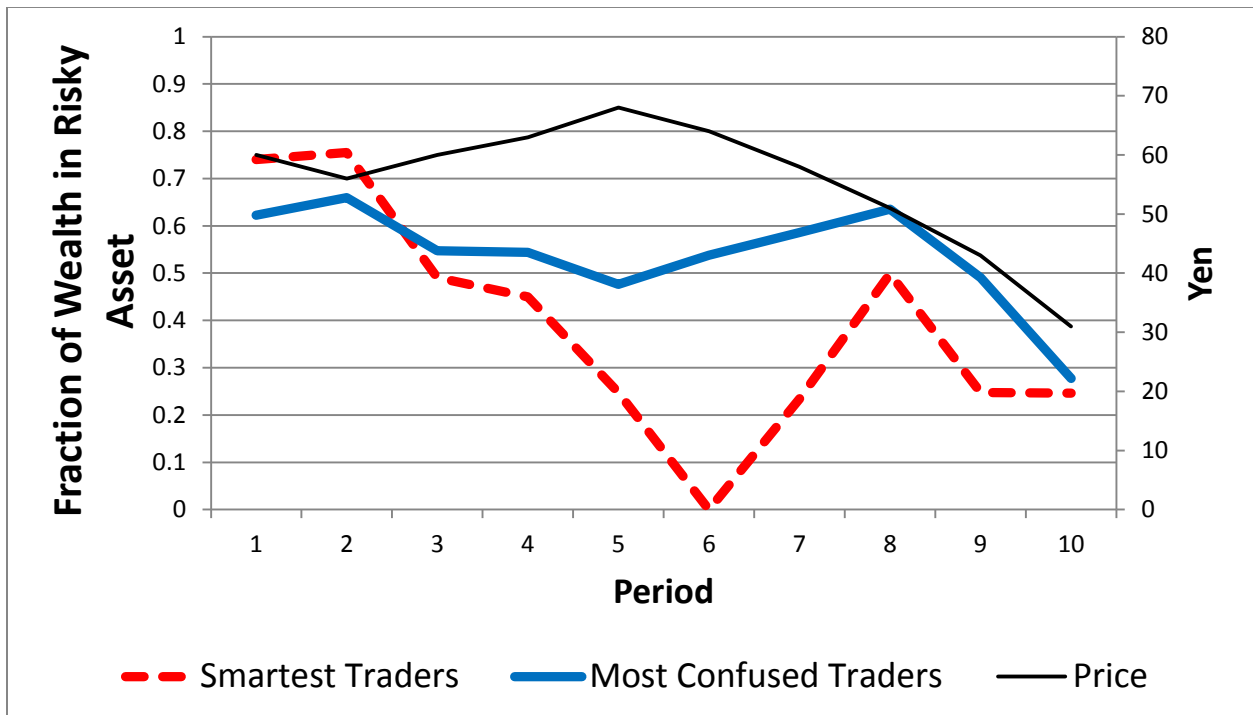# Figure 5b: Average Asset Shares in Market 1 (Extreme Groups)

Figure 7a: Average Net Buying in Market 2

Legend: All Subjects — Smart Traders — Price

Figure 7b: Average Asset Shares in Market 2

Legend: All Subjects — Smart Traders — Price