Visual Representation and Observational Learning in Asset Market Bubbles

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Abstract

We report a laboratory experiment that investigates the impact of observational learning and visual information display on bubble formation in asset markets with inexperienced and experienced traders. We first vary whether the continuously-updated transaction prices are displayed in a column of text or in a graphical display (with time on the X-axis and price on the Y-axis). Second, to explore observational learning we employ pre-market training in which each participant is 'matched' with a trader from a different prior market and observes all trading details but does not participate in trading directly. We find that among inexperienced and once-experienced traders, markets with the tabular display result in bubbles that are greater in amplitude relative to markets with the graphical display. In addition, we find that observational learning, similar to experience, significantly reduces the amplitude of bubbles in subsequent markets. The latter finding suggests that observation of prices is a key mechanism through which experience mitigates bubbles.

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1. Introduction

Asset markets throughout history have experienced episodes with prices that increase far above fundamental value, followed by a rapid drop. This is often referred to as a 'bubble' and 'crash' pattern. Examples range from the Dutch Tulip craze of the early 1600s, to the recent worldwide housing bubble of 2003-2008. Rational expectations models predict that common expectations about the value of the asset should never result in bubbles (Tirole, 1982), yet bubbles have consistently formed even with commonly-known and objective intrinsic values assigned in laboratory experiments; see Porter and Smith (2003), Noussair and Tucker (2013) and Palan (2013) for overviews.

While the bubble and crash phenomenon has been observed in modern markets, two major technological changes have emerged in recent years that may affect the formation and persistence of bubbles. First, computing power can now readily take large datasets and display them in an easy to interpret – and often graphical – format. While graphical displays have been available for professional and institutional investors for decades, tablets and smartphones have put nearly real-time graphical feedback on transaction prices at the fingertips of ordinary investors. Second, the widespread adoption of this powerful computing software makes it much easier for potential investors to experience and observe how past asset prices evolve even before investing. Websites and apps dedicated to helping investors decide on financial strategies show many graphical formats of data, and mock investing websites can help new investors learn before engaging in actual trading.[1] The field of visual analytics – the science of analytical reasoning facilitated by visual interfaces - has emerged in response to dramatic increases in computing

[1] Morningstar.com, Google Finance, Yahoo Finance, and others all display the time trends for stock indices and individual stocks graphically. Data are updated in real time (for instance, see https://www.google.com/finance). MarketWatch, offered by the Wall Street Journal, provides a mock investing platform. Sites such as Scottrade and ETrade allow the novice investor to dabble in mock trading.

power (Keim et al., 2006). However, while visual analytics is meant to improve decision-making, the impact of visualizing data on decision-making in financial markets is largely unexplored.

We contribute new empirical evidence on this issue through a laboratory experiment that investigates how decision-making in a trading environment responds to two innovations: the use of instantly-updated visual representation of trade prices, and allowing for observational learning. If confusion about price trends and the relationship of prices to asset fundamental values is an underlying reason for bubble formation, then increased understanding provided by visual representation of prices may reduce bubbles. In addition, related work has found that experience is one of the few ways to consistently reduce bubbles in laboratory asset markets. Yet, the mechanism through which experience works is not clear. Thus, we are motivated to study observational learning as well as experience to investigate whether the information gained from mere observation, rather than active trading, is sufficient to reduce asset market bubbles.

We find that among inexperienced and once-experienced traders, markets with a visual representation of trade prices (the graphical display) result in bubbles that are lower in amplitude relative to markets with prices reported in text format (the tabular display). This suggests that limited human information processing capability can at least partially explain asset mispricing, and that display format is important to consider when conveying transaction price information. We also find that observational learning, similar to experience, significantly reduces the amplitude of bubbles in subsequent markets. While related work has consistently found that experience mitigates bubbles, the mechanisms through which this effect operates are unclear. Our finding suggests that observation may be a key mechanism through which experience operates, and that it can substitute for direct participation.

Policy-makers have to date focused on the content of information conveyed to consumers, but have paid little attention to the format of the information. Our findings highlight the practical importance of display format. In practical application, we suggest that using visual displays in financial markets for individuals, managers, educators and policy-makers may result in improved outcomes as compared to using text-based displays.

2. Related Literature

We use a version of the standard Smith, Suchanek and Williams (1988) trading environment, which employs a single continuous double auction for traders to buy and sell a finitely lived asset that pays a random dividend to all asset holders at the end of each trading period (Smith et al., 1988). This environment has been shown to consistently yield a bubble and crash pattern of trading prices for inexperienced traders. According to a recent review, to date over 60 research studies have reported experiments using this environment (Palan, 2013).

A rich literature has investigated the possible behavioral causes of the 'irrational' behavior of overbidding that drives up transaction prices in asset markets. Speculation is of course one rational reason for bubble formation, yet bubbles are still observed in a market where resale (and thus speculation) is not possible (Lei et al., 2001). The conclusion of Lei et al. (2001) is that departures from fundamental values are primarily caused by irrational behavior. Cheung et al. (2014) shows that making it common knowledge that traders have received training about fundamental values, but not training alone, leads to decreased mispricing. Oechssler (2011) also finds decreased bubbles when traders have the opportunity to chat with one another. However, one of the most persistent explanations of asset market bubbles is trader confusion (Huber and Kirchler, 2012; Kirchler et al., 2012). In particular, confusion (and bubbles) seem to be reduced when fundamental values are displayed in graphical rather than text form in the instructions (Huber and Kirchler, 2012), or when the asset is called a ‘depletable gold mine’ (Kirchler et al., 2012). Baghestanian and Walker (2014) also find that presenting the fundamental value visually at the beginning of the market causes an anchoring effect that reduces the likelihood of bubbles. As Noussair and Powell (2010) and Stöckl et al. (2014) point out, the pattern of market fundamentals also matters. Markets with a ‘peak’ in which fundamentals rise and then fall are more likely to have prices that track fundamentals compared to markets with a ‘valley’ in which fundamentals fall and then recover. Simplifying or otherwise modifying the experimental environment in the laboratory does not address the goal of reducing potential mispricing in the field, however, so our experiment takes a different approach. We investigate how information presentation or observational learning can improve price discovery in an environment where bubbles reliably occur.

One of the strongest stylized results in the asset market bubble literature is the effect of experience, defined as previous participation in a similar asset market, on reducing bubbles (Porter and Smith, 2003; Palan, 2013). The impact of experience has been documented extensively in laboratory asset market experiments (Haruvy et al., 2007; Dufwenberg et al., 2005; Smith et al. 1988; Van Boening et al., 1993). However, experience in one market does not reliably transfer to other markets. As soon as the parameters of the market are changed, bubbles are rekindled (Hussam et al., 2008; Xia and Zhang, 2012).[2] Hussam et al. (2008) observe a rekindling of the bubble when the variance of the dividend distribution is increased, and when liquidity is increased. Individuals who make predictions about future prices usually do so taking past trends in the current and previous markets into account (Haruvy et al., 2007). More

[2] Oechssler et al. (2011) also do not observe a decline in bubbles due to experience, possibly because parameters of the market change over time in their experiment.

experienced traders are able to utilize more information for predictions and make more appropriate trading decisions, although they still often over-estimate the time remaining before the downturn in prices (Haruvy et al., 2007). While a great deal of literature has focused on the role of experience in abating bubbles, the mechanisms through which experience functions are not well understood. Our paper allows us to tease out one key mechanism – the observation of prices – in mitigating asset bubbles in subsequent markets.

Observational learning in our paper also shares similarities to experiments in which there are 'generations' of players who participate in asset markets sequentially. For example, Deck et al. (2014) employ 3 'overlapping' generations of traders. Inactive traders observe the trading screen and predict average prices in each period, so this study also investigates observational learning. New traders entering the market also create a new injection of cash, which is known to promote bubbles (Caginalp et al., 1998). Thus, while Deck et al. (2014) do not find a reduction of bubbles over time, the isolated effect of observational learning is not known. Similarly, in Xie and Zhang (2012) inflows of inexperienced traders to markets with previously experienced traders create sustained bubbles. Lei and Vesely (2009) also report an experiment showing that when traders experience a pre-market session during which they experience a dividend flow themselves, bubbles are reduced. However, they do not provide a control group where a pre-market phase is not utilized.

Alevy and Price (2012) also conduct an asset market experiment with generations of agents. Traders participate in a market and are then replaced by others who continue in the same role. They find that written advice from a predecessor trader influences market outcomes similar to own experience, suggesting that it is the information rather than the act of participating that is relevant. Adding detailed information about the market activity of the predecessor does not significantly affect pricing if advice is being provided, suggesting that the marginal impact of historical prices is not of great value in this setting. However, Alevy and Price (2012) did not measure the role of history alone, which is most similar to what we do in our observational learning treatment.

One of our interests is the impact of a graphical display of prices on behavior in the asset market. While some previous studies have displayed past prices graphically, such as Deck et al. (2014), none have systematically varied the information feedback displayed to determine its influence on subsequent pricing. Several strands of literature have explored the use of visual displays for decision-making. Computer scientists are concerned with developing new visual and interactive computer interfaces to understand or reason about data (Card and Mackinlay, 1997; Card et al., 1999; Keim et al., 2008). Decision scientists are interested in the use of basic (generally static) graphics as a decision support tool to assist in understanding data such as that found in financial statements (e.g., Jarvenpaa, 1989). Our research fits most closely with the decision scientists, in the sense that we attempt to learn about how graphical interfaces can affect decision-making in the asset market task. We use research insights from studies of perception and computer science to design our graphical interface and provide conjectures about its efficacy. Unlike most previous research in computer science we explore how the graphical display affects decision-making in a real problem with real (monetary) consequences.

3. Experimental Design & Procedures

3.1 Procedures

The experiment was conducted at the Vernon Smith Experimental Economics Laboratory. Participants were recruited using ORSEE (Greiner, 2004) from a subject pool of undergraduate students at Purdue University. A total of 240 subjects participated in 12 sessions, with 20 subjects participating in each session. Ten participants interacted in each market and were able to trade together for the duration of the experiment. We conducted two independent market groups per experimental session. All subjects participated in only one session of this study. Upon arriving to the lab, subjects were seated at individual computers and the experimenter read the instructions out loud while subjects followed along. (See Appendix I for the complete instructions provided to subjects.) Earnings in experimental dollars were converted to US dollars at the rate of 150 experimental dollars = $1. Each experimental session lasted approximately two hours and subjects earned an average of about $39 each.

3.2 Trading Environment

Our market environment is a variant of the standard long-lived asset trading experimental environment pioneered by Smith et al. (1988). Participants could act as both buyers and sellers of assets in a continuous double auction using a computerized trading platform (programmed in zTree; Fischbacher, 2007). In this trading institution, traders could submit a bid or ask at any time while trading was open, and they could also accept any other trader’s bid or ask in continuous time.

Traders participated in three consecutive markets, where each market consisted of 12, two-minute trading periods with a hard close. We conducted three sequential markets to observe the behavior of traders both before and after they gained experience. Traders knew how many markets would be conducted in their session, but instructions for each market were only distributed immediately before that market opened for trading. Earnings were cumulative across the three markets.

At the beginning of each market, traders were randomly endowed with one of two portfolio types, with exactly half of the market trading group endowed with "High Cash, Low Shares" and half of the market trading group endowed with "Low Cash, High Shares." Table 1 summarizes these portfolio endowments.[3] At the end of each period, shares paid a dividend that was announced to the entire market at the end of the period. The dividend was randomly determined and uniformly distributed over the values {0*e*, 8*e*, 28*e*, 60*e*}. The one period expected value of each share was 24*e*, so the value of each share at the beginning of the market was 12 periods × 24*e* = 288*e*. Shares were not redeemable for cash at the end of the market; moreover, shares were not transferable across markets. Therefore, these assets had a commonly known and declining (by 24*e* each period) fundamental value. The declining fundamental value was explained in a table in the instructions.

3.3 Experimental Treatments

The experiment included four different treatments, as summarized in Table 2, with traders participating in three markets for each treatment. Treatments varied either the display of trade prices or the extent of participation, while the underlying market structure (e.g., initial endowments, dividend process) remained the same across treatments. In markets featuring a Text display, trade prices were displayed as columns of text, which is common in the literature (see Figure 1).[4] The display also showed the updated average transaction price for the period immediately following each trade. In markets featuring a Visualized display, trade prices were

[3] The Cash / Asset (CA) ratio in the market in our experiments is 0.625, which is below the CA ratios in related work. For instance, Huber and Kirchler (2012) and Dufwenberg et al. (2005) have CA ratios of 1. This may potentially reduce the size of bubbles in this experiment, but of course the CA ratio is identical across treatments so it does not impact the treatment comparisons.

[4] As shown in the figure, past period transaction prices remain on the screen throughout the market. This differs from standard price feedback in earlier studies that typically only display current period transaction prices. We chose to display all previous prices to portray the entire transaction history for every market in every treatment.

displayed in real time in a graphical interface, with time on the X-axis and trade price on the Y-axis (see Figure 2). Average trade prices within each trading period were also computed and instantaneously displayed using a horizontal line following each trade. Therefore, the history of prices for the entire market was made available in both Text and Visualized markets. The Text treatment consisted of 3 consecutive Text markets, and the Visualized treatment consisted of 3 consecutive Visualized markets. While some studies display price formation in graphical format (e.g., Stöckl et al., 2012), this is the first experiment to explicitly compare the effect of displaying price formation in these two ways.[5]

To explore the impact of observational learning, in the Pre-Text and Pre-Visualized treatments, market 1 was an observation stage only. Each participant in market 1 was "matched" with a participant from a prior market 1 and passively observed pre-recorded trades from that market (visualized graphically, as in the Visualized treatment, for Pre-Visualized; and text based, as in the Text treatment, for Pre-Text). We matched participants 1:1 such that each participant in the observational stage in market 1 was matched with a different participant with the same portfolio type from the pre-recorded market from a previous session. This way, even though each trader in the observation stage had a slightly different experience (observing the specific trades of a different past trader), overall the traders in the observation market had the same range of experiences and observed the same public transaction prices unfolding as the participants in the pre-recorded market that they were observing.[6]

In the observation market, subjects had access to the exact same information as their match. In addition, each participant was paid the same amount that his/her "match" was paid.

[5] Only one other study considers the effect of graphical representation on asset market bubbles, and it focuses on graphical representations of fundamental value (Huber and Kirchler, 2012). The results of this earlier study indicate that graphical presentation of the declining fundamental value reduces asset market bubbles.
[6] Session 1 of the observation market was matched to session 1 of the corresponding pre-recorded market; session 2 to session 2, session 3 to session 3 and so on.

The only interaction that participants in Pre-Visualized or Pre-Text market 1 had with the market was to press the ‘continue’ button at the end of each period to reveal the dividend outcome and to advance to the next trading period. These observers also recorded information on hardcopy record sheets each period, just like their matched trader. The identity of the “match” was not revealed. Thus, the only difference in market 1 of Pre-Visualized and Pre-Text treatments as compared to Visualized and Text treatments is that subjects never made their own bid/asks. The remaining two markets (markets 2 and 3) in the Pre-Visualized treatment were Visualized markets with normal trading; similarly, the remaining two markets in the Pre-Text treatment were Text markets with normal trading. This means that in Text and Visualized, we have data on decision-making in 3 different markets; in Pre-Visualized and Pre-Text, however, we have decision data only from Markets 2 and 3 for those participants (since in Market 1 they only observed).

Our comparisons of Text-Market 1 and Visualized-Market 1 allow us to investigate the role of graphical representation on asset market behavior. We also compare Market 1 to Markets 2 and 3 to investigate the role of experience in both visual and text-based interfaces. Finally, we compare Market 2 behavior between Pre-Visualized and Visualized treatments and between Pre-Text and Text treatments to investigate the role of observational learning, as compared to participatory experience, on reducing asset market bubbles.

4. Empirical Conjectures

If agents are fully rational and have infinite information-processing capacity, as assumed by the rational expectations hypothesis, changing the display type should have no effect on decision-making. However, empirical evidence suggests that humans have limited information processing ability and are boundedly rational (Simon, 1987). Sims (2003) proposes rational inattention theory as a way to explain how agents will allocate scarce processing resources to different cognitive tasks. If the confusion observed in asset markets is due to the incomplete processing of pricing information, then reducing the cost of information processing may improve understanding.

We conjecture that providing traders with information that is easier to process may result in more information being processed, which can translate to more informed decision-making in the asset market. Cognitive Fit theory from the management information systems literature postulates that display of information that is in line with the task to be performed results in the greatest performance in the task, in terms of accuracy and time required (Vessey, 1991). According to this theory, graphical displays are most ideal for perception of spatial information – that is, learning about two or more points on a graph and overall trends. Text displays are most ideal for symbolic information – that is, learning about the value at one specific point. When graphical displays are used for tasks involving spatial information, the performance in terms of accuracy and time spent is improved (Vessey, 1991). Put another way, research finds that "incongruent" or non-fitting display to task projects results in an increased time/effort cost and decreased accuracy (Jarvenpaa, 1989). Given the large volume of trades present in most trading periods, learning about an overall trend will provide the user with greater understanding than learning about each price individually. Thus, Cognitive Fit theory predicts that the Visualized Market will outperform the Text Market for increasing understanding of the price history.

In line with Vessey (1991), it is clear why the Visualized Market will be better than the Text Market at displaying trends. We display prices in two different ways in our experiment. In the Text Market, prices are displayed numerically in a column. Thus, in order to discern the price trend, users must continually make simple inequality calculations (e.g., is p_t greater than or less than p_{t-1}, and by how much?). In the Visualized Market, the graphical display represents trades in a 2D graph with time on the X-axis and price on the Y-axis. The Visualized market takes advantage of Cleveland's Graphical Features hierarchy in its design (Cleveland and McGill, 1984; Cleveland, 1985). According to Cleveland (1985), position along a common scale is the best way to engage the perceptual system to perceive the direction of a trend. This type of graphical display shifts information processing to the perceptual system, allowing the user to quickly see trends and patterns in the data, which reduces the necessity for higher-order information processing (Lurie and Mason, 2007).

We therefore conjecture that the Visualized market should reduce confusion about market prices, since a clear price trend is more apparent to traders and little information processing is required. If immediate understanding of the price trend is relevant for higher-order calculations, such as estimating the probable future behavior of others in the market and the future equilibrium market trading price, then participants in the Visualized market may be less likely to fall prey to the asset market bubble as compared to participants in the Text market. This assumption is similar to the finding that understanding the decreasing fundamental value trend decreases bubbles (Huber and Kirchler, 2012). This brings us to the first conjecture:

Conjecture 1_0: The Visualized market will result in a reduction in bubble formation relative to the Text market.

Alternatively, if agents use past prices to form expectations about future prices (Haruvy et al., 2007), an improvement in information processing may actually cause greater understanding of an increasing price trend that occurs during bubble formation. This can make mispricing worse. That is, the easier information processing could facilitate learning of the *wrong* price trend.[7] This is different from the work on emphasizing the negative fundamental value trend (Huber and Kirchler, 2012), since emphasis on an increasing price trend occurring at the beginning of a bubble could change the direction of prices upward whereas the emphasis on decreasing fundamental value may decrease prices. Thus, our alternative conjecture is:

Conjecture 1_a: The Visualized market will result in an increase in bubble formation relative to the Text market.

Our second variable of interest is observational learning, or 'learning by not doing.' Observational learning has been identified as an evolutionary phenomenon, and has been studied in other economic settings in which decision-making biases persist (Merlo and Schotter, 2003). However, the effect of observational learning in asset markets is not well understood. We are particularly interested in observational learning due to the robust finding that experience plays such an important role in reducing asset market bubbles. What is it about experience that affects behavior in subsequent markets? Is it the observations of information alone – observing prices going up and then quickly down? Or is it the actual act of participating in a market that matters? Again, the rational expectations hypothesis predicts that two identical agents attempting to maximize the same objective function would make the same decision, and learning (either own or observational) plays no role. However, Merlo and Schotter (2003) find that observational learning actually outperforms learning by doing in a decision number task. This suggests conjecture 2:

Conjecture 2: Exposure to a market will promote observational learning and decrease the amplitude of price bubbles in subsequent markets, similar to previous findings that indicate experience reduces subsequent bubbles.

[7] Since a visualized market may also "anchor" individuals to price below fundamental value if the Y-axis does not have a sufficiently high range, we utilized a Y-axis ranging from 0 to 700 in order to avoid the possibility of anchoring as an explanation for our results.

5. Results

5.1 Main Treatment Effects

The experiment employed 60 subjects and 6 independent market-trading groups for each of the four treatments. Figure 3 provides an overview of the average trading prices, employing a different figure panel for each treatment. Bold black lines represent the average prices across all sessions, while lighter gradient lines represent the time series of average prices by session. The declining fundamental value is represented by a dotted line. Deviations from fundamental value are greatest in market 1 relative to markets 2 or 3. For the inexperienced participants in market 1, deviations are greater in the Text market than in the Visualized market. Also, prices in the Text treatments show greater variability across sessions compared to prices in the Visualized treatment.[8]

To explore formally the visual impression regarding the price comparison provided by Figure 3, we conduct statistical tests using the relative absolute deviation (RAD) measure of mispricing and valuation as suggested by Stöckl et al. (2010): $RAD = (1/N)\sum_{p=1}^{N}|\bar{P}_t - FV_t|/|\overline{FV}|$ where $\bar{P}_t$ is the volume-weighted mean price in period *t*, FV_t is the fundamental value in period *t*, $\overline{FV}$ is the average fundamental value of the market and *N* is the number of periods in the market. RAD, similar to bubble amplitude, measures absolute "mispricing" in the market.

Table 3 provides the RAD mean and standard deviation across sessions for each treatment and market. Across all markets, we observe significantly positive RAD, suggesting a substantial level of mispricing, as typically seen in previous studies (e.g., Smith et al., 1988). We turn first to exploring Conjecture 1 – the effect of visual or tabular display of prices on

[8] Transaction volumes (not shown) are fairly large in all treatments, especially considering the total asset stock is only 40 shares in total. Total trade volume across all periods averages 140, 95 and 98 in markets 1, 2 and 3, respectively, indicating total share turnover between 2.35 and 3.5 on average.

inexperienced participants. In the inexperienced Market 1, average RAD in the Visualized treatment is 0.47 while RAD in the Text Market 1 is almost double that, at 0.89. A Wilcoxon Mann-Whitney nonparametric test, which employs independent trading group RAD values as the units of observation, reveals that RAD is lower among inexperienced traders in the Visualized market compared to in the Text market (*p*-value=0.023).[9] The larger bubble observed in the Text treatment is also significantly different than the Visual treatment in Market 2 even among once-experienced traders (*p*-value = 0.037). These results provide support for Conjecture 1_0, that visualizing the price trend graphically reduces the bubble as compared to listing prices as text:

Result 1: Among inexperienced and once-experienced traders, visualizing price in a graph significantly decreases RAD compared to displaying price in a table.

We obtain similar results using an alternate measure of absolute mispricing usually labeled as amplitude (Hussam et al., 2008); these are reported in Appendix II. As reported in this appendix, no significant differences exist for asset market bubble duration or turnover. This suggests that the visual display only impacts the absolute level of mispricing and not other characteristics of the bubble.

Our next question concerns the effects of experience versus observation. Figure 4 displays RAD changes, which provide support for Conjecture 2. Experience and observation both decrease RAD in the Visualized and Text markets, but the effect appears to be stronger for experience than for observation alone. Among Text market participants, experience drops average RAD from 0.89 in Market 1 to 0.38 in Market 2, while observation alone results in an

[9] Notice in Figure 3 that there is a large *negative* bubble in market 1 of session 2 in the Text treatment. However, even when removing this outlier observation our results that RAD is significantly lower in Visualized versus Text continue to hold (Wilcoxon Mann-Whitney *p*-value = 0.045). Because the severe mispricing of this negative bubble "cancels out" some of the more common positive mispricing, no significant differences exist between the visual and text display for Stöckl et al.'s (2010) other measure that reflects average (signed) price errors in the market, relative deviation (RD).

average RAD of 0.55 in Market 2. Among Visualized market participants, experience drops RAD from 0.47 in Market 1 to 0.17 in Market 2, while observation alone results in an RAD of 0.29 in Market 2.

Nonparametric tests comparing the asset bubble measures in Market 2 of the observation treatments to both Market 1 and Market 2 of the experience treatments confirm the result that both experience and observation significantly decrease bubble amplitude. Among participants in the text display markets, the Pre-Text Market 2 RAD is significantly lower than Text Market 1 (Wilcoxon Mann-Whitney p-value = 0.037). Among participants in the Visualized markets, we observe the same effect significant at the 10% level for RAD (p-value = 0.078). However, RAD in Pre-Text Market 2 is not significantly different from Text Market 2 (p-value > 0.10) and RAD in Pre-Vis Market 2 is not significantly different from Visualized Market 2 (p-value >0.10). This suggests that observation alone may be a sufficient proxy for experience. This brings us to our next result:

Result 2: Observational learning reduces subsequent bubble mispricing in the market, similar to bubble reductions due to direct, own-experience.

Our study design also allows us to explore the effect of experience by comparing bubbles in Market 1 to Markets 2 and 3. It is well established that experience significantly decreases asset market bubbles (Haruvy et al., 2007; Dufwenberg et al., 2005; Smith et al. 1988; Van Boening et al., 1993). Consistent with this literature, we find that RAD is about 60% lower in Market 2 than in Market 1 in Visualized and in Text (Wilcoxon Sign-Rank test p-value = 0.028 and 0.046, respectively). The effects of experience appear to be at least as large as the transaction price display condition, since by Market 3 we no longer observe significant differences between Visualized and Text markets (p-value >0.10).

Result 3: Experience significantly decreases RAD, and by Market 3 the degree of mispricing is statistically indistinguishable across all four treatments.

Overall, we conclude that graphical representation, mere observation, as well as direct experience can reduce mispricing. In a series of (unreported) excess bid regressions (as in Smith et al., 1988), we find that excess demand—as proxied by the number of bids minus the number of asks submitted in a period—generally led to increased mean prices in the following period. Consistent with Alevy and Price (2012), the strength in these momentum price trends declines with experience. No significant differences in these price momentum effects exist between the Text and Visualized markets.

5.2 Individual Trader Strategies and Observational Learning

A novel design feature of this experiment is the random assignment of traders in the observational learning treatments to different experiences, uncorrelated with their own decisions. This design feature allows us to observe the causal effect of that exogenous observational experience on later decision-making. Here we look at both individual learning of strategies and session-based observational learning.

In this analysis, we classify individual strategies based on traders' early period decisions about whether to acquire or sell assets. To classify traders' share acquisition strategy for each market, we calculated their net trading activity (shares purchased minus shares sold) after the first four periods of each market.[10] Traders with a positive net trading activity measure were early net buyers, and traders with a negative net trading activity were early net sellers. Since in most sessions prices were below fundamental value in early periods, a strategy of acquiring

[10] While this four-period cutoff is obviously ad hoc, similar conclusions follow when using other cutoffs such as the first quarter (three periods) or the first half (six periods) of the 12-period market.

assets in early periods is more profitable than a strategy of early period sales.[11]

The data indicate that the number of net shares bought by individual traders is highly correlated across markets, suggesting that the strategies that traders adopted are relatively stable as they gain experience. (Individuals' initial share endowments in period 1 were identical in all three markets, although as shown in Table 1, half began each market with three shares and half began with five shares.) The correlation in traders' net trading position examined after four periods ranges between 0.53 and 0.69 when considered across any two adjacent markets in each of the four treatments, and this correlation is always highly significant (two-tailed *p*-values are always less than 0.04, based on linear regressions with robust errors based on session clustering). Thus, traders who adopt early buying strategies usually continue to maintain early buying strategies in the subsequent market, and net sellers also tend to remain net sellers.

Recall that the first, observational market in the Pre-Text and Pre-Visualized treatments paired each subject to observe the individualized trading behavior of a different subject in their paired Text or Visualized market. Therefore, these observational learners could see the individual trading activity and net trading position taken by their match, as well as the profitability of this strategy. We might expect that observing the profitable (net buying) strategy would increase the probability that the trader would adopt this strategy in the following market. However, the correlation between the number of net shares bought in Markets 2 and 3 for the Pre-Text and Pre-Visualized treatments and the number of net shares bought by the matched trader observed in Market 1 is weak. It ranges between -0.11 and 0.28, and never approaches statistical significance (p-values>0.25 for all estimates). Although Result 2 indicates that smaller mispricing and bubble sizes occur through significant observational learning in the aggregate,

[11] Pooled across all markets and treatments, a net buying strategy for these early periods led to a 34 percent increase in market profits over a net selling strategy. For each additional share bought in the early third of the market, total earnings increased on average by 133 experimental dollars.

this learning apparently does not occur through adoption of observed early net trading strategies.

Although we do not see traders systematically adopt the individual net trading strategies that they observe, observational learners may reach different conclusions about the market, depending on the price trends seen in their matched markets. Since we match each session with a different previous market session, traders observe exogenous and substantially different overall price trends across the different sessions. The data provide some evidence to suggest that observation of particular price trends result in similar price patterns in the following market. We focus on the strongest examples of mispricing, which include both mispricing that is above and mispricing that is below the fundamental value. In particular, in one session of the Text treatment we observe an instance in which a *negative* bubble forms and remains for the entire session. In another session of the Text treatment, we observe and instance of a very large *positive* bubble that persists throughout most periods of the first market.

Figure 5 displays the prices observed across the three markets for the Pre-Text treatment, highlighting the sessions with the negative (Session 2) and strongly positive (Session 3) bubbles. During Market 2, Text Session 2 (highlighted with squares) experiences a negative bubble similar to that observed for the replay in Market 1; while Text Session 3 (highlighted with circles) experiences the large positive bubble in Market 2 similar to that observed for the replay in Market 1. Interestingly, by Market 3, Session 3 exhibits a price trend that is more in line with average price trends. Similarly, by Market 3, session 2 is no longer observing the unusual negative bubble: session 2 actually exhibits the largest positive bubble during Market 3. These sessions suggest that the observed price trend is learned, but that a single market of own experience mitigates the effect. Note also that similar instances of high mispricing are not observed in the Visual treatments, so this conclusion is restricted to the Text treatments.

6. Conclusion

This study provides evidence and insight into how experience and visualized data display can improve pricing accuracy in a classic “bubble and crash” asset market environment. Our first major finding is that the visual presentation of prices reduces mispricing for inexperienced and once-experienced traders. This suggests that visual representation of the price trend may improve understanding of the market, as predicted by Cognitive Fit theory, which in turn dampens bubbles. This is consistent with related work in the field of visual analytics that seeks to improve cognition through visual analytic displays in related economic problems (Savikhin et al., 2011; Rudolph et al., 2009).

Our second major finding is that observational learning may be an effective substitute for own-experience learning. While related work has consistently found that experience mitigates bubbles, the mechanisms through which this effect operates are unclear. Our results point to observation as a key mechanism, since mere observation of the bubble and crash price pattern substantially dampens subsequent bubbles. While experience also reduced bubbles in our setting, in the third market the bubble amplitude was similar between experience and observation markets. Together with other recent work, this study helps advance the literature beyond the simple conclusion that ‘experience matters.’ Relatedly, recent work has found positive effects for simulation based learning in other domains, notably in financial investing (e.g., Kaufmann et al., 2013; Bradbury et al., 2014).

Not only does the mere observation of markets have a significant effect at mitigating bubbles, but the format of the information presented matters. Policy-makers have to date focused on the content of information conveyed to consumers, but have paid little attention to the format of the information. Our results point to the importance of considering the role that visual displays can play for reducing mispricing in financial markets. While our work focuses on asset markets, future work should investigate the impact of visual representations in other market environments and economic decision-making problems.

Related work has shown that while experience dampens bubbles, bubbles are rekindled when the environment is changed (Hussam et al., 2008). Future work should also consider whether rekindling also occurs in markets with visual representation. Psychologists call a type of learning that can be transferred across environments ‘meaningful learning’ (Holyoak and Spellman, 1993). Yet the conditions required for ‘meaningful learning’ in economic environments are still unclear (Rick and Weber, 2010). A large literature exists in the education field about learning through graphical or visual displays (Schontz, 2002). A question for future work includes whether visual representation could impart meaningful learning, thereby dampening the ‘rekindling’ of the bubble when parameters of the market change.

While this experiment clearly documents a bubble-dampening effect of visual representation, more work is needed to understand the role of different visual displays in various economic environments with large information sets. For instance, certain visual displays may be better than others, and visual displays may not have the same intended effect in all asset market environments. More work in this area may yield interesting new findings of both theoretical and practical relevance. From a theoretical standpoint, we may learn more about the channels through which visual representation affects decision-making. From a practical standpoint, once we understand how graphical representations improve understanding, policy-makers can create regulations incorporating format into the information transmitted to consumers.

Finally, our finding that observational learning reduces asset market bubbles in a subsequent market deserves additional investigation. In Deck et al. (2014), individuals observe the market as a whole; in our experiment, however, individuals observe both the market and a single dividend flow from their ‘match.’ Our evidence suggests that the observation of a market trend, rather than the observation of a single dividend flow of the ‘match,’ may have a greater influence on future behavior. It would be valuable to learn which of these experiences is most important for observational learning to occur.

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TABLES AND FIGURES

Table 1: Portfolio Endowments

Portfolio Type	**Initial Cash**	**Initial Shares**	**Initial Portfolio Value**
High Cash, Low Shares	1080*e*	3 shares	1944*e*
Low Cash, High Shares	504*e*	5 shares	1944*e*

Note: Each market had 2 portfolio types. Traders were evenly distributed across the two types.

Table 2: Summary of Treatments

Treatment	**Market 1**	**Market 2**	**Market 3**
1. Text Treatment	Text Market	Text Market	Text Market
2. Visualized Treatment	Visualized Market	Visualized Market	Visualized Market
3. Pre-Text Treatment	Text Market Observation	Text Market	Text Market
4. Pre-Visualized Treatment	Visualized Market Observation	Visualized Market	Visualized Market

Table 3: Relative Absolute Deviation (RAD) by Treatment and Market Number

	Relative Absolute Deviation (RAD)		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	0.89 (0.31) N=6	0.38 (0.22) N=6	0.37 (0.25) N=6
2. Visualized Treatment	0.47 (0.13) N=6	0.17 (0.10) N=6	0.30 (0.10) N=6
3. Pre-Text Treatment		0.55 (0.18) N=6	0.25 (0.19) N=6
4. Pre-Visualized Treatment		0.29 (0.13) N=6	0.29 (0.14) N=6
Statistical Analysis Summary (Wilcoxon Mann-Whitney non-parametric tests)	Text different from Visualized: *p*-value = 0.023	Text different from Visualized: *p*-value = 0.037 Pre-Text different from Market 1 Text: *p*-value = 0.037 Pre-Visualized different from Market 1 Visualized: *p*-value = 0.078 Text not significantly different from Pre-Text in Market 2: *p*-value >0.10 Visualized not significantly different from Pre-Visualized: *p*-value>0.10.	No statistical differences between any treatments in Market 3

Standard Deviations in Parentheses.

Figure 1: Text Market Display

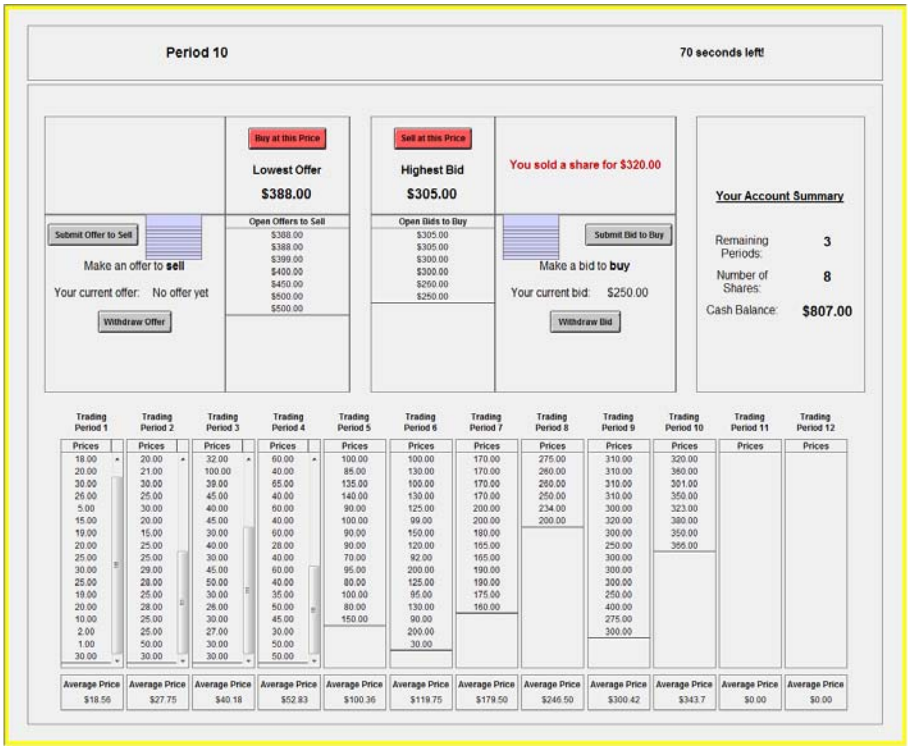


Figure 2: Visualized Market Display

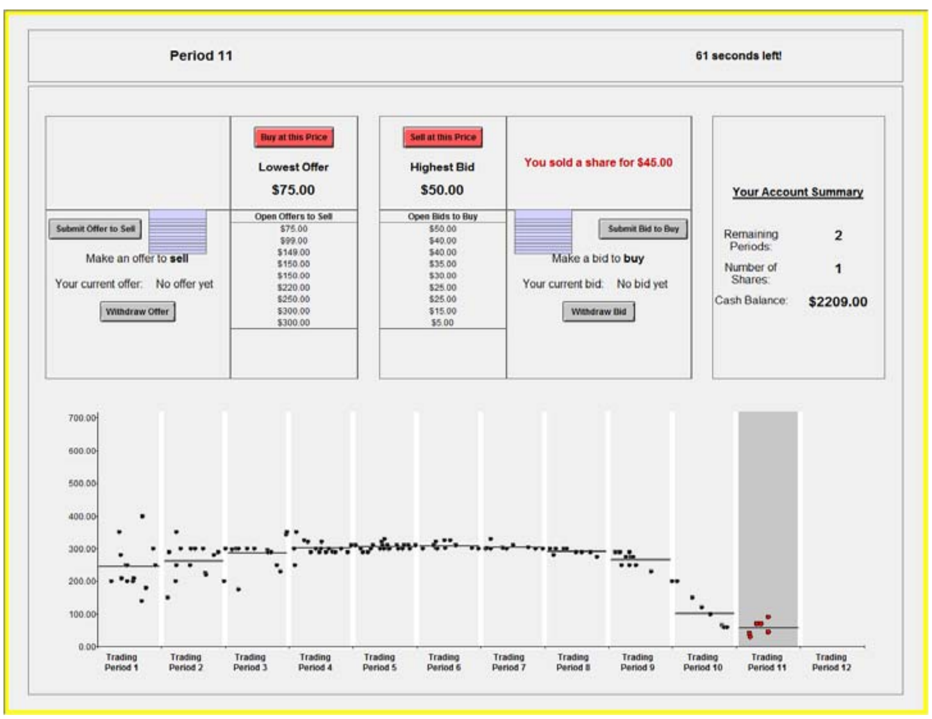
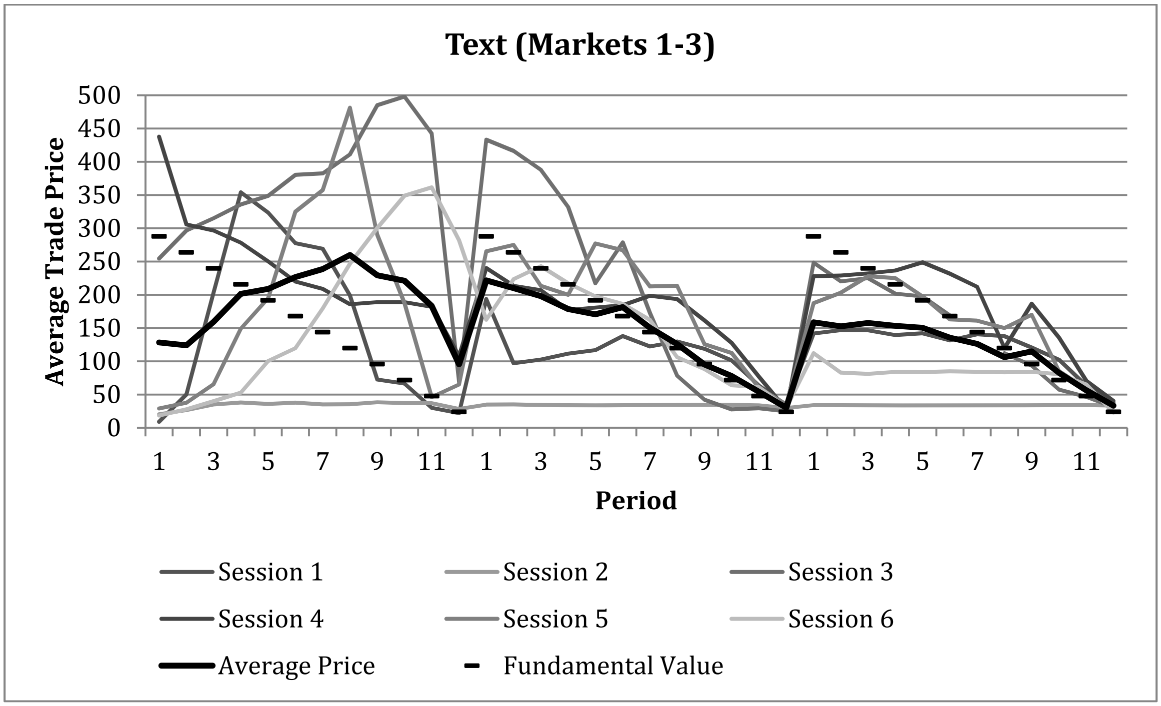


Figure 3: Average Trade Prices, by Treatment (Text, Pre-Text, Visualized, Pre-Visualized)



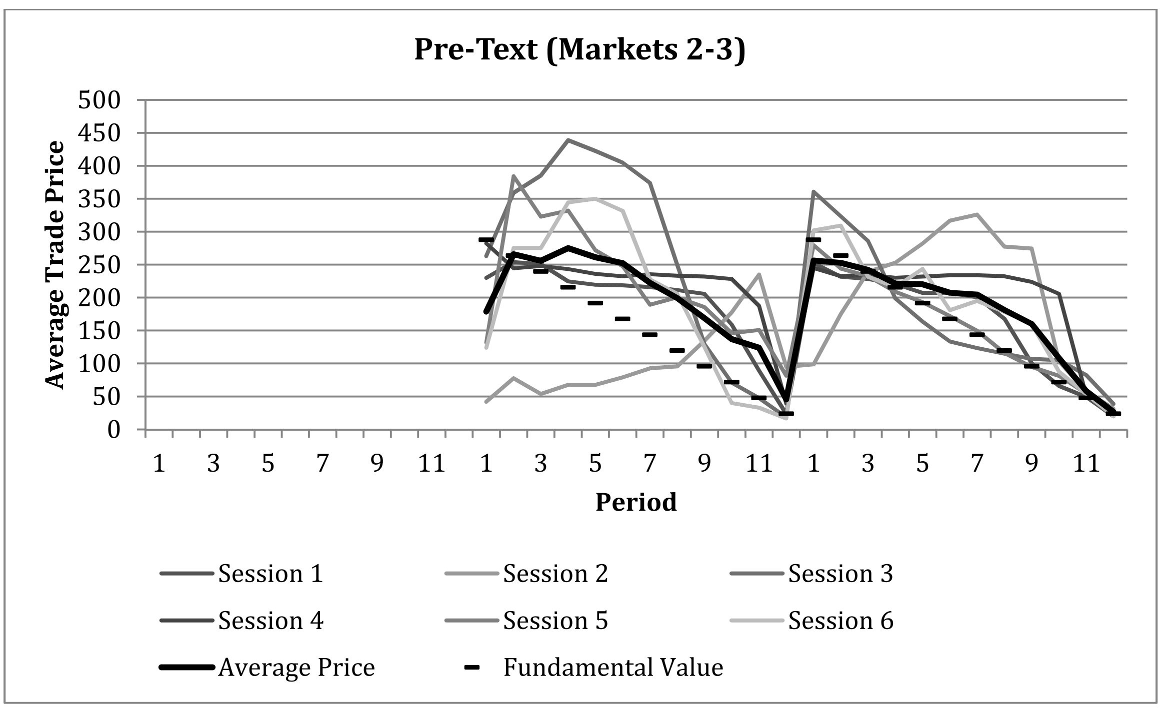
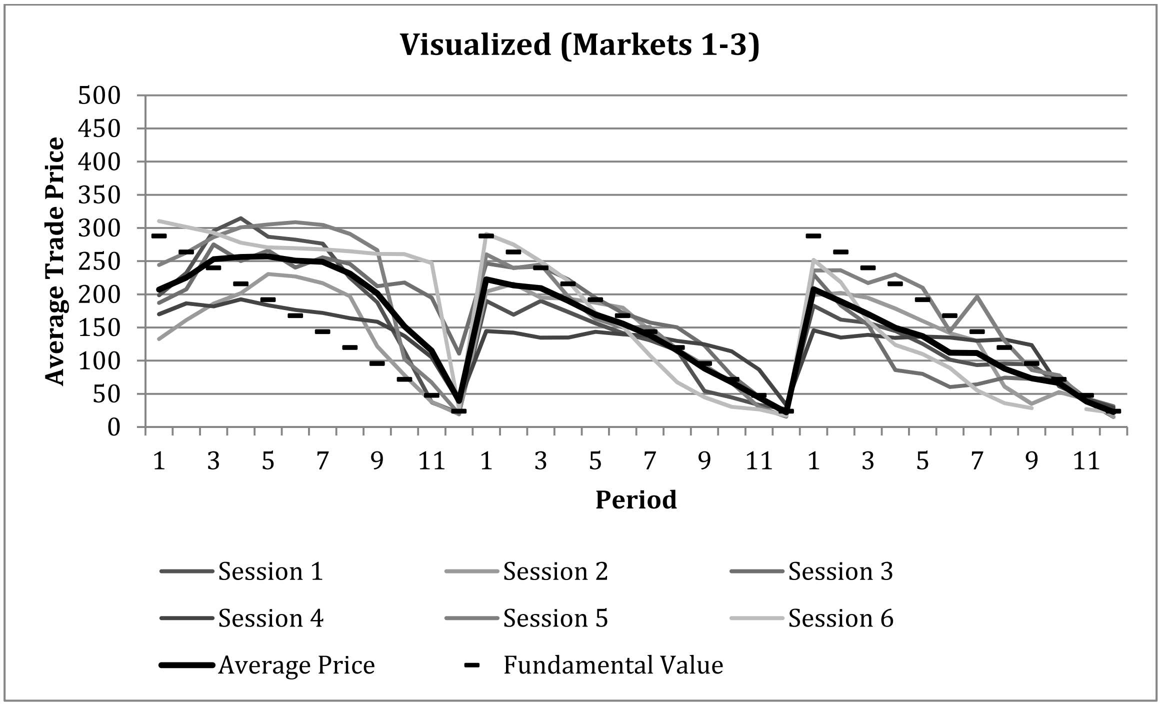


Figure 3 (continued):



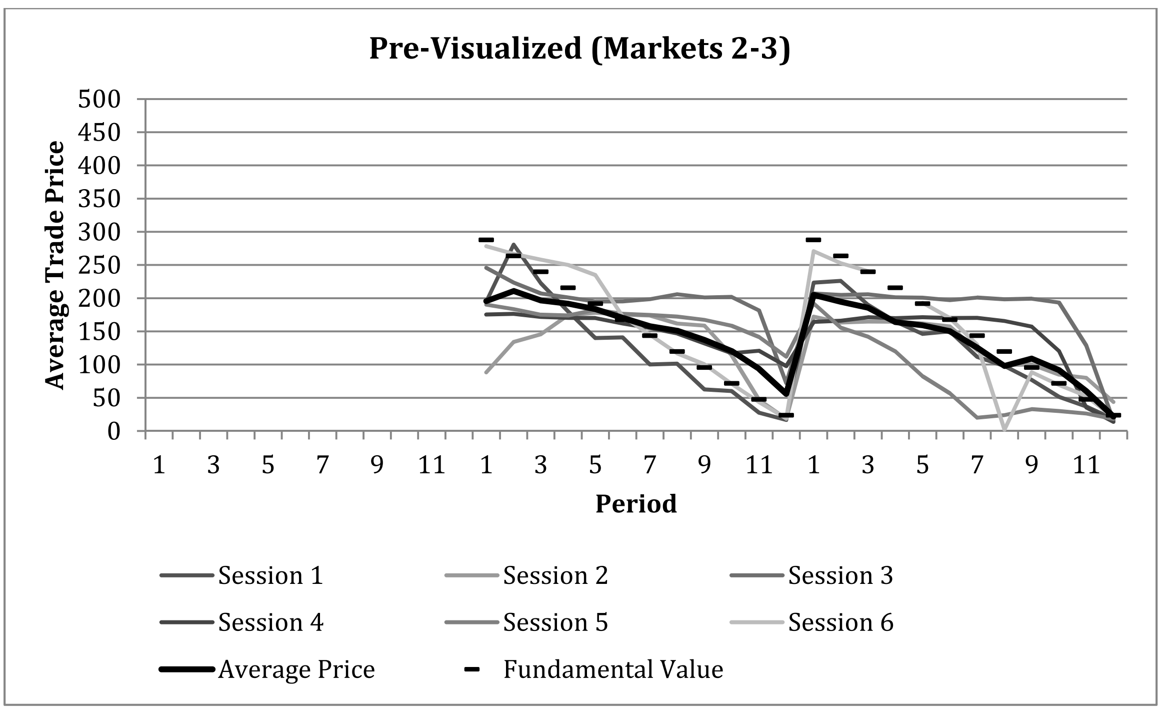


Figure 4: RAD, by Treatment Across Markets

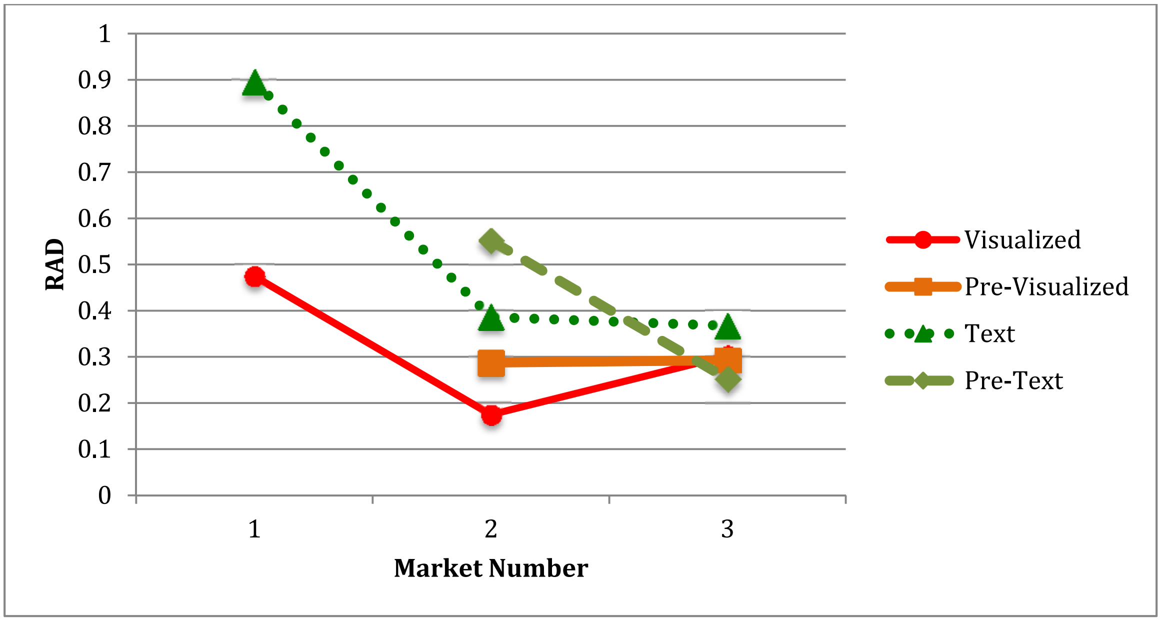
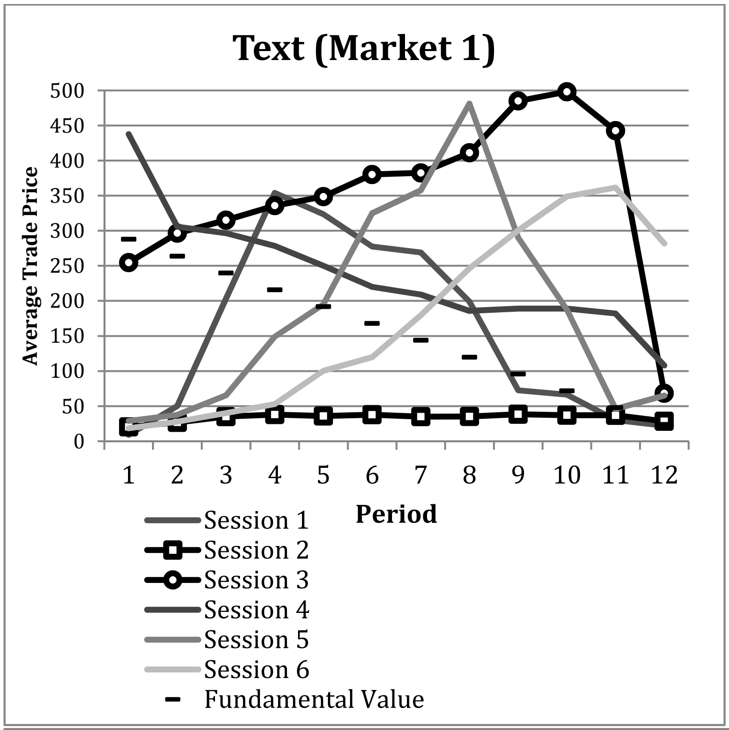
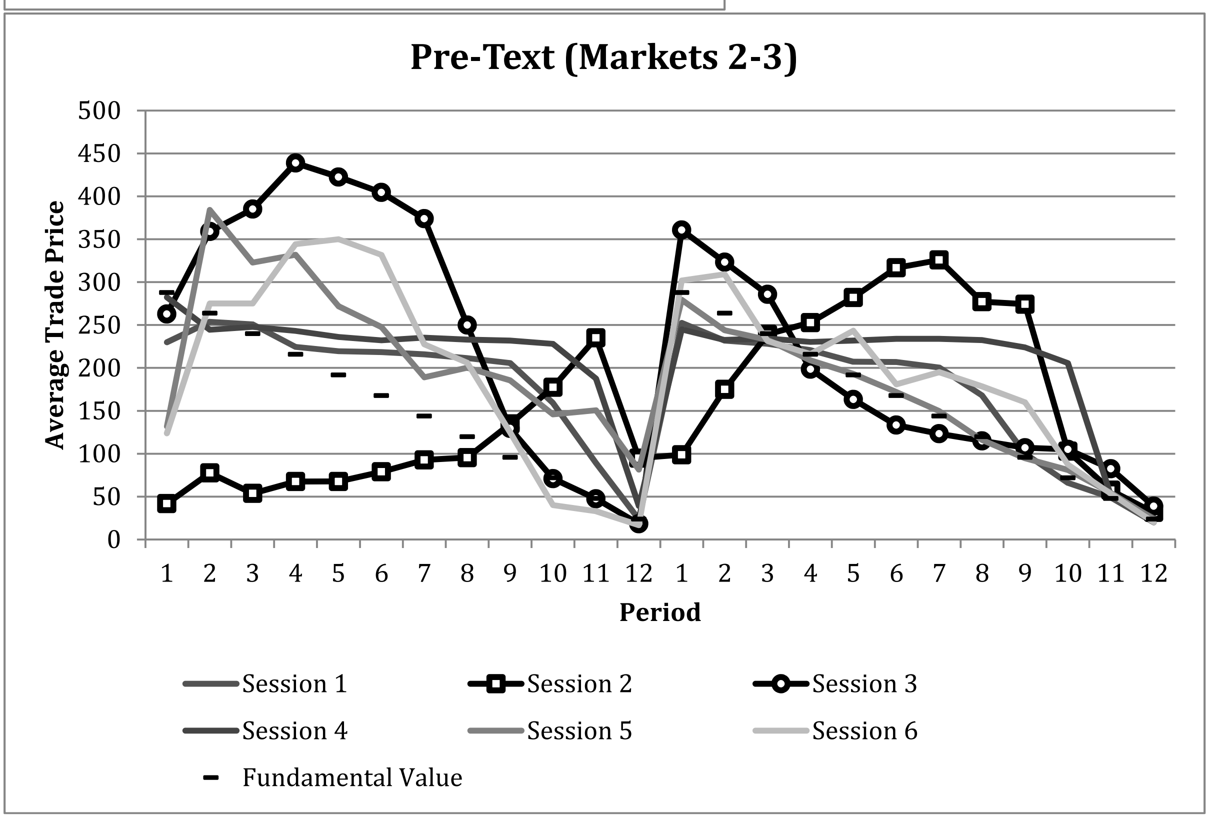


Figure 5: Mean Prices for Text (Market 1) and Paired Pre-Text Sessions (Markets 2 and 3)





Appendix I: Experiment Instructions

Experiment Instructions -

Overview

In this experiment, you will be placed in a group of **10 participants** (including you). You will remain in the same group for the entire experiment. The experiment will consist of **3 consecutive parts of 12 trading periods each.** Each part may have different rules, and assets and shares do not carry over from one part to the next part (e.g., your money and asset stores "start over" at the beginning of each part). You will learn the rules of each part immediately before each part starts. However, you will remain in the same group of 10 participants for all 3 parts of the experiment.

Part 1

(Note to readers: This small section highlighted here in italics was included in the observational learning treatments. Other relatively minor edits were made to remove the second-person nature of the instructions and refer to the decisions of "your match.")

You and everyone else in the room will be observers for this part – this means you will not be making any decisions of your own. Other students like you participated in the experiment previously, and you will randomly be matched with one of them. This means the following:

- *you will observe the past decisions of your match, the outcomes of the decisions, and the decisions of the others in the group of your match*
- *your group members will each be matched with 1 person from the group of your match, but also will not make decisions of their own*
- *your profits in this part* ***will be exactly equal to the profits your match received*** *based on his/her decisions*
- *thus, you should think of any money or shares owned by your match as "your" shares*

In each period, there will be a market open, in which you may buy or sell shares of a good called X. These shares of X can be considered an asset with a life of 12 periods, and your inventory of X shares carries over from one trading period to the next (but will never carry over to the next part of the experiment). Each share of X in your inventory at the end of each trading period pays a dividend to you.

At the end of each trading period, the computer will randomly determine the dividend paid for that period. Each share of X held by you at the end of each period pays a dividend of 0, 8, 28 or 60 experimental dollars. These four outcomes are equally likely, so that **on average**, you can expect to earn 24 experimental dollars from each share in one period (24 = (0+8+28+60)/4). As explained below, you can calculate the **average** value of each share in each period by multiplying the number of periods remaining by the expected dividend value.

Participants will have a different number of shares of X and of cash at the beginning of period 1 of the experiment. The number of shares of X and of cash assigned to you will be revealed on your screen when we begin, and is known only to you but not to the other participants in your group. You will have the opportunity to buy and sell X shares in the market.

Your cash on hand and your inventory of X shares will carry over from period to period beginning in period 1. That means that your cash and your inventory of X at the beginning of period 2 will remain the same as it was at the end of period 1, etc.

Your profits in this part are the total of the dividends that you receive on shares of X in your inventory at the end of each market period plus your initial cash balance and changes in your cash holdings due to trades you make. Experimental dollars will be converted to U.S. dollars at the rate of $1 = 150 Experimental Dollars.

Average Holding Value Table

You can use your **AVERAGE HOLDING VALUE TABLE** to help you make decisions. There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of this part of the experiment. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of this part of the experiment. The fourth column, labeled Average Dividend Per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the expected total dividend for the remainder of this part for each unit held in your inventory. That is, for each unit you hold in your inventory for the remainder of this part, you receive on average the amount listed in column 5. The number in column 5 is calculated by multiplying the numbers in columns 3 and 4.

AVERAGE HOLDING VALUE TABLE

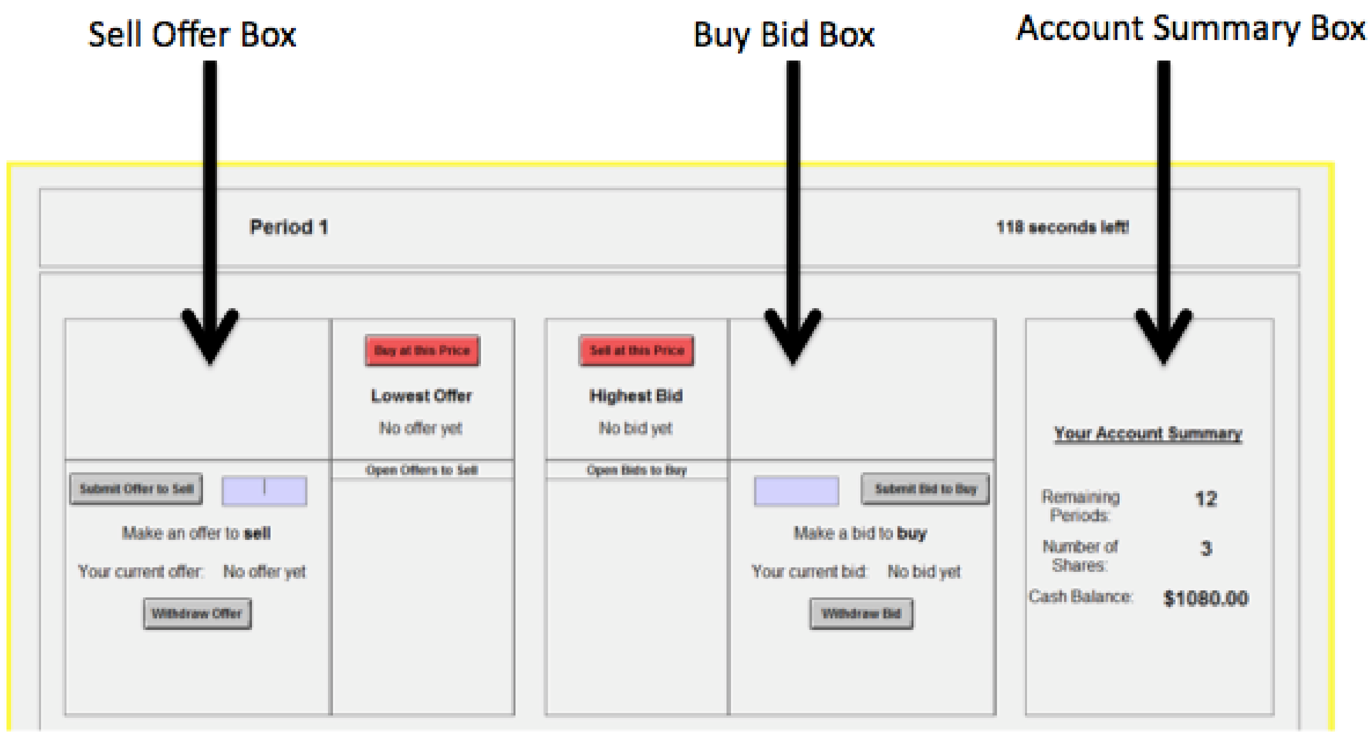
(1) ENDING PERIOD	(2) CURRENT PERIOD	(3) HOLDING PERIODS REMAINING	(4) AVERAGE DIVIDEND PER PERIOD	(5) AVERAGE HOLDING VALUE PER UNIT OF INVENTORY
12	1	12	24	288
12	2	11	24	264
12	3	10	24	240
12	4	9	24	216
12	5	8	24	192
12	6	7	24	168
12	7	6	24	144
12	8	5	24	120
12	9	4	24	96
12	10	3	24	72
12	11	2	24	48
12	12	1	24	24

Trading Stage: How to Buy and Sell Shares of X

During the trading stage, shares of X can be purchased from and sold to other participants in your group. At any time during the trading stage, everyone is free to make an offer to buy a share of X at a price they choose; likewise, everyone is free to make an offer to sell a share of X at a price they choose. Also at any time during the period, everyone is free to buy at the best offer price specified by someone wishing to sell, and everyone is free to sell at the best offer price specified by someone wishing to buy. Of course, there are some limits: to sell a share or make a sales offer, you need to have a share to sell. And to buy a share or make a buy offer, you need to have enough cash to pay.

You will enter offer prices and accept prices to execute transactions using your computer. Figure 1 shows the market trading screen for one of the trading period. You will have 2 minutes to buy and/or sell shares of X in each trading period. The time left in the period is shown on the upper right of the trading screen. The current period is shown on the upper left, and the number of remaining periods is shown on the right in the “Account Summary” box. The “Account Summary” box will also show you the number of shares that you currently hold and your current cash balance.

Figure 1:



Selling shares of X

Participants interested in selling can submit offer prices by entering a price and clicking the "Submit Offer to Sell" button on the left side of the screen. This offer price is immediately displayed on all traders' computers on the left part of the screen, labeled "Open Offers to Sell." Once this offer price has been submitted, it is binding in the sense that anyone wishing to buy can accept this price offer. Such an acceptance results in an immediate trade at that price. Your current sell offer price will be listed on the left side of the screen - if you need to withdraw your offer to sell, click on the "Withdraw Offer" button directly below your listed current offer.

Another way to sell shares of X is with the red "Sell at this Price" button in the middle of the screen. Anyone wishing to sell can accept the best (that is, highest bid price) by simply clicking the "Sell at this Price" button on the top of their computer screen. This results in an immediate trade at that price.

Regardless of how you sell shares of X, your share and cash totals will be updated at the time of sale in the box on the far right. You will also see a notice alerting you of the sale. Note that if you attempt to submit a sell offer that is lower than a current standing bid to buy, you will get an error message alerting you to use the "Sell at this Price" button in the middle instead. This gives you a higher sales price and therefore greater trading profits.

Buying shares of X

Similarly, participants interested in buying can submit bid prices by entering a price and clicking the "Submit Bid to Buy" button in the middle of the screen. This bid price is displayed on traders' computers, labeled "Open Bids to Buy." Once this bid price has been submitted it is binding, and if it is accepted this results in an immediate trade at that price. If you need to withdraw your bid to buy, click on the "Withdraw Bid" button directly below your listed current bid amount.

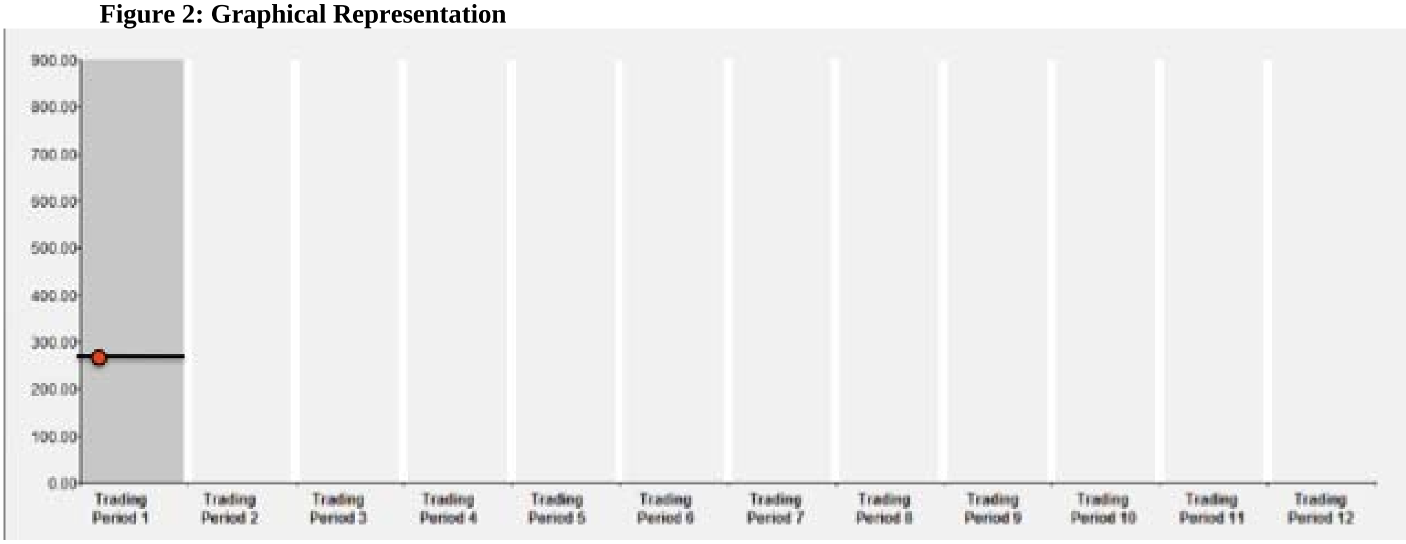
Another way to buy shares of X is with the red "Buy at this Price" button. Anyone wishing to buy can accept the best (that is, lowest offer price) by simply clicking this button. This results in an immediate trade at that price.

Regardless of how you buy shares of X, your share and cash totals will be updated at the time of sale in the box on the far right. You will also see a notice alerting you of the purchase. Note that if you attempt to submit a buy bid that is higher than a current standing offer to sell, you will get an error message alerting you to use the "Buy at this Price" button on the left instead. This gives you a lower purchase price and therefore greater trading profits.

Graphical Representation ***(Note to readers: This section was used for Visualized Market Treatment)***

To assist you in making your decisions, we have provided you with a graphical representation of trades that will be visible on the screen at all times (see Figure 2). The graphical representation will display the trade price and progression of all completed trades (both buys and sells) in the market to all participants in your group.

Figure 2: Graphical Representation



In the graphical representation, each trading period is represented on the horizontal axis, and the trading price is on the vertical axis. The current trading period is highlighted in gray. As soon as a trade occurs, a red dot will appear on the screen at the relevant price – for example, in Figure 2, the red dot represents an initial trade at a price of $288 early in the period. The horizontal black line represents the average price of trades in that period, and adjusts immediately as trades occur. Therefore, looking at the graphical representation can give you an idea about trade prices occurring in your group. After each period is completed, the past trades from earlier periods are converted to black dots.

Past Prices List ***(Note to readers: This section was used for Text Market Treatment)***

To assist you in making your decisions, we have provided you with a list of past trade prices that will be visible on the screen at all times (see Figure 2). The table will display the trade price and progression of all completed trades (both buys and sells) in the market to all participants in your group.

Figure 2: Past Prices

Trading Period 1	Trading Period 2	Trading Period 3	Trading Period 4	Trading Period 5	Trading Period 6	Trading Period 7	Trading Period 8	Trading Period 9	Trading Period 10	Trading Period 11	Trading Period 12
Prices	Prices	Prices	Prices	Prices	Prices	Prices	Prices	Prices	Prices	Prices	Prices
321.00											
225.00											
Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price	Average Price
$273.0	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00

In this table, each column represents a trading period. As soon as a trade occurs, the trade price will appear on the screen at the top of the price list – for example, in Figure 2, the lower number represents an initial trade at a price of $225 followed by a price of $321 shown in the higher number. The average price of trades in that period is shown at the bottom and adjusts immediately as trades occur. Looking at these numbers can give you an idea about trade prices occurring in your group.

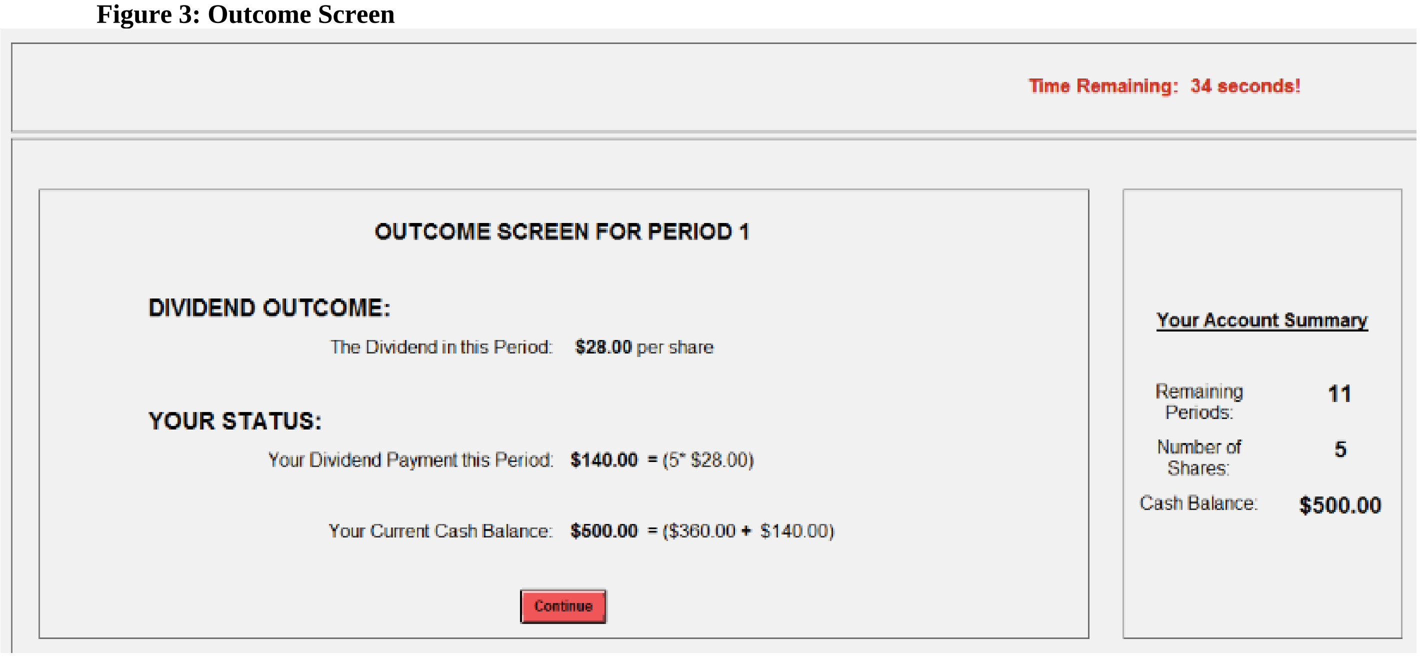
Outcome Screen & Record Sheet

At the end of the period, you will click to continue on to the outcome screen. The sample outcome screen is displayed in Figure 3. On the right, you will still see your account summary as before.

On the left, you will see the dividend outcome – this is the experimental dollars paid in this period for each dividend you hold. This dividend outcome is randomly determined by the computer and is the same for all participants in the group.

You will also see your status – the total dividend payment you received in this period (this is calculated as the number of dividends you currently hold * dividend outcome). Finally, you will see your current cash balance (calculated as the cash balance from the previous round plus the total dividend payment).

Figure 3: Outcome Screen



Please record the dividend per share, current number of shares held, and total dividend payment, as well as your total cash balance on your record sheet before you click "Continue."

Your total earnings for Part 1 are the total of your dividend earnings for periods 1-12 plus your initial cash balance, as recorded in the amount of cash you hold at the end of Period 12. Your shares of X cannot be traded anymore after Period 12 ends; therefore, after the last dividend payment in Period 12, shares of X are worth $0 experimental dollars. Remember that shares do not carry over from Part 1 to the next Part 2.

Part 2

Part 2 of the experiment will proceed exactly like part 1. There will be 12 trading periods as before. You will continue to interact in the market with the same 9 other participants.

Note that you will receive a new initial cash endowment and new shares of X at the beginning of period 1, and these will carry over from period to period during Part 2. Remember that shares do not carry over from Part 2 to the next Part 3.

At the end of Part 2, your total experimental dollar earnings will be converted to US dollars at the rate of $1 = 150 Experimental Dollars and will be added to your earnings in Part 1.

Part 3

Part 3 of the experiment will proceed exactly like part 1 and part 2. There will be 12 trading periods as before. You will continue to interact in the market with the same 9 other participants.

Note that you will receive a new initial cash endowment and new shares of X at the beginning of period 1, and these will carry over from period to period during Part 3.

At the end of Part 3, your total experimental dollar earnings will be converted to US dollars at the rate of $1 = 150 Experimental Dollars and will be added to your earnings in Parts 1 and 2.

Note to readers: For the observational learning treatments, the Part 2 instructions began with the following section, and then included a review (identical to the Part 1 instructions shown above) about how to make trades.

Part 2 (Observational Learning Only)

The market trading rules in Part 2 of the experiment are exactly the same as the rules in Part 1 – with one major difference – **now you and everyone in your group will be making your own decisions**. This means that:

- you will make your own decisions and you will observe the decisions that members of your group make on their own
- your profits will depend only on your decisions and the decisions of your group members

There will be 12 trading periods as before. You will be matched with the same 9 participants as before, only this time you will all be making your own decisions. Let's review how you can make decisions:

Appendix II: Additional Bubble Measures, by Treatment and Market Number

We also conducted additional tests as are standard in the literature:

- $Amplitude = \mathbf{max}\left\{\frac{|P_t - f_t|}{E} : t = 1, \dots, 12\right\} - \mathbf{min}\left\{\frac{|P_t - f_t|}{E} : t = 1, \dots, 12\right\}$
- $Duration = \mathbf{max}\{m: P_t - f_t < P_{t+1} - f_{t+1} < \cdots < P_{t+m} - f_{t+m}\}$
- $Turnover = \sum_t \frac{V_t}{S}$
- *Relative Deviation (RD)* – $RD = (1/N)\sum_{p=1}^{N}(\bar{P}_p - FV_P)/|\overline{FV}|$
- *Payoff variance – using each trader's mean earnings (payoff variance variable)*

The table below provides a summary of averages for each of the measures in each market and treatment. Numbers in parentheses represent standard deviation. Using Amplitude as a measure of bubble magnitude, we observe similar results as reported in the paper for RAD. However, treatment does not affect pricing along the other dimensions, including duration, turnover, RD or payoff variance.

	Amplitude		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	0.97 (0.34) N=6	0.49 (0.22) N=6	0.46 (0.25) N=6
2. Visualized Treatment	0.50 (0.12) N=6	0.25 (0.14) N=6	0.34 (0.11) N=6
3. Pre-Text Treatment		0.57 (0.19) N=6	0.31 (0.21) N=6
4. Pre-Visualized Treatment		0.38 (0.18) N=6	0.37 (0.08) N=6
	Duration		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	7.50 (3.20) N=6	5.17 (3.54) N=6	6.83 (3.37) N=6
2. Visualized Treatment	6.33 (3.08) N=6	5.00 (2.61) N=6	5.67 (2.34) N=6
3. Pre-Text Treatment		5.83 (2.79) N=6	5.67 (1.97) N=6
4. Pre-Visualized Treatment		5.17 (3.54) N=6	5.33 (2.73) N=6
	Turnover		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	3.93 (1.79) N=6	3.80 (3.98) N=6	2.73 (1.93) N=6
2. Visualized Treatment	3.43 (1.08) N=6	2.50 (1.29) N=6	2.21 (0.99) N=6
3. Pre-Text Treatment		2.66 (0.96) N=6	2.57 (0.88) N=6
4. Pre-Visualized Treatment		3.25 (1.95) N=6	2.67 (1.97) N=6
	RD		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	0.30 (0.27) N=6	-0.09 (0.39) N=6	-0.24 (0.35) N=6
2. Visualized Treatment	0.22 (0.67) N=6	-0.13 (0.09) N=6	-0.28 (0.14) N=6
3. Pre-Text Treatment		0.27 (0.35) N=6	0.14 (0.12) N=6
4. Pre-Visualized Treatment		-0.00 (0.16) N=6	-0.16 (0.22) N=6
	Payoff Variance		
	Market 1	**Market 2**	**Market 3**
1. Text Treatment	0.64 (0.21) N=6	0.44 (0.11) N=6	0.37 (0.07) N=6
2. Visualized Treatment	0.53 (0.06) N=6	0.37 (0.06) N=6	0.34 (0.08) N=6
3. Pre-Text Treatment		0.52 (0.13) N=6	0.39 (0.07) N=6
4. Pre-Visualized Treatment		0.41 (0.10) N=6	0.39 (0.06) N=6

Standard Deviation in Parentheses.