Bubbles, Crashes and Endogenous Uncertainty in Linked Asset and Product Markets*

Taylor Jaworski† Erik O. Kimbrough‡

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Abstract

In laboratory asset markets, subjects trade shares of a firm whose profits in a linked product market determine dividends. Treatments vary whether dividend information is revealed once per period or in real-time and whether the firm is controlled by a profit-maximizing robot or human subject. The latter variation induces uncertainty about firm behavior, bridging the gap between laboratory and field markets. Our data replicate well-known features of laboratory asset markets (e.g. bubbles), suggesting these are robust to a market-based dividend process. Compared to a sample of previous experiments, both real-time information revelation and endogenous uncertainty impede the bubble-mitigating impact of experience.

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†University of Arizona, Department of Economics. tjaworski@gmail.com.

‡Corresponding Author: Simon Fraser University, Department of Economics. ekimbrough@gmail.com.

1 Introduction

In financial markets, information about the value of a firm is revealed gradually as traders observe the actions of managers and the firm's profitability. In a class of asset pricing models, firm value is derived from (rational) expectations about the future dividend stream provided to shareholders. These models often assume that dividends are determined by draws from a known distribution (or that share values follow a random walk). However, fundamentally, financial market investments reflect beliefs about the behavior of people (e.g., employees, managers, and CEOs), who are themselves reacting to information about the state of the firm and market. Thus, traders of an individual firm's stock must form expectations about the firm's future profitability, taking into account both the randomness of future events and the decisions of managers. The impact of the resulting uncertainty and the timing of its resolution on the informational efficiency of asset markets is an important open question.

In this paper, we analyze laboratory financial markets in which asset values depend on the profits earned by a firm in a linked product market. In standard experimental asset markets, subjects trade shares of a finitely lived asset that pay a dividend determined by a draw from a known distribution. Despite publicly available information on fundamental value, extensive replications document the tendency of these markets to produce price bubbles.[1] Surprisingly, no previous studies use real (market) activity to determine the dividend underlying fundamental value.

In our environment, traders buy and sell shares of a product market monopolist who chooses a price at which to sell units of a homogeneous good to a sequence of demand-revealing robot buyers. At the end of each period, traders are paid a dividend based on the monopolist's profitability in that period. In three treatments, we vary the timing of information revelation regarding the monopolist's profitability and whether the monopolist is controlled by a profit-maximizing robot or a human subject. Thus, we separately test the impact on asset prices of varying *exogenous* uncertainty about product market demand and *endogenous* uncertainty about the actions of firm managers. This design addresses two fundamental questions: (1) do traders find it easier to form common expectations when firm value is revealed in real-time as trading unfolds, and (2) how does information aggregation depend on uncertainty about the behavior of the product market firm?

[1] See e.g., Smith et al. (1988, 1993); Van Boening et al. (1993); Porter and Smith (1995); Sunder (1995); Caginalp et al. (1998, 2000); Lei et al. (2001); Dufwenberg et al. (2005); Noussair and Tucker (2006); Haruvy and Noussair (2006); Haruvy et al. (2007).

To establish a benchmark, our *Base* treatment closely follows the pattern of information revelation from the standard experimental asset market environment due to Smith et al. (1988; hereafter SSW). The firm is controlled by a profit-maximizing robot which, given the distribution of buyer values, generates a constant expected dividend per period. Dividends are revealed at the end of each trading period, and traders receive no within-period feedback about the accumulation of firm profits.

Then, in our *Info* treatment, we reveal information about the end-of-period dividend in real-time. Specifically, we record the monopolist's (simulated) transaction history over 10 periods and replay the data to traders in the asset market as they buy and sell shares. Thus, exogenous uncertainty about the dividend is slowly eliminated over the course of the trading period. Regarding (1) above, evidence suggests that one important cause of bubbles in laboratory asset markets is failures of common information to induce common expectations. With this treatment, we explore whether the gradual revelation of information about the value of a share can provide a source of common expectations and subdue speculative tendencies.

To address (2), our *Human* treatment maintains the information revelation process of the *Info* treatment except that traders know that the monopolist is controlled by another human subject, who may or may not set the profit-maximizing price. This design moves research on laboratory financial markets in a direction that more closely approximates the problem faced by traders in real-world financial markets, in which they face both relevant kinds of uncertainty. While in this treatment, both types of uncertainty are eventually resolved through continued observation of the monopolist, traders must make decisions prior to this resolution if they hope to profit from their trades. *Ex ante* the expected impact of this manipulation is unclear. If endogenous uncertainty is perceived as additional risk, then risk-averse traders will value shares at less than fundamental value, and prices should be lower. If instead endogenous uncertainty interferes with the ability to form common expectations, then mispricing may be more likely.

We collect data on 39 new experimental asset markets. Our findings suggest that *actual* dividend realizations are a (slightly) better predictor of prices in the asset market than fundamental value; however, our *Info* treatment, which combines detailed framing with real-time revelation of the process underlying dividends, does not appear to provide a common source of expectations sufficient to eliminate price deviations from fundamental value. Moreover, in comparisons to the *Base* and *Info* treatments, the impact of the *Human* treatment is gener-

ally small. In general, our data replicate the stylized facts of earlier asset market experiments, suggesting that bubbles are robust to the introduction of a market-based dividend. In fact, in direct comparisons with a database of 39 previous asset market experiments, our *Info* and *Human* treatments appear to slightly exacerbate bubbles by reducing the bubble-mitigating effects of trading experience.

A few features of our experimental design and our findings may be better understood in the context of the literature. For example, our decision to describe the market process that generates dividends is informed by a recent contribution due to Kirchler et al. (2012). They find that reframing the standard asset market experiment as buying and selling shares of a gold mine (as opposed to shares of a firm with declining fundamental value) reduces confusion and dampens price bubbles. One crucial difference between the description of the gold mine and the firm in their experiment is that the process by which profits are generated is only described in the gold mine treatment–dividends are paid only if the miners strike gold, which happens half the time. In their firm treatment, the dividend structure is the same, but subjects do not receive information explaining *how* dividends are produced. By describing to subjects exactly the market in which the firm is operating, our design is also intended to reduce confusion and thereby isolate the motivations relevant to our research questions. Our *Info* treatment, by providing real-time information about accumulated profits, goes a step further in illuminating the black box of the dividend process. Nevertheless, comparing our data to previous experiments, we find no evidence that our manipulation of trading context reduces the size of bubbles.

Our experimental design is also related to previous work in laboratory asset markets that analyzes the relationship between the timing of information revelation and mispricing (Smith et al., 2000; Lin and Rassenti, 2011). For example, Smith et al. (2000) find that concentrating information regarding dividend value at the end of a market's trading horizon provides a common source of expectations and thereby reduces the prevalence of bubbles. Consistent with these findings, in our environment, we observe that gradually revealing information about the end-of-period dividend does *not* dampen bubbles.

Outside the SSW asset market environment, our paper contributes to a large literature that studies coordination failures in markets with strategic uncertainty (Morris and Shin, 2004; Angeletos and Werning, 2006). In experiments, coordination failures may persist because of the presence of strategic uncertainty (Kogan et al., 2011), even when public information helps resolve fundamental uncertainty (Heinemann et al., 2004; Qu, 2013). In

our setting, the endogenous uncertainty resulting from the *Human* treatment may generate a form of strategic uncertainty. In product market equilibrium, traders face no uncertainty about the strategy being followed by the monopolist. But suppose the monopolist fails to charge the profit-maximizing price. Then traders are forced to make inferences about his strategy in order to determine the value of the asset. Thus traders may be uncertain both about the underlying dividend generating process (because they cannot read the mind of the monopolist) and about the strategies being followed by other traders (because they do not know what strategy others have inferred from the monopolist's prices). If traders' inferences are misaligned, this may generate a failure of common expectations.[2]

Indeed, we find some evidence that endogenous uncertainty in the *Human* treatment exacerbates asset market mispricing in later markets by reducing the beneficial impact of experience. We believe our results provide additional evidence that "common information is insufficient to induce [...] common expectations" (SSW, p. 1148). In the end, our experiments maintain one kind of uncontrolled uncertainty that is common to all asset markets: uncertainty about the behavior of other traders.

Taken together, our findings reproduce many of the stylized facts from the experimental asset market literature, e.g. the bubble-crash pattern, Walrasian price dynamics, and the role of trading experience. Thus our extension of the standard environment provides a foundation for exploring the connection between the real and financial economy in a laboratory setting, while allowing researchers to draw on the substantial existing literature.

2 Experimental Design

Our experiment is designed to examine how introducing a "real" dividend process to the classic experimental asset market environment affects asset pricing. In our asset markets, participants trade shares of a finitely-lived monopolist in a continuous double auction, and the dividends paid per share in each period reflect the profits earned by that monopolist as it attempts to sell a fictitious good to a sequence of demand-revealing robot buyers in an external product market (see e.g. Deck and Wilson, 2003, 2006).[3] We record the real-

[2]Van Huyck et al. (1993) report an experiment in which a market is able to resolve strategic uncertainty because the price at which an asset (the right to play a coordination game) is sold reveals information about how its purchaser intends to use it. In our setting, the firm does not trade in the asset market, so there is no opportunity for the firm to reveal its own information/beliefs about the value of a share.

[3]We chose a monopoly for the product market to abstract away from the effects product market competition may have in this setting. However, as we note in the conclusions, it will be interesting to extend this environment to the case of multiple firms.

time pricing and transaction history of the product market so that we can replay the entire history to traders in the asset market. In what follows we summarize the essential features of both markets, but for the curious reader, details of both the product and asset markets are available in the Appendix.

We report data from three treatments varying (1) the amount of real-time information traders receive about the monopolist, and (2) whether the monopolist's price is set by another human participant or by a profit-maximizing robot.

In our *Base* treatment, which mimics the information conditions of the classic experimental asset market paradigm, the monopolist firm is controlled by a profit-maximizing robot, and dividends are revealed only at the end of each trading period. In contrast to the paradigmatic case, in which dividends are drawn from a known discrete distribution, we inform participants in the instructions that the dividends they receive are generated by the activities of a profit-maximizing monopolist firm. This firm faces a constant marginal cost ($c = 75$), posts a price p and is approached in each trading period by a sequence of $N = 60$ demand-revealing robot buyers with private values drawn from a known uniform distribution, $[v_L, v_H] = [25, 125]$. The firm makes each product to order and accumulates profits ($\pi_n = p_n - c$) on each successful sale, and accumulated profits in each period are divided equally to be paid as a dividend on each share, ($d_t = \frac{\sum_{n=1}^{60} \pi_n}{\#\text{ Shares}}$). We inform participants that this combination of buyer values and profit-maximization (i.e. $p \equiv 100 \ \forall \ t$) by the monopolist generates a constant expected dividend per period of 10.4 cents. Participants are also told that the firm will live for exactly $T = 10$ periods and that the expected return from holding a share starting in the first period is equal to the expected dividend per period multiplied by the number of periods the firm will live. Thus, the fundamental value f of a share in period t is just $(T - t + 1) * 10.4$ (see the Appendix for details). Participants are also explicitly told that after the firm pays its last dividend, shares of the asset are worth nothing. Thus, as in classical asset market experiments, participants have sufficient information to compute the fundamental value of a share, and in the absence of heterogeneous risk preferences and/or speculation, assets should trade at fundamental value or not at all.

In our *Info* treatment, product market conditions are exactly the same as in the *Base* treatment. The only difference between the *Base* and *Info* treatments is that we introduce real-time information about the posted price, transaction history, and profitability of the monopolist. Traders observe the activities of the monopolist in real time as they buy and sell shares in the asset market. Specifically, as each buyer approaches the product market

monopolist, asset traders observe (1) the monopolist's marginal cost, (2) the price offered to the buyer, (3) the conditional profit per unit solid, (4) accumulated profits so far, and (5) the number of completed sales as a fraction of the number of buyers that have arrived so far. Thus, information about the value of the dividend trickles in over the course of a trading period, and uncertainty about the dividend has been resolved by the end of a period. Since product market conditions are identical to those in the *Base* treatment, prices here should also correspond closely to fundamental value.

In our *Human* treatment, the information conditions with respect to the product market are identical to those in the *Info* treatment. The only difference is that participants are informed that the role of the monopolist is played by another experiment participant who may set any price. We collected data on 4 product market monopolists prior to running our asset market sessions, and we use data from one of those sessions to generate the dividend process for these experiments. Participants in the asset market observe the behavior of the monopolist and the complete history of the robot buyers' decisions in real-time as they trade. Because the monopolist is controlled by a human participant, asset market traders face uncertainty about the future conditions of supply in the product market. Thus, they must form asset value expectations based on inferences about the future behavior of the monopolist in the shadow of uncertainty about firm behavior.[4]

Since traders' experience is well-known to play an important role in price formation, each session consists of three 10-period asset markets so that we collect observations on subjects when they are completely inexperienced and after one and two markets' worth of experience. We employ a randomized, blocked within-subjects experimental design so that we observe each participant in one 10-period market of each treatment. With three treatments, there are six possible orders in which they may be introduced: *Base-Info-Human*, *Base-Human-Info*, and etc. In total we collected data on 13 experimental sessions. We collected at least two observations on each ordering, and due to experimenter error, we have 3 observations on the *Base-Info-Human* ordering. This means we have data on 39 total asset markets, 13 markets per treatment and at least 4 observations on each treatment at each experience level (zero, once- and twice-experienced).

In the *Base* and *Info* treatments, the product market data are generated independently by making $N \times T = 600$ draws for each treatment from the uniform buyer value distribution and computing the profit earned in each period by a profit-maximizing monopolist. This

[4]Note that decisions in the asset market have no bearing on outcomes in the product market, so our environment reflects the situation in which the firm is not an active trader of its stock.

allows us to "play back" the product market data in real time in the *Info* treatment and ensures that we are not engaging in deception in the *Base* treatment. As noted above, in the *Human* treatment, the product market data are generated by a human subject. All *Human* treatment markets are based on the behavior of the same subject; Figure 1 shows transaction prices in the *Human* treatment product market. One might argue that basing our asset market dividends on only 3 product markets (1 per treatment) reduces the generalizability of the results, but we chose to trade off comparability between sessions against the possibility of introducing a greater variety of dividend processes. Moreover, the claim that efficient markets will yield asset prices reflecting firm value does not depend on the particular firm or the characteristics of the industry.

2.1 Research Questions

We compare observed prices to both fundamental value (derived from theoretical considerations) and realized value (which results from the random draws of individual buyer values and the actual decisions of the product market monopolist). Let $\pi_{n,t}$ be the profit earned on buyer n in period t. Then, the realized value (RV) of the firm is given by: $RV = \Pi = \sum_{t \in T} \sum_{n \in N} \pi_{n,t}$. And the realized value of a *share* in period t' is just the sum of as yet unrealized dividends: $r_{t'} = \sum_{t=t'}^{T} d_t$. Figure 2 displays fundamental and realized value for the product markets underlying each of our treatments. Note that the value derived from the *Human* treatment monopolist was similar to that of the robots.

These two measures constitute alternative metrics for evaluating the informational efficiency of the asset market. Under a version of the rational expectations hypothesis that typically sets the standard of comparison in experimental asset markets, the price of a share of the asset should be equal to the future expected dividend stream of the asset. However, since traders in our *Info* and *Base* treatments face some uncertainty about the empirical distribution of buyer values and traders in our *Human* treatment face uncertainty about seller behavior, it is unclear what should be the source of these expectations. Our metrics, which we refer to as fundamental value (f) and realized value (r) capture this tension.[5]

Question 1: Is fundamental or realized value a better predictor of asset prices?

Since our *Base* treatment essentially replicates previous asset market environments with

[5] While we realize this terminology is nonstandard, we think it captures the flavor of the difference between these two metrics. In a real sense, a share is *fundamentally* worth its expected value in equilibrium, but to what extent this value is *realized* depends on the behavior of the monopolist and draws from the buyer value distribution.

declining fundamental values, previous evidence suggests that bubbles are likely (Kirchler et al., 2012). In the presence of bubbles, price changes are well-known to be driven by Walrasian dynamics (as in SSW). Thus we ask:

Question 2: Will asset prices follow Walrasian dynamics when dividends are based on the actions of a product market firm?

Behavior in our *Info* and *Human* markets may be expected to differ in important ways from the standard asset market experiments (e.g. our *Base* markets) because our market-based dividend process provides constant feedback about the expected value of the dividend in a given period. Since traders in these treatments observe as the monopolist accumulates profits, they may find it easier to forecast dividends and also more difficult to find buyers who are overly optimistic about the future value of a share. Thus, we might observe smaller than usual bubbles.

In all our treatments and all asset market experiments, traders face uncertainty regarding the behavior of other traders. Our treatments examine the effects of two types of uncertainty regarding the value of a share: (1) in all three treatments, uncertainty about the realizations of buyer values and the resulting uncertainty about the monopolist's profit,[6] and (2) in the *Human* treatment, endogenous uncertainty about the pricing decisions of the product market monopolist. Introducing uncertainty into the dividend process through the channel in (1) should, if it has any effect at all, only encourage prices to be lower because, e.g. risk-averse traders may value shares at less than their expected value. The potential impact of channel (2) is more ambiguous. While endogenous uncertainty may be perceived as risk, having a similar impact to channel (1), it is also possible that such uncertainty may reduce the ability of traders to correctly form price expectations more generally, potentially exacerbating mispricing. Therefore we ask:

Question 3: How do the introduction of gradual information revelation (in the *Info* and *Human* treatments) and endogenous uncertainty about product market behavior (in the *Human* treatment) impact the magnitude and duration of bubbles?

2.2 Procedures

All subjects were recruited from the population of a large public university in Canada. In total, we recruited 119 participants. We conducted 4 product market sessions of 1 subject

[6] This kind of uncertainty is also present in the SSW environment with stochastic dividends.

each, 11 asset market sessions of 9 subjects each, and 2 asset market sessions of 8 subjects each.[7] The past experience of product market participants was unrestricted while asset market participants had never participated in an asset market experiment.

Upon arriving at the laboratory, subjects were seated at visually isolated computer terminals. In all treatments participants read through self-paced instructions. The asset market instructions included an interactive training period that taught participants how to use the interface as well as a "demo" that allowed participants to gain experience observing the information they would learn about the product market and the dividend draws while trading was prohibited.[8] At the conclusion of the demo, the participants were given the opportunity to review the instructions and then the first 10-period market began. At the beginning of each market, all 9 traders receive identical endowments of 500 cents in cash and 4 shares of the asset. At the conclusion of each trading period, dividends are added to the cash endowment. Total earnings for a market were equal to the final cash endowment.

At the completion of each market, subjects observed their earnings from that market as well as their total earnings up to that point. Once subjects indicated that they were ready to go on, a shorter set of instructions described the information conditions and the dividend process for the upcoming market, and they observed a new "demo". At the conclusion of the demo, participants could review the instructions once more and the next 10-period market began. Copies of the instructions are provided in online Appendix A.

Subjects were paid in CAD the sum of their earnings from all three treatments in the experiment plus a \$7 show-up payment. On average, subjects earned \$9.70 in the product market sessions and \$26.75 over three markets in the asset market sessions (min = \$4.69, max = \$45.87), excluding the show-up payment. A trader that held his shares through each treatment without trading would earn \$26.75 + \$7. Actual payments were rounded up to the nearest dollar. Product market sessions lasted around 45 minutes, and asset market sessions lasted approximately 120 minutes.

3 Results

Our results test a number of different hypotheses about price formation. Two potential outcomes of the market process in this environment could be considered informationally

[7] In sessions 5 and 11, the 9th trader was a 'ghost trader' who never bought or sold; this was an unfortunate consequence of recruited participants who did not arrive as scheduled.

[8] We do this, following Huber and Kirchler (2012), in order to eliminate mispricing that is due to confusion.

efficient (in the sense of prices correctly representing the value of a share): (1) subjects trade at prices equal to *fundamental* value or (2) they accurately react to the endogenous flow of market information and price according to the *realized* dividend stream. To compare observed prices to these metrics, we report regressions of mean and closing contract prices on fundamental and realized value.[9,10]

3.1 Determinants of Asset Prices

Let $\bar{P}_{i,t}$ be the *mean* (*closing*) contract price in period t of the ith market, and let $f_{i,t}$ and $r_{i,t}$ be the fundamental and realized value of an asset in period t of market i. We estimate the following linear models with standard errors clustered by experimental session:

$$\bar{P}_{i,t} = \alpha_0 + \beta_0 f_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$\bar{P}_{i,t} = \alpha_1 + \beta_1 r_{i,t} + \varepsilon_{i,t} \tag{2}$$

If asset prices reflect fundamental value, then $\alpha_0 = 0$ and $\beta_0 = 1$ in (1). Similarly, if asset prices reflect realized value, then $\alpha_1 = 0$ and $\beta_1 = 1$ in (2).

Finding 1 *Mean and closing contract prices are significantly different from both realized and fundamental value ($\alpha_0 \neq 0$, $\beta_0 \neq 1$ and $\alpha_1 \neq 0$, $\beta_1 \neq 1$, respectively).*

Evidence: Column 1 of Tables I and II reports estimates of equation (1) where the dependent variables are mean and closing contract prices, respectively. Column 2 of each table reports analogous estimates of equation (2). Columns (3) - (8) report the same regressions separately for each treatment. While the estimated coefficients on fundamental and realized value are always positive and significant, indicating that prices are correlated with both value metrics, our estimates reveal substantial mispricing. F-tests reject the joint hypothesis that the estimates of β_0 are equal to one and α_0 are equal to 0 for both mean and closing prices, and similar additional F-tests reject the joint hypothesis that the estimates of β_1 are equal to one and α_1 are equal to 0 (all p-values < 0.01). Thus, neither fundamental value (f) nor realized value (r) can fully account for asset prices in this environment. Nevertheless, the

[9] Closing prices provide a particularly interesting case because by the final transaction most of the information from the product market could, in principle, be incorporated into dividend expectations. Thus, we might expect these to be most accurate. We also ran the same regressions using the median price, but we do not report them since the results are no different than those for the mean.

[10] In our regression results, we report standard errors clustered on session. Because of the small number of clusters, we also used the refinement suggested by Cameron et al. (2008) to calculate standard errors clustered on session. Standard errors calculated in this way are qualitatively similar and tend to be smaller.

estimated coefficients on r tend to be higher than those on f, and this provides suggestive evidence that prices respond more to realized value than to fundamental value.

This pattern of price deviation from share value is evident in Figure 3 which shows the time series of mean price and fundamental value for each session by treatment and experience (Figure B1 in online Appendix B shows the same data for closing price). From the figures it is clear that a non-negligible subset of our asset markets display the familiar bubble and crash pattern observed in the experimental asset market literature. Next, we explore to what extent our environment displays predictable price dynamics similar to those observed in previous asset market experiments.

3.2 Price Adjustment

One hypothesis for the presence of asset price bubbles is that traders form endogenous expectations of capital gains. To estimate the impact of such expectations on price dynamics, SSW formulate what they call the "lagged Walrasian adjustment hypothesis," which predicts that price changes in period t are driven by excess demand in period $t-1$, i.e., traders incorporate market activity into their notion of share value. Under this hypothesis, when prospective buyers submit many bids that are rejected by sellers, prices will increase in the following period as buyers adjust their price expectations upward and increase their subsequent bids. Similarly, the presence of excess supply, in the form of relatively many rejected asks, indicates to prospective sellers that they should reduce their subsequent asking prices.

To test this hypothesis, SSW ask whether a count of lagged excess bids predicts the direction and magnitude of next period price movements. In their markets displaying a bubble and crash pricing pattern, they find strong evidence that a market thick with bids relative to asks tends to display increasing prices and that a relative thinning of bids (indicating sellers' desire to unload assets) precedes the eventual crash. We analyze whether price movements in our asset markets can be described by the same Walrasian mechanics.

Assuming constant absolute risk aversion (CARA) and the absence of expected capital gains, SSW use the Arrow-Pratt measure of the risk premium to demonstrate that the expected change in price is equal to the expected dividend plus compensation for the average risk preference: $(\bar{P}_{i,t} - \bar{P}_{i,t-1}) = -E(d_{i,t}) + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ is a measure of average risk preference. Then to introduce endogenous expectations of capital gains via the Walrasian adjustment hypothesis, they construct the following measure of excess demand: let $B_{i,t}$ be

the number of bids to buy submitted in period t of market i, and let $A_{i,t}$ be the number of asks submitted by sellers. Then excess demand is defined as $B_{i,t} - A_{i,t}$. To compute the impact of excess demand on price adjustment, we estimate separate regressions for each asset market:

$$(\bar{P}_{i,t} - \bar{P}_{i,t-1}) = \alpha_2 + \beta_2(B_{i,t} - A_{i,t}) + \varepsilon_{i,t} \tag{3}$$

Thus, under the aforementioned assumptions, our estimate of α_2 should equal the average dividend, and a positive and significant estimate of β_2 will indicate that prices respond to lagged excess demand by increasing when excess demand is positive and decreasing when excess demand is negative. The magnitude of the estimate indicates the speed of adjustment (or the rate at which the bubble inflates and deflates).

Finding 2 *Walrasian adjustment accounts for price movements in our environment.*

Evidence: Figure 4 displays time series of bids and asks for each market in each session. Note the presence of substantial bubbles and crashes in a number of sessions. Surprisingly we also observe some instances in which, even with extensive market experience, bubbles persist until the end of the experiment. Following Dickhaut et al. (2012), we calculate the percentage of speculative trades and find that roughly one-third of all trades in our markets can be considered speculative.[11] This may partially explain the presence of sustained bubbles, and our evidence on Walrasian adjustment provides additional support for this explanation. Table III displays the estimation results of equation (3) on the pooled data set and separately for each treatment.

Table B1 in online Appendix B displays the same equation estimated separately for each session. In general, the results show that sessions with notable bubble and crash patterns (e.g. Session 12) also exhibit large coefficients of Walrasian adjustment, though the majority of our markets have coefficients insignificantly different from 0. Furthermore, in those sessions that do not exhibit the bubble and crash pattern (e.g. Sessions 6 and 11), the estimated constant term is typically insignificantly different from $-E(d) = -\frac{\sum_t^T d_t}{T}$, which provides

[11] Following Dickhaut et al. (2012) we consider a trade made by a given individual speculative if he/she follows a purchase (sale) immediately by an attempt to sell (buy) at a higher (lower) price than the previous transaction. Our estimate of speculative trades is lower than that reported in their paper, though there are other substantial differences between these environments. A similar calculation can be made to construct a simple measure of confusion. We consider a trade confused if a purchase (sale) is immediately followed by an attempt to sell (buy) at a lower (higher) price than the previous transaction. By this measure less than 2% of trades are confused.

evidence that market fundamentals are occasionally reflected in asset prices.

3.3 Impact of the Info and Human Treatments

To assess the impact of gradual information revelation and human control of the product market monopolist, we estimate four regression equations. The dependent variables are the four bubble characteristics described below, and the independent variables in each equation are dummy variables for the *Info* and *Human* treatments, dummy variables for once-experienced and twice-experienced participants and interactions between the experience and treatment dummies. The excluded group includes subjects in the *Base* treatment with no market experience. To facilitate comparison across treatments we compute the following four normalized bubble characteristics, generating one observation for each market (Stöckl et al., 2010):

1. *RAD* measures the average deviation of price from fundamental value, where positive and negative deviations are not offsetting. Formally, $\frac{1}{T}\sum_{t=1}^{T}|\overline{P}_t - f_t|/|\overline{f}|$, where $\overline{P}_t$ is average price in period t and $\overline{f}$ is fundamental value averaged over the number of periods.

2. *RD* measures the average deviation of price from fundamental value, where positive and negative deviations are offsetting. Formally, $\frac{1}{T}\sum_{t=1}^{T}(\overline{P}_t - f_t)/|\overline{f}|$.

3. *Duration* measures the consecutive number of periods in which market price increases relative to share value. Formally, $D = \max\{m : P_t - f_t < P_{t+1} - f_{t+1} < \cdots < P_{t+m} - f_{t+m}\}$.

4. *Turnover* measures trading activity in each market session. Formally, $T = \sum_t V_t/S$, where V_t is trade volume in period t and S is the total number of shares.

Finding 3 *The Info and Human treatments have a negligible impact on asset price bubbles.*

Evidence: Table IV displays means of each bubble measure by treatment and experience level, and Table B2 in online Appendix B reports the same statistics for each session. Table V reports our regression analysis. The coefficients on the *Info* and *Human* dummy variables are given in rows 1 and 2, respectively. None of the *Info* treatment coefficients are statistically significant. Only in column (3) is the coefficient on the *Human* treatment marginally statistically significant and negative, suggesting that bubble duration is lower in the *Human* treatment. However, in the same equation, the estimated coefficient on the interaction between the *Human* treatment and twice experienced is positive and significant, suggesting

that the bubble-reducing impact of the *Human* treatment is attenuated in later markets.

Thus we find scant evidence that gradual information revelation in the asset market reduces bubbles. The weakly negative coefficient on the *Human* treatment in the duration equation suggests that bubbles pop more quickly with endogenous uncertainty about product market outcomes, though that effect does not persist with experience.

Finding 4 *Experience reduces the duration and magnitude of bubbles.*

Evidence: In keeping with previous findings in experimental asset markets, we observe that market experience reduces the magnitude of mispricing and bubble duration. Negative and significant estimated coefficients on the once-experienced dummy in column (3) and on the twice-experienced dummy in columns (1) and (3) indicate that bubbles are both somewhat smaller and shorter-lived with market experience.

In sum, the data suggest that prices weakly track share value and that price changes are the result of Walrasian dynamics. Compared to the *Base* treatment, we find little evidence that the *Info* and *Human* treatments, which, respectively, reduce *exogenous* uncertainty and introduce *endogenous* uncertainty about the value of a share, have a substantial impact on asset prices. We take the latter result to imply that these types of uncertainty alone cannot account for divergent expectations among traders. Ultimately, tailoring the trading environment to the problem faced by traders in the field is not sufficient to reduce bubbles. This provides evidence that an additional kind of uncertainty, common to all asset markets, is a crucial determinant of asset prices: uncertainty about the behavior of other traders (SSW, Lei et al. 2001). Regardless of the information provided to traders about the dividend process, they still cannot know how their counterparts will interpret this information. This is emphasized in our experiments because even though information conditions differed across our treatments, the realized value of a share was fairly similar and so was behavior.

3.4 Comparison to Previous Asset Markets

To compare the behavior of traders in our environment with observations from classic asset market designs, we obtained data from a large set of experimental asset markets reported in previous research. The database includes our 39 markets along with 39 other markets, all of which employ the standard dividend process of SSW.[12] Using this database, we evaluate

[12]In addition to the 39 new markets reported here, our data includes: (1) 4 markets with inexperienced traders from Smith et al. (2000) employing a continuous double auction trading institution (hereafter *cda*),

the effect of our market-based dividend process on asset price bubbles in markets employing the continuous double auction trading institution. We have excluded experiments employing call markets or any other institutional feature that differs substantially from those we employ. Because we are comparing across time, subject pool, and software interface, we sought to minimize other variability between the designs. The results are intended to connect our work to previous work and highlight any notable differences.

We compute the same four bubble metrics as in the section above because these were designed to facilitate comparison across asset market designs (Stöckl et al., 2010), and we report the results of additional regression analysis in Table VI. The bubble measures serve as our dependent variables, and our independent variables include dummies for each of our treatments and dummies for once- and twice-experienced traders. All sessions listed in footnote 12 constitute the excluded group. In the end, we find minimal evidence that our treatments lead to substantial changes in trader behavior, and thus we are comfortable in suggesting that our design and related designs can be compared to previous work.

Finding 5 *The Base treatment has a negligible impact on bubbles.*

Evidence: Most of the *Base* treatment and treatment×experience interaction terms in Table VI are insignificantly different from zero, suggesting that in the treatment of our experiment that most closely corresponds to the standard asset market environment, our markets are generally comparable to those in the literature. In column (3), we find evidence that bubble duration is longer in the *Base* treatment, and a marginally significant coefficient on the interaction with twice experienced in column (1) suggests a weakly reduced effect of experience.

Finding 6 *The Info and Human treatments reduce the bubble-mitigating impact of experience.*

Evidence: The estimated coefficients in columns (1) and (2) of Table VI indicate that experience tends to reduce the magnitude of bubbles in previous asset market experiments. However, in our *Info* and *Human* treatments, the beneficial impact of experience is muted, as indicated in the positive and significant interactions between those treatments and expe-

(2) 6 *cda* markets, 2 inexperienced, 2 once-experienced, and 2 twice-experienced, reported in Van Boening et al. (1993), (3) 21 *cda* markets, 9 inexperienced, 9 once-experienced, and 3 twice-experienced, reported in SSW, and (4) 8 unpublished *cda* markets, 4 inexperienced and 4 once-experienced, from a replication of SSW performed at George Mason University in 2007 by Shengle Lin.

rience. In columns (3) and (4), the positive and significant estimated coefficients on Twice Experienced × *Human* suggest that in addition to inducing larger bubbles, this treatment also increases duration and turnover.

4 Discussion

According to the efficient markets hypothesis, asset prices will fully reflect the underlying value of a share. Empirical analysis based on comparisons of national stock market data with observed dividends yields mixed results (Fama, 1970; Shiller, 1981; Blanchard and Watson, 1982; Diba and Grossman, 1988; West, 1988), so to evaluate this hypothesis, some researchers have turned to the laboratory. SSW and many others show that a bubble-crash price pattern is a recurring feature of a particular multi-period asset market environment. Bubbles emerge in early trading periods, inflate rapidly, and crash when traders' expectations converge so that prices often reach fundamental value in the final periods.

In a standard laboratory asset market, the dividend process is similar to the configuration used by SSW in which share returns are independent of economic activity and are instead determined by a draw from a known distribution. While this is consistent with modeling practice, it does not necessarily reflect the circumstances faced by traders in the field. To begin to bridge this gap, we develop a novel experimental environment in which dividends are determined by the activities of a firm interacting in a linked product market, and we vary (1) whether information about the dividend is revealed once per period at the end of trading or gradually over the course of trading, and (2) whether the firm is controlled by a profit-maximizing robot or a human subject. We collect data on 39 new asset markets to evaluate the impact of these manipulations on pricing.

In our newly collected markets, we find evidence that prices respond, at least partially, to changes in the value of a share. We observe speculative bubbles (and crashes), and we find that price movements are driven naturally by Walrasian dynamics. However, we find no evidence that our *Info* treatment, which gradually reveals the value of each dividend over the course of the trading period, reduces bubbles relative to our *Base* treatment. We also find limited evidence that the nature or magnitude of mispricing is influenced by the introduction of endogenous uncertainty about the behavior of the product market firm (in our *Human* treatment). We interpret these findings as evidence that uncertainty about the behavior of other traders, which is a feature of our environment as well as most asset markets, is a crucial determinant of asset prices.

When we compare our newly collected markets to a sample of previous experimental markets, we find that gradual information revelation in both the *Info* and *Human* treatments tends to mitigate the typically beneficial impact of trading experience on mispricing. This effect of gradual information revelation is also consistent with evidence from Smith et al. (2000) and provides further reason to think that our new environment provides a building block for future work. While we were somewhat surprised by the failure of our market-dividend process to reduce bubbles, evidence suggests that the bubbles we observe are not artifacts of our environment. Our data instead suggest an important role for speculation and reinforce the insight that even minor within-session changes to the trading environment can reinflate bubbles (Hussam et al., 2008).

In sum, we replicate familiar patterns observed in the experimental literature on asset markets suggesting that those findings extend to a more realistic market context in which traders buy and sell shares of a linked product market firm. Thus our extension of the standard environment provides a useful platform for experimentally examining the interaction between the real economy and financial markets. Future research can comfortably employ designs similar to ours while maintaining the connection to previous laboratory research that highlights the role of experience, speculation, dividend structure, etc., on asset prices.

One line of research should explore under what variants of the *Human* treatment behavior might differ substantially from analogous *Base* or *Info* treatments. For example, one could consider the role of product market competition in asset pricing or whether asset prices will accurately reflect differences in firm profitability across different markets. In environments in which human subject behavior differs more sharply from equilibrium (e.g. Cournot oligopolies and investment trust games, see Davis and Holt, 1993; Berg et al., 1995), we might expect to observe more mis-coordination of trader expectations and thus more differences in the price of assets whose value is based on behavior in those markets. Such investigations will provide carefully controlled tests of how aspects of the real economy influence the financial economy.

A second line of research should use our *Human* treatment as a baseline to explore the effects of further experimental integration of the product and asset markets. For example, if firm managers are also traders of the stock, we might expect them to employ their better knowledge of firm value to arbitrage away speculation. Moreover, in the current experiment, we only consider the effect of product market profitability on asset market fundamental value. Extensions to this research could address the crucial role asset markets play in raising

and allocating capital and the associated principal-agent concerns. For example, firms might offer stock to finance expansion of production (or cost reductions) in the product market. Would asset prices adjust to reflect changes in expected profitability?

Finally, there are a variety of well-known studies that examine the impact of asymmetric information, induced explicitly (e.g. Copeland and Friedman, 1987, 1991; Huber et al., 2008; Sutter et al., 2012) or implicitly via mixed-experience groups as in Dufwenberg et al. (2005), on mispricing in experimental asset markets. All of these studies employ exogenous dividend processes, and they too might benefit from introducing asymmetric information about the activities or profitability of a real firm. We leave these issues for future research.

Appendix: Experiment Details

The Product Market

In each trading period $t \in T = \{1, 2, \ldots, 30\}$, a monopolist faces a constant per unit marginal cost c_t. Fixed costs are assumed to be 0. Each second, one prospective buyer $n \in N = \{1, 2, \ldots, 60\}$, approaches the monopolist attempting to purchase a single unit of the good. Each buyer's value for one unit, v_n, is randomly drawn from a uniform distribution with support $[v_L, v_H]$. Each buyer faces a posted price p_n. Hence, for each buyer in a period, the monopolist earns profit

$$\pi_{n,t} = \begin{cases} p_n - c_t & \text{if } p_n \leq v_n \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

and the total profit earned by the monopolist in period t is $\sum_{n \in N} \pi_{n,t} \geq 0$.

The computer interface for the *Human* treatment product market is shown in Figure B2 in the online appendix. On the left portion of the screen the monopolist can access a vertical slider to set and change the posted price p_n. At the beginning of each period, the monopolist selects an initial price and then clicks the green "Set Initial Price" button in the bottom left corner. Once the period begins, this price can be changed at any time by clicking on and moving the slider. The graph to the right of the slider displays the per-unit cost, c_t, as a red line and the current posted price as a blue line.[13] As buyers approach, a vertical line

[13] We restrict the seller to set the price at or above c_t. In the *Base* and *Info* treatments, the seller always charges the profit-maximizing price.

moves across the graph to provide a visual representation of how many buyers have arrived and how many remain. When each buyer approaches, the graph indicates the outcome by displaying a green-shaded arrows at the posted price when a transaction occurs and nothing otherwise.

The "Sales Log" in the top-middle portion of the screen records the price faced by each buyer, whether a sale was made, and the seller's profit on each sale. To the right, the "Status" pane tracks the current number of sales and the total period and experiment profit. At the end of each period, product market monopolists observe their total accumulated profit up to that point in the experiment. Before the next period begins, they set an initial price. Once the price is set, the next period begins, and this process continues until the end of the session. Finally, in the "History" pane, the seller observes the profit, number of sales out of the total possible sales, average sale price, and cost in each of the previous periods. At the end of each period, the bar along the bottom of the screen displays the total profit in the most recent period. At the end of a session the subject receives his or her total earnings in cash.

In the asset market, participants trade shares of the product market firm. Whether the monopolist's behavior is controlled by a robot, as in the *Base* and *Info* treatments, or by a human participant (the *Human* treatment), we record the real-time pricing and transaction history for each monopolist so that we can replay the entire history to traders in the asset market. As we describe below, dividends in the asset market are based on the profitability of the product market firm. Note that monopolists were unaware that their decisions would be observed in later asset market sessions.

The Asset Market

Each asset market is conducted using a continuous double auction market.[14] Figure B3 in the online appendix displays the trading interface shown to participants in the *Info* and *Human* treatments.[15] Cash may be exchanged for shares and vice versa by submitting bids to buy and offers to sell in the "Market Order Book". Any new bid (offer) must improve upon the current highest bid (lowest offer) in the market. Subjects with sufficient cash can always buy at the current lowest offer by clicking the "Buy Now @" button, and subjects

[14] An alternative trading institution is the uniform-price sealed-bid-offer call market. Previous studies find that the two institutions yield similar patterns of bubble and crash (Van Boening et al., 1993; Caginalp et al., 2000; Haruvy et al., 2007).

[15] The panel labeled "Firm A Market Info" is visible in the *Info* and *Human* treatments and invisible in the *Base* treatment.

with sufficient shares can always sell at the current highest bid by clicking the "Sell Now @" button.[16] As traders enter bids and make offers to sell, the computer ensures that the sum of a trader's bids does not exceed his available cash and that the number of offers to sell does not exceed his available shares.

When a transaction occurs, the share is transferred from the Seller to the Buyer in exchange for cash equal to the accepted price. Then, the transacted bid or offer is removed from the market order book and the highest (lowest) of the remaining bids (offers) becomes the new "Buy (Sell) Now @" price. A trader's cash and share endowment is displayed in the upper-left corner of the screen. As a trader buys and sells shares, his current cash and share holdings update to reflect his current positions.

In the *Info* and *Human* treatments only, the asset market traders also observe the outcome of *each* prospective buyer's arrival in the product market in the panel labeled "Firm A Market Info" in Figure B3 in the online appendix. Specifically, we replay the product market data at 1/2 speed (i.e. one buyer arrives every 2 seconds $\rightarrow$ 120-second periods) so that asset market traders in period t may observe p_n, c_t, and $\pi_{n,t}|v_n \geq p_n$ for each buyer $n \in N$. As each buyer arrives in the market, the Sale bar either flashes green to indicate that a transaction occurred or remains blank to indicate that the buyer chose not to purchase. Accumulated profit is displayed so that after the arrival of the jth buyer, the box labeled "Total Profit" displays $\sum_{n=1}^{j} \pi_{n,t}$, and we also provide subjects with the ratio of consummated product market transactions to j.

At the end of each trading period, each share of the asset yields a dividend. The dividend per share in each period of our market is determined by dividing the total profit of the product market monopolist in that period by the total number of shares. Specifically, if S is the total number of shares in the asset market, the dividend d_t, in period t is given by:

$$d_t = \frac{\sum_{n \in N} \pi_{n,t}}{S} \geq 0 \tag{5}$$

Figure B4 in the online appendix displays the screen observed by asset market traders at the end of a period, though as before, the "Firm A Market Info" pane is visible only in the *Info* and *Human* treatments. The "Asset Math" pane displays the monopolist's total profit, the dividend per share, and the trader's total dividend earnings in the period. Dividends are added to each trader's cash endowment for the following period, and the market order book

[16] We do not allow subjects to sell shares short; nor do we allow them to borrow cash.

is cleared. Once subjects have reviewed their earnings and indicate that they are ready to go on, the next trading period begins. This process continues until the 10th period ends, at which point the market closes, the final dividend is paid, and the assets are worth nothing.

Fundamental Value of a Share

The structure of the product market outlined above (i.e., the number of potential buyers, the distribution of buyer values, and the seller's marginal cost) defines the price-setting problem faced by the seller. The profit maximization problem can be solved using standard techniques, and the solution implies the expected value of the dividend. Since the number of remaining periods is finite and always known, it also implies the fundamental value of the asset in each period.

In the product market, firms have complete information about their costs and about the distribution of buyer values, so it is straightforward to compute the equilibrium price charged by a risk-neutral, profit-maximizing monopolist:

$$p_t^* = \frac{v_H + c_t}{2} \tag{6}$$

This price provides a benchmark against which we can judge to what degree our monopolist firms earned the profits that were potentially available to them, which we will refer to as fundamental value (FV).

Given the equilibrium price, when the seller faces N buyers, the expected profit per period is:

$$E\left[\sum_{n \in N} \pi_{n,t}\right] = Pr(v_{n,t} \geq p_t^*)(p_t^* - c_t)N = \frac{(\frac{v_H - c_t}{2})^2}{v_H - v_L} N \tag{7}$$

and the FV of the firm is the total expected profit of a firm that lives for T periods:

$$FV^* = E(\Pi) = \sum_{t \in T} \frac{(\frac{v_H - c_t}{2})^2}{v_H - v_L} N \tag{8}$$

Therefore, the initial fundamental value of one share of the asset is $f^* = \frac{FV^*}{S}$, and the fundamental value of a share in period t' is just the expected value of the dividend for the

remaining periods:

$$f_{t'} = \sum_{t=t'}^{T} \frac{(\frac{v_H - c_t}{2})^2}{v_H - v_L} N \tag{9}$$

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Tables and Figures

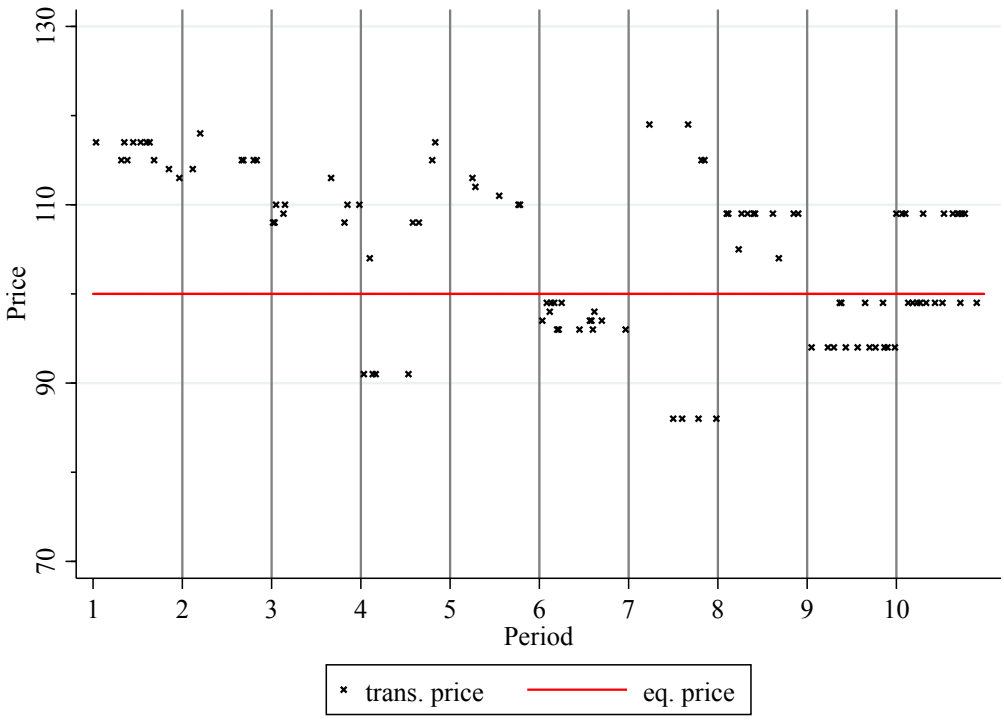
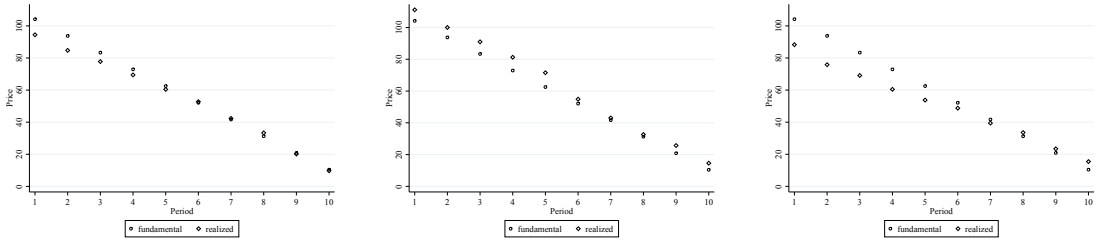


Figure 1: Human Product Market Transactions



A. *Base* Treatment B. *Info* Treatment C. *Human* Treatment

Figure 2: Fundamental and Realized Value

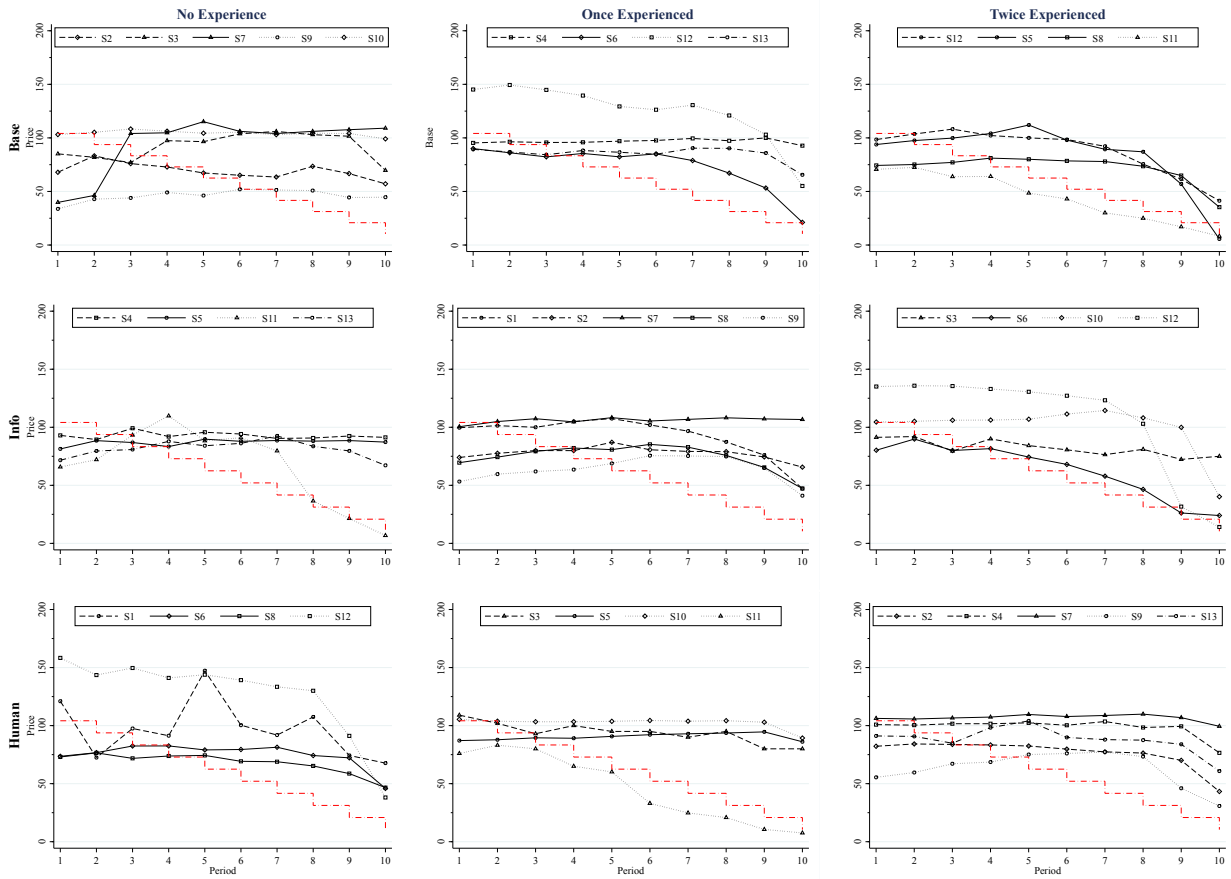


Figure 3: Average Price by Experience and Treatment

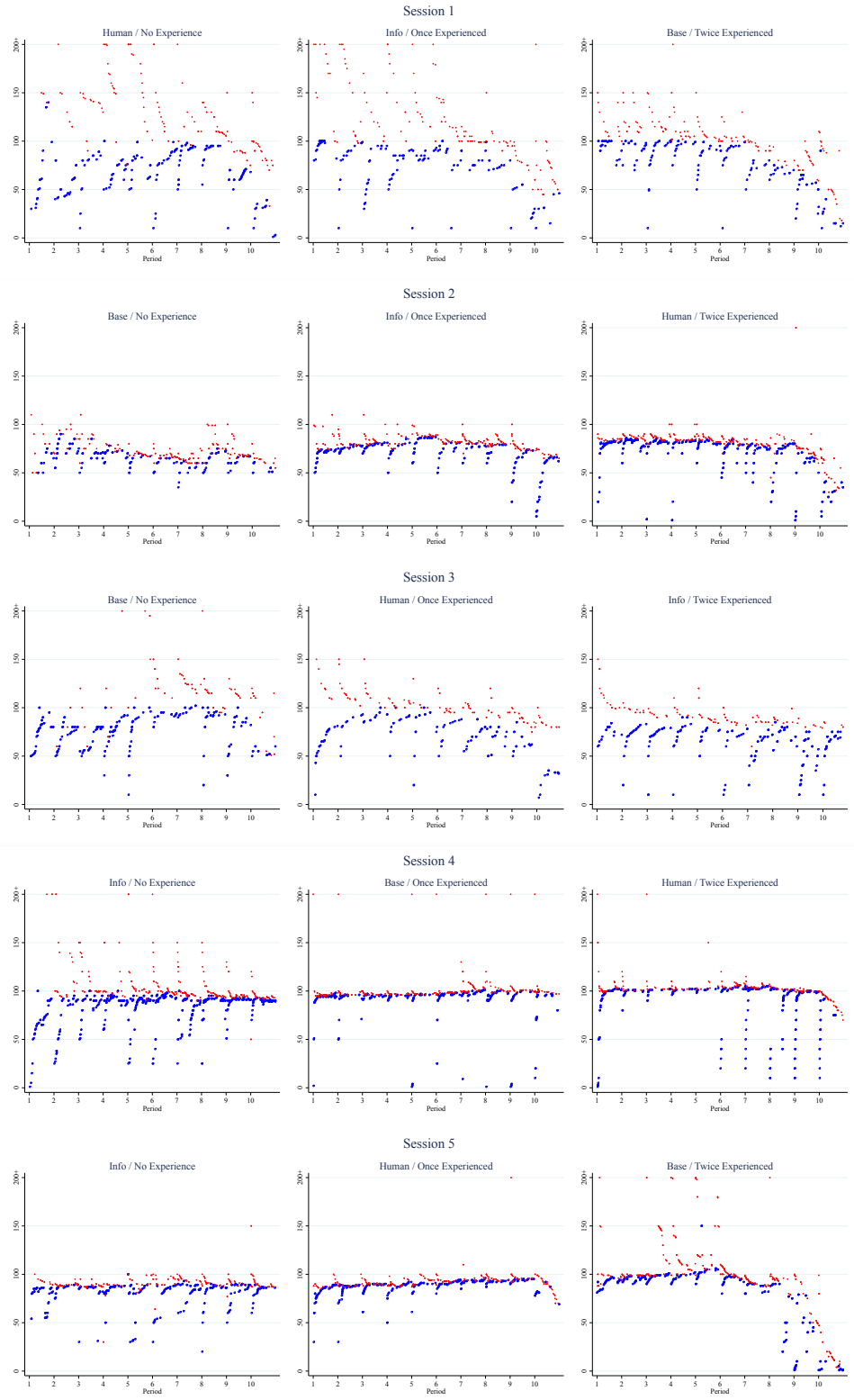


Figure 4: Bids and Asks by Session

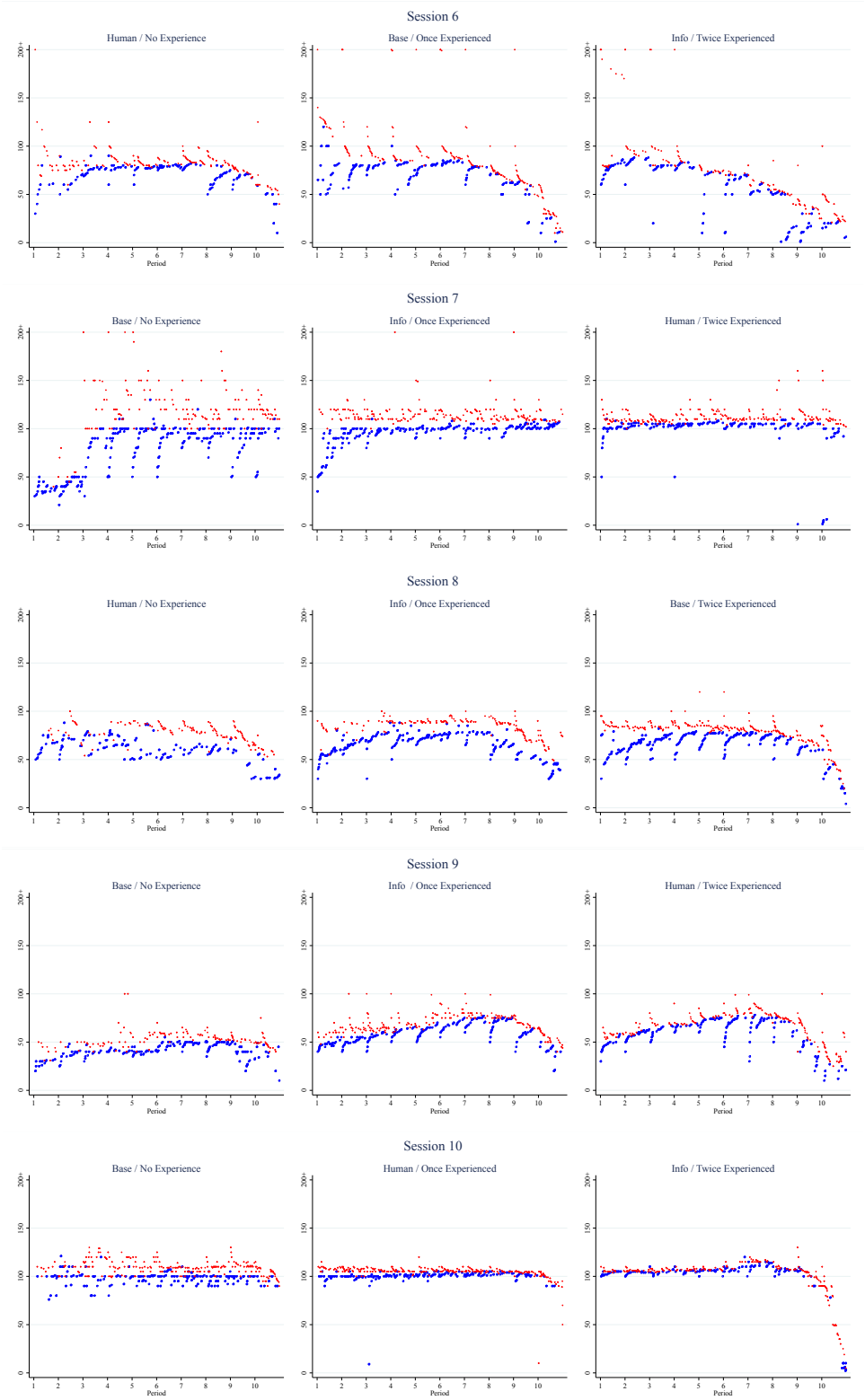


Figure 4: Bids and Asks by Session (continued)

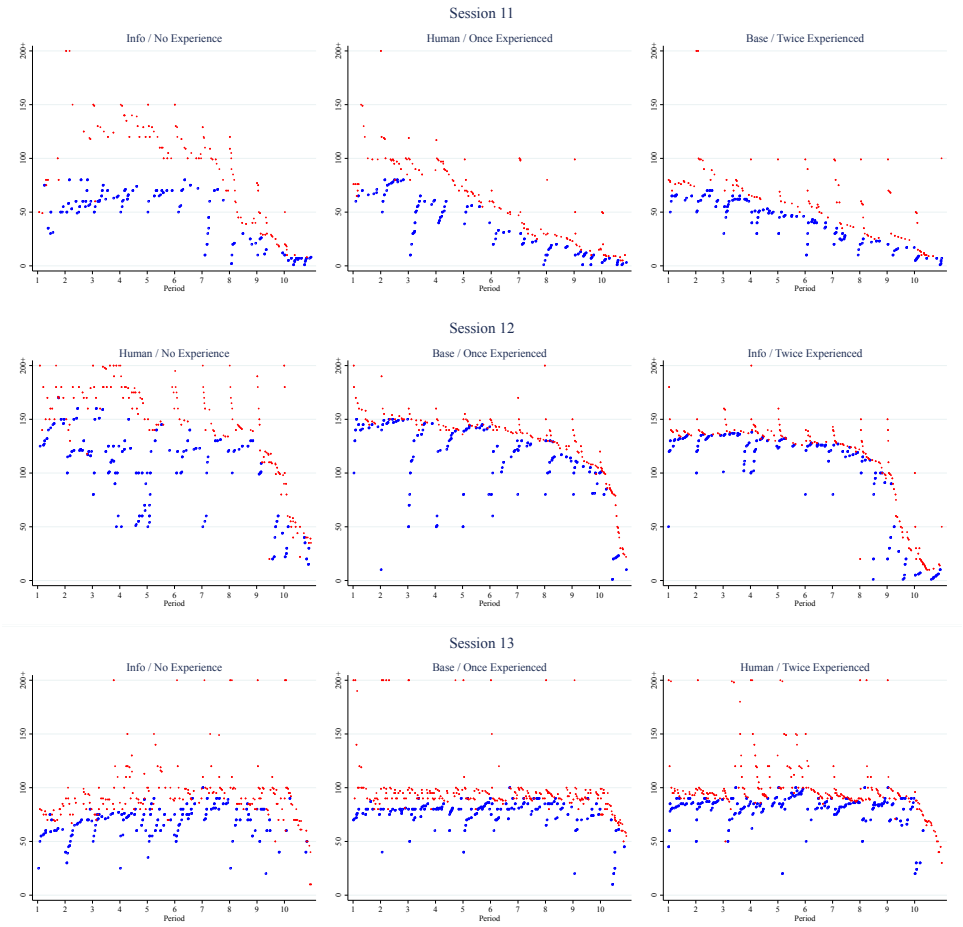


Figure 4: Bids and Asks by Session (continued)

Mean Price	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fundamental Value	0.27***		0.24*		0.28**		0.29***	
	(0.088)		(0.114)		(0.105)		(0.084)	
Realized Value		0.29**		0.28**		0.26**		0.40***
		(0.094)		(0.128)		(0.098)		(0.113)
Constant	69.01***	68.53***	69.14***	67.20***	67.86***	67.61***	70.02***	66.57***
	(7.306)	(7.591)	(9.206)	(9.533)	(7.090)	(7.214)	(7.891)	(8.469)
R^2	0.098	0.093	0.065	0.075	0.131	0.126	0.113	0.115
Treatment	All	All	*Base*	*Base*	*Info*	*Info*	*Human*	*Human*

Standard errors in parentheses. * denotes significant at $p < 0.1$, ** at $p < 0.05$, and *** at $p < 0.01$. $\mathbf{N} = 390$

Table I: Mean Price and Asset Valuation

Closing Price	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fundamental Value	0.35***		0.32**		0.42***		0.32***	
	(0.090)		(0.118)		(0.111)		(0.088)	
Realized Value		0.39***		0.38**		0.39***		0.44***
		(0.095)		(0.134)		(0.104)		(0.118)
Constant	63.70***	62.22***	62.50***	59.93***	61.13***	60.75***	67.47***	63.44***
	(7.159)	(7.416)	(8.797)	(9.152)	(7.156)	(7.243)	(8.324)	(9.045)
R^2	0.133	0.138	0.102	0.116	0.194	0.187	0.115	0.121
Treatment	All	All	*Base*	*Base*	*Info*	*Info*	*Human*	*Human*

Standard errors in parentheses. * denotes significant at $p < 0.1$, ** at $p < 0.05$, and *** at $p < 0.01$. $\mathbf{N} = 390$

Table II: Closing Price and Asset Valuation

Treatment	α_2	β_2	R^2	N
All	-3.18$^+$	0.26*	0.90	351
Base	-2.84$^+$	0.25*	0.10	137
Info	-3.21$^+$	0.32*	0.14	137
Human	-3.61$^+$	0.20	0.04	137

$^+$ denotes significantly different from $-\sum d_t/T$ at $p < 0.1$.

* denotes significant at $p < 0.1$.

Table III: Walrasian Price Adjustment by Treatment

Experience	**Treatment**	RAD	RD	Duration	Turnover
None	*Base*	0.700	0.417	0.978	5.144
None	*Info*	0.566	0.430	0.806	5.284
None	*Human*	0.712	0.599	0.694	3.389
Once	*Base*	0.703	0.656	0.833	4.236
Once	*Info*	0.608	0.446	0.911	4.017
Once	*Human*	0.555	0.434	0.806	4.257
Twice	*Base*	0.439	0.259	0.583	3.493
Twice	*Info*	0.581	0.537	0.750	2.743
Twice	*Human*	0.617	0.509	0.800	4.756

Table IV: Mean of Deviation, Duration, and Turnover by Experience and Treatment

Dependent Variable:	(1) RAD	(2) RD	(3) Duration	(4) Turnover
Info	-0.13	0.01	-0.17	0.14
	(0.136)	(0.217)	(0.164)	(1.667)
Human	0.01	0.18	-0.28*	-1.76
	(0.223)	(0.304)	(0.135)	(1.200)
Once Experienced	0.00	0.24	-0.14*	-0.91
	(0.212)	(0.273)	(0.076)	(1.505)
Twice Experienced	-0.26*	-0.16	-0.39***	-1.65
	(0.141)	(0.261)	(0.127)	(1.626)
Once Experienced × *Info*	0.04	-0.22	0.25	-0.36
	(0.260)	(0.373)	(0.202)	(2.299)
Once Experienced × *Human*	-0.16	-0.40	0.26	1.78
	(0.395)	(0.524)	(0.182)	(2.785)
Twice Experienced × *Info*	0.28	0.27	0.34	-0.89
	(0.237)	(0.379)	(0.247)	(2.726)
Twice Experienced × *Human*	0.17	0.07	0.50**	3.02
	(0.286)	(0.435)	(0.223)	(1.891)
Constant	0.70***	0.42*	0.98***	5.14***
	(0.119)	(0.192)	(0.023)	(1.136)
R^2	0.124	0.102	0.280	0.161

Standard errors in parentheses. * denotes significant at $p < 0.1$, ** at $p < 0.05$, and *** at $p < 0.01$. $\mathbf{N} = 39$.

Table V: Estimates of the Deviation, Duration, and Turnover

Dependent Variable:	(1) RAD	(2) RD	(3) Duration	(4) Turnover
Base	-0.02	-0.02	0.38***	0.74
	(0.140)	(0.211)	(0.053)	(1.245)
Info	-0.16	-0.00	0.21	0.88
	(0.104)	(0.145)	(0.158)	(1.312)
Human	-0.01	0.17	0.10	-1.01
	(0.195)	(0.246)	(0.133)	(0.745)
Once Experienced	-0.33***	-0.31**	-0.08	-1.74***
	(0.100)	(0.118)	(0.100)	(0.494)
Twice Experienced	-0.54***	-0.33***	-0.24***	-1.53*
	(0.094)	(0.117)	(0.085)	(0.777)
Once Experienced × *Base*	0.33	0.54*	-0.06	0.83
	(0.222)	(0.281)	(0.122)	(1.488)
Once Experienced × *Info*	0.37***	0.32	0.19	0.47
	(0.134)	(0.196)	(0.185)	(1.427)
Once Experienced × *Human*	0.17	0.14	0.19	2.60
	(0.235)	(0.322)	(0.197)	(1.666)
Twice Experienced × *Base*	0.28*	0.17	-0.16	-0.12
	(0.162)	(0.270)	(0.146)	(1.704)
Twice Experienced × *Info*	0.56***	0.44*	0.18	-1.01
	(0.178)	(0.221)	(0.181)	(1.576)
Twice Experienced × *Human*	0.45**	0.24	0.34*	2.89***
	(0.214)	(0.282)	(0.177)	(0.985)
Constant	0.72***	0.43***	0.59***	4.40***
	(0.084)	(0.110)	(0.048)	(0.653)
R^2	0.278	0.118	0.454	0.255

Standard errors in parentheses. * denotes significant at $p < 0.1$, ** at $p < 0.05$, and *** at $p < 0.01$. $\mathbf{N} = 78$.

Table VI: Comparisons to Previous Asset Markets (Deviation, Duration, and Turnover)

Additional Appendices (for online publication)

A Experiment Instructions

A.1 Asset Market Instructions (Part I)

Introduction

This is an experiment in market decision making, and you will be paid for your participation in cash at the end of the experiment. Different participants may earn different amounts. What you earn depends on your decisions and the decisions of the 8 other people in the experiment.

The experiment will take place through computer terminals at which you are seated. We will start with a detailed instruction period. During the instruction period, you will be given a complete description of the experiment and will be taught how to interact with the computers.

If you have any questions during the instruction period, raise your hand and your question will be answered so everyone can hear. If any difficulties arise after the experiment has begun, raise your hand, and a monitor will come and assist you.

The Market Basics

We will now describe the mechanism you will be using to make trades and the accounting system that keeps track of your earnings and trades.

The "Market Order Book A" is divided into two areas. You can submit Bids to Buy units of the asset at the bottom portion of the Market Order Book. At the top portion you can submit Offers to Sell units of the asset. Let us go through some examples to see how this market works.

Making and Retracting Bids to Buy

If you want to buy a unit of the asset for 50 cents, you must create a Bid to Buy one unit at that price. You would submit this order by typing 50 in the box next to the button and then clicking the button.

Once you click the Bid button, your bid will be listed in the Market Order Book. Your available cash to make bids will be reduced by 50 cents because you have provisionally committed to this order.

If you want to submit a Bid to the market, you must improve on the highest current Bid by

#BidIncrement#. That is, you must bid more than the current highest Bid. The highest bid will be displayed at the top of the bid queue.

You may retract your highest bid at any time by pressing the Retract Bid button.

Lets practice submitting bids. Please click "Next" when you are ready to practice. You will be asked submit a bid of 50 cents. Type 50 into the box next to the button and then click the Bid button.

Making and Retracting Offers to Sell

Now suppose you want to sell a unit of the asset at 100 cents. Then you must submit an Offer to Sell one unit of the asset for 100 cents. You can submit an offer at 100 by typing 100 in the box next to the Offer@ button and then clicking the button.

Once you click the Offer@ button, your offer will be listed in the Market Order Book along with another all other offers in the market. The number of units available to sell is now reduced by one because you have provisionally committed to this order.

If you want to submit an Offer to the market, you must improve on the lowest current Offer by #BidIncrement#. That is, you must offer to sell for at least #BidIncrement# less than the current lowest Offer. The lowest offer will be displayed at the bottom of the offer queue.

You may retract your lowest offer at any time by pressing the Retract Offer button.

The sum of your Bids to buy may not exceed the Cash Endowment you have (see the summary information frame). The number of your Offers to sell may not exceed the number of units you own (see the asset accounting frame).

Lets practice submitting offers. Please click "Next" when you are ready to practice. You will be instructed submit an offer of 100 cents. Type 100 into the box next to the button and then click the Offer button.

Buying and Selling

At any time you can buy the unit at a price equal to the lowest displayed Offer by clicking on the Buy Now@− > button. Your Cash Endowment will be reduced by that amount and the number of assets you own will increase by one.

Similarly at any time you can sell the unit at a price equal to the highest displayed Bid by clicking on the Sell Now@− > button. Your Cash Endowment will be increased by that amount and the number of assets you own will decrease by one.

Once someone has purchased at the lowest offer, the next lowest is moved down. Similarly once someone has sold at the highest bid, the next highest bid will be moved up. Any new higher bid can displace this bid, and any new lower offer can displace the current lowest

offer.

A listing of all contracts will be displayed below the Market Order Book in the Sales Log.

Lets practice buying and selling. Please click "Next" when you are ready to practice, and follow the instructions in red on the screen.

Summary

This concludes the portion of the instructions teaching you how to use the Market Order Book. If you are ready to go on, please click "Start".

If you want to go back and practice any aspect of trading again, click the back button. You will be able to skip any of the practice items that you do not wish to repeat.

Once everyone has clicked "Start", we will explain the assets that are being traded in this experiment.

A.2 Asset Market Instructions (Part II)

The Basics

In this market, you will begin with a Cash endowment of 500 and 4 Assets which you will be able to trade with the other people in this market. Each asset will live for EXACTLY 10 periods, after which the market will end. After each period the asset will earn a Dividend in cents that will be paid to the person who possesses the asset.

The amount of the dividend in each period depends on the behavior of a firm called Firm A. The dividend payoff for each asset is determined by the firms total profit in a period. Specifically,

$$\text{Dividend} = \text{Firm A's Total Profit}/\text{The Total Number of Assets}$$

For example, if Firm A earns 50 in a period and there are 5 total assets, the dividend payment for each asset will be equal to $50/5 = 10$.

If you own 2 assets, then your total dividend payment will be $10 \times 2 = 20$. In other words, your asset represents a share in the earnings of Firm A.

Continuing the example, if Firm A earns 50 in every single period, and you keep your 2 assets (out of 5 total) for all 10 periods, your total dividends over the course of the market would be:

$$10 \times (50/5) \times 2 = 10 \times 10 \times 2 = 200$$

Then, your total earnings from the market would be your Cash endowment + your total Dividends. Note that after the final Dividend payment, you will receive no additional payoff for holding assets at the end of the market. They are worth nothing.

Firm A's Decision

Each period, Firm A faces a cost of producing a fictitious good. The cost is incurred by the Firm only when it sells a unit of the good, so if the Firm never makes a sale, it will pay 0 cost.

Similarly, the Firm chooses a price at which it is willing to sell a unit of the good, and the firm receives this price only when it sells a unit of the good. The Firm may not set its price below its cost.

Note: since the Firm only pays its cost when it makes a sale and must set its price above its cost, the Dividend each period will always be at least 0. This means you cannot lose money by holding an asset.

Firm A's Profit

Together the price and cost determine the Firm's potential per unit profit.

$$\text{Profit Per Unit} = \text{Price} - \text{Cost}$$

For example, you may see that Firm A is selling at a price of 10 and has a cost of 5. Then, for each unit that Firm A is able to sell at that price, it will earn a profit of: $10 - 5 = 5$ per unit.

The firms total profit is determined by its total sales and the profit it earned on each sale. Specifically if the firm makes N sales in a period,

$$\text{Total Profit} = ProfitSale1 + ProfitSale2 + \cdots + ProfitSaleN$$

So, in this example, if the Firm with a cost of 5 sells 10 units at a price of 10, its total profit for that period will be:

$$10 \text{ units} \times 5 \text{ profit per unit} = 50$$

Buyer Behavior

The reason Firm A may choose to change its price is that its buyers may not be willing to pay as much for the good as Firm A wants to charge or because the Firm thinks that it

could make more money by selling at higher prices.

In each period, Firm A will be approached by a total of 60 buyers wishing to purchase a single unit of the good. One buyer will approach the Firm every 2 seconds. So each period will last 120 seconds.

Each buyer has a randomly assigned, privately known value for the good between 25 and 125, where each value is equally likely. A buyer will only purchase the good if their value is higher than the price listed by Firm A.

Profit Maximizing Firms

Given the values of the buyers and the cost incurred by the firm, there is a profit-maximizing price that Firm A can charge.

Because buyer values between 25 and 125 are equally likely and because Firm A faces a cost of 75, the profit-maximizing price for Firm A is 100.

At this price, the expected profit in each period is 375. There are a total of 36 assets in the market. Thus, the expected dividend is 10.4 cents per period.

On average, if the firm is profit-maximizing, and if you hold one Asset for all 10 periods, your expected total dividend payment is $10 \times 10.4 = 104$ cents.

Who Controls Firm A?

In this market, Firm A is controlled by the computer, and will always charge the profit-maximizing price.

Human Treatment Version

[In this market, Firm A is controlled by another experiment participant who was allowed to set any price he/she wanted. They had the same information as you about buyers' values and knew their own costs.]

Info Treatment Additional Content

[In the bottom portion of your screen, you will see a pane labeled "Firm A Market Info". This pane gives you information about Firm A's current price, cost, per-unit profits, total sales and total profits.

Each time a buyer approaches Firm A, the "Firm A Market Info" pane will update. The price offered to that buyer will be displayed under Price, and the Per Unit Profit will adjust accordingly.

If the buyer purchases a unit, the Sale pane will flash green and the Profit and Sales text boxes will update to reflect that a sale has been made. If the buyer does not make a purchase,

only the Sales text will update to indicate that a buyer attempted to buy but was unable to do so.]

At the end of the period, you will receive a dividend payment as described earlier. It will be displayed in the bottom left corner of the screen in the "Asset Math" pane.

Practice Observing Firm A's Behavior

You will now participate in 3 observation periods of the experiment. These periods will help familiarize you with Firm A's behavior and how the dividend is determined. You will NOT be paid for the observation periods.

For the observation periods you will hold an initial Cash endowment of 500 and 4 assets. In each period, 20 buyers will approach Firm A.

Each observation period will last 40 seconds and one buyer will approach the seller every 2 seconds.

Each observation period will reveal a single dividend payment in the "Asset Math" pane.

At the end of each period, earnings are calculated based on your asset holdings and the profits earned by Firm A. Remember, the Dividend paid on each asset is equal to the Total Profit earned in that period by Firm A divided by the total number of assets.

In the observation periods there are 36 total assets. So in each period if you hold 1 asset, you will receive $(1/36) \times$ Firm A's Profit as your dividend. If you hold 2 assets, you will $(2/36) \times$ Firm A's Profit, and so on.

Your total dividend payment in Period 1 will be added to your total Cash endowment for Period 2, and so on.

Please note that Firm A's profit and the dividends in the observation periods may be different from Firm A's behavior and the dividends in the actual experiment!

Summary

1. You begin the first period with 4 assets and 500 in cash. During each period, you may submit bids to buy assets and offers to sell assets.
2. At any time, you may retract any bid or offer that has not been accepted in the Market Order Book.
3. If you want to buy or sell an asset at a price listed by someone else, use the Buy Now @ or Sell Now @ button.
4. Firm A is controlled by another experiment participant and may set any price it desires, so long as the price is not below its cost.
5. At the end of a period, the queue of bids and asks will be emptied. Any assets that you offer but are unable to sell will be added back to your total. Similarly, any cash

that you provisionally committed in a bid will also be added back to your cash total.

6. At the end of the period, the Dividend per asset for that period is calculated in the "Asset Math" pane and your Total Earnings from Dividends are displayed. These earnings are added to your Cash Endowment. Note that your Cash Endowment may have changed since the beginning of the period if you bought or sold assets.
7. The dividend per asset is just the total profit earned by Firm A divided by the number of assets (36 in this case).
8. To go on to the next period, you need to click the "Ready to Go On" button in the summary information frame. Once everyone has clicked, all bids and offers are cleared from the Market Order Book, and the next period will begin. Your total cash will carry over from the previous period.
9. The experiment will last for 10 periods. At the end of the tenth period, assets are worth nothing.

Please raise your hand if you have any questions. Once the questions are answered, the experiment will restart and you will participate in 10 periods of trading.

A.3 Product Market Instructions

Introduction

This is an experiment in the economics of decision-making. The instructions are simple. If you read them carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment.

In this experiment you will be a seller for a series of trading periods. Each period will last 60 seconds. As a seller you have the ability to produce an unlimited amount of a fictitious good. As a seller you also set/choose the price of that good.

In any given period, each unit costs the same to produce, for example, 30. Your cost can be different in different periods. In period 1, your cost could be 30, but in period 2 your cost could be 35.

You earn profit by selling at a price greater than your cost. For example, suppose that your price is 40. Your profit from selling one unit at that price is $40 - 30 = 10$. More generally, your profit on each unit you sell is

$$\text{Profit} = \text{Price Received - Cost.}$$

Note: you only pay a production cost when you sell a unit. If you sell no units in a period your profit is zero for that period.

Buyers

The computer will act as the buyers in this experiment. Every #BuyerFrequency# second(s) a buyer will attempt to purchase a unit from you. Each buyers value (or willingness to pay) is assigned randomly.

A buyer's value will never exceed #MaxBid#, but as long as the price you offer is less than (or equal to) the maximum value the buyer is willing to pay for that unit, then you will make a sale and receive a profit on that unit.

In fact, each buyer's maximum value will be a random number between 25 and 125, where each number is equally likely. This means that the average buyer's value will be 75. It also means that on average one-half of the buyers will have values greater than 75 and one-half will have values less than 75.

Seller Decisions

As a seller, you have the ability to set and alter the price at which you wish to sell a unit. To set your price move the "Current Price" slider located along the left side of the screen. When you move your price, you will see the green line indicating your price move up and down on the graph.

You can adjust your price at any time by moving the slider with the mouse. Left click on the slider and move it to the desired price. As soon as you release the mouse button, the price will be set.

If you choose to move the slider with the Arrow Keys on the keyboard, then you will have to set your new price by clicking the Submit Your Price button.

You cannot set a price below your cost or above *#MaxBid#*.

Seller Feedback

When a buyer makes a purchase, your screen will flash Green, and you will see your earnings update in real time.

If a buyer attempts to buy but your price is set higher than the maximum that buyer is willing to pay, your screen will flash Red indicating that you did not sell to that buyer.

A Sales Log on the right side of the screen displays the history of your prices submitted to the market. It is color-coded according to the action of the buyer.

Next to the Sales Log is a Status screen that shows your total earnings in Experimental Currency Units (ECU) to that point in the experiment and the number of sales you've made.

The left side of the screen displays your cost in the current period, your current price, and

arrows indicating all the buyers that previously attempted to purchase in the market.

History Information

History Information After each period, the table in the lower right corner of the screen will record your profit, the number of sales you made (out of the number of possible sales), your average selling price, and your cost in that period.

If you have any questions, please raise your hand and a monitor will come by to answer your question. Your earnings in the experiment are in Experimental Currency Units (ECU) and they will be converted to Dollars ($) at a rate of 750 ECU = $1.

B Additional Tables and Figures

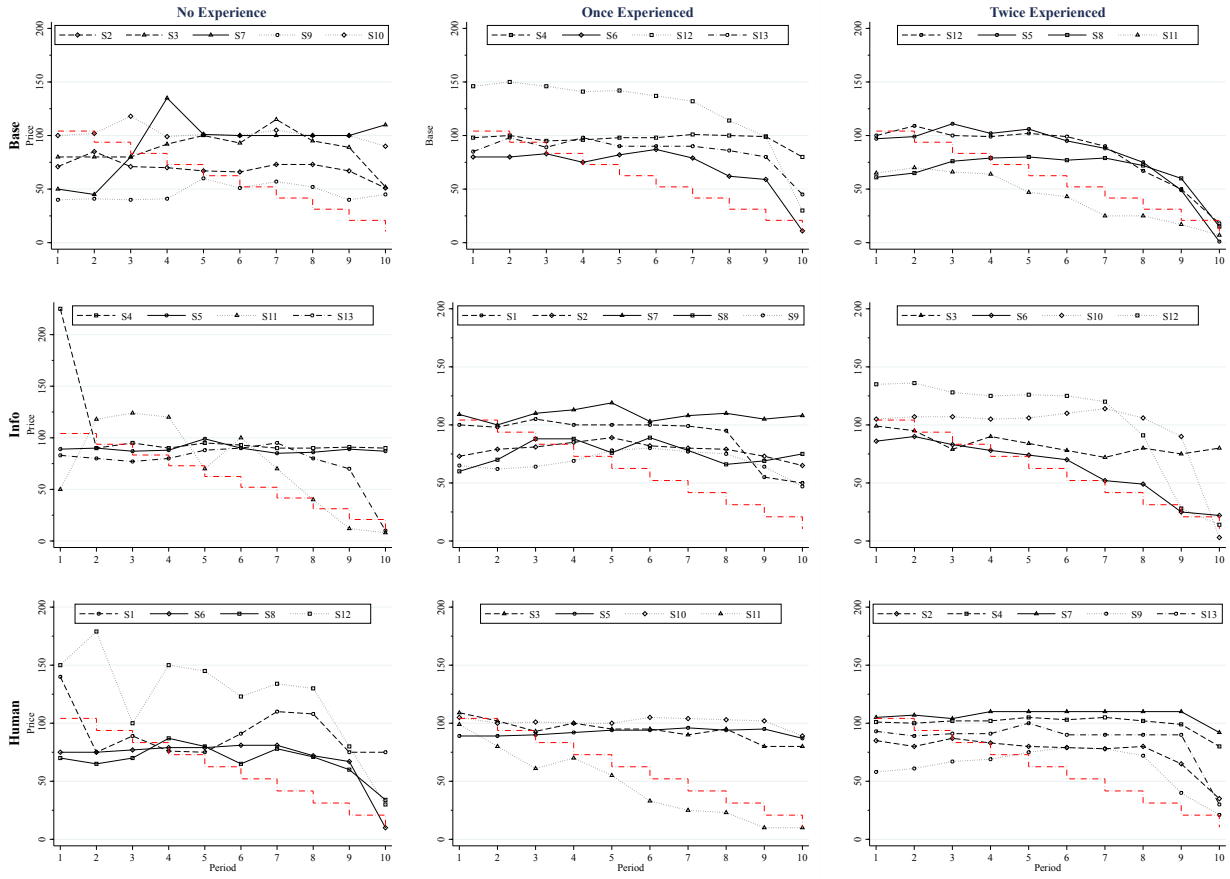


Figure B1: Closing Price by Experience and Treatment

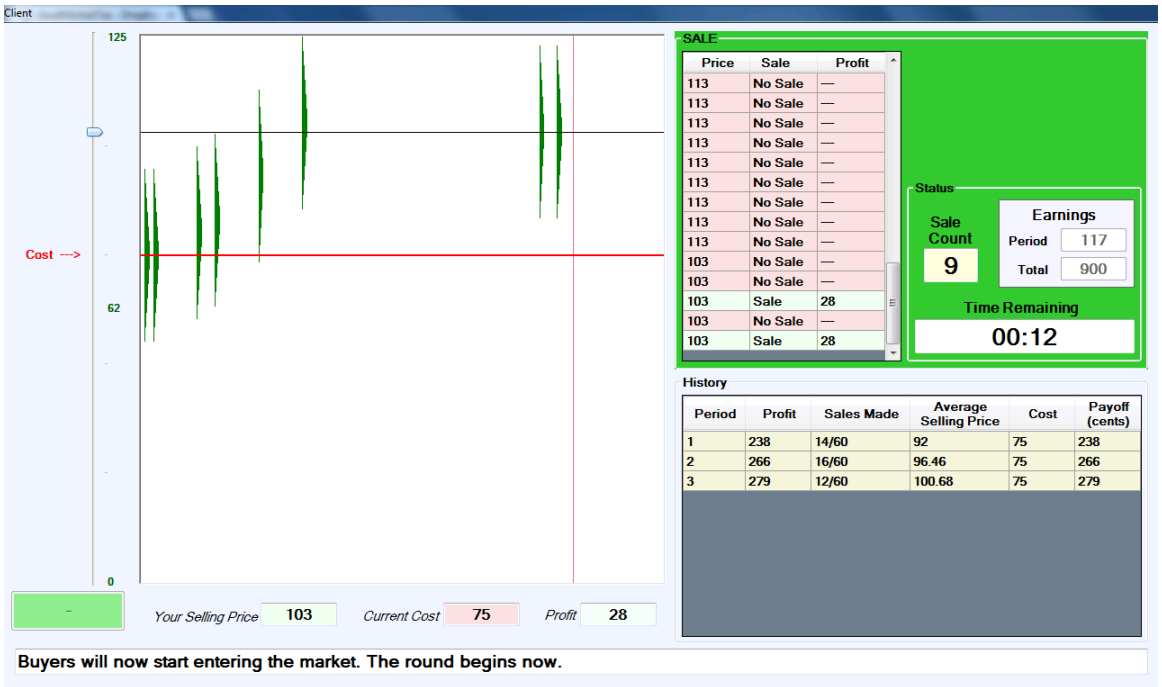


Figure B2: The Product Market Interface

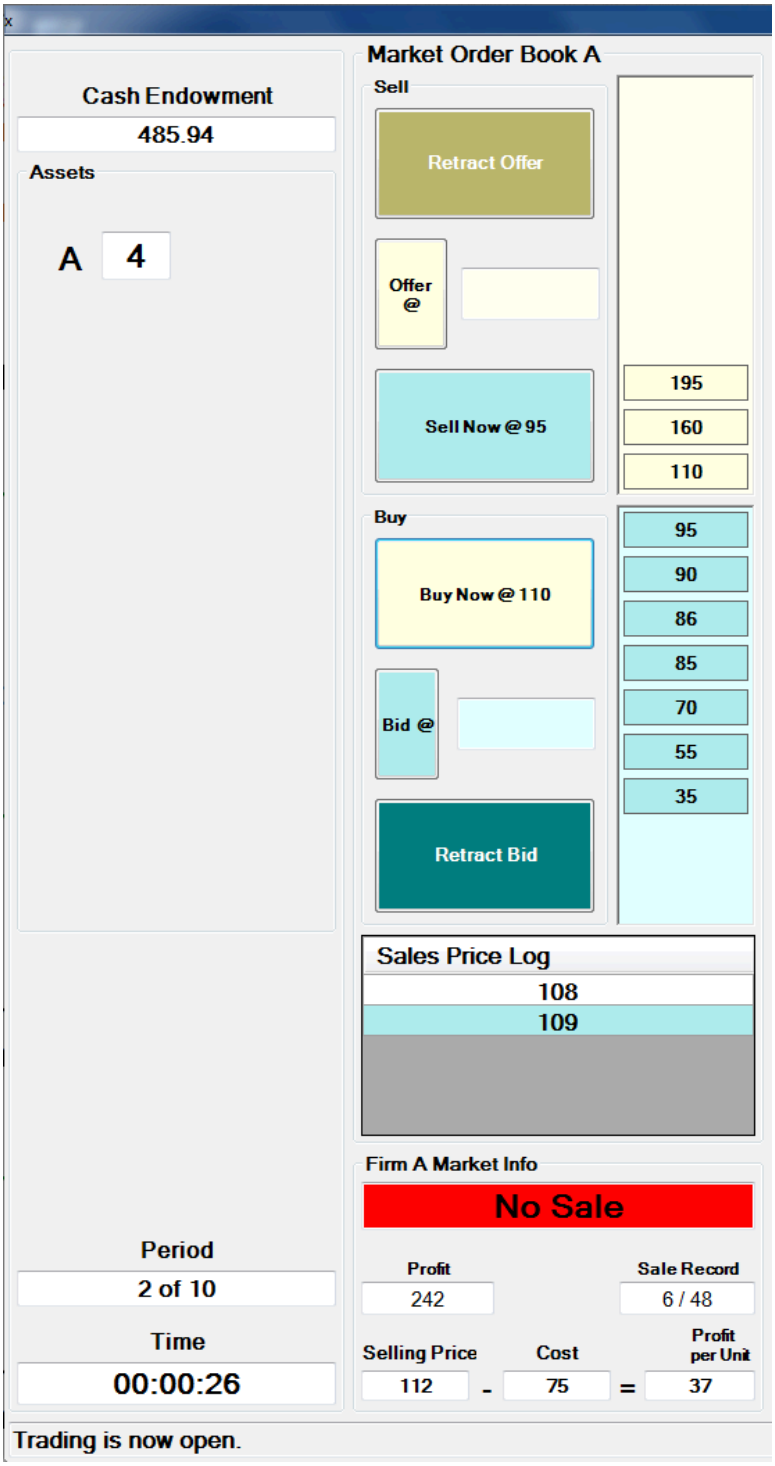


Figure B3: The Asset Market Interface

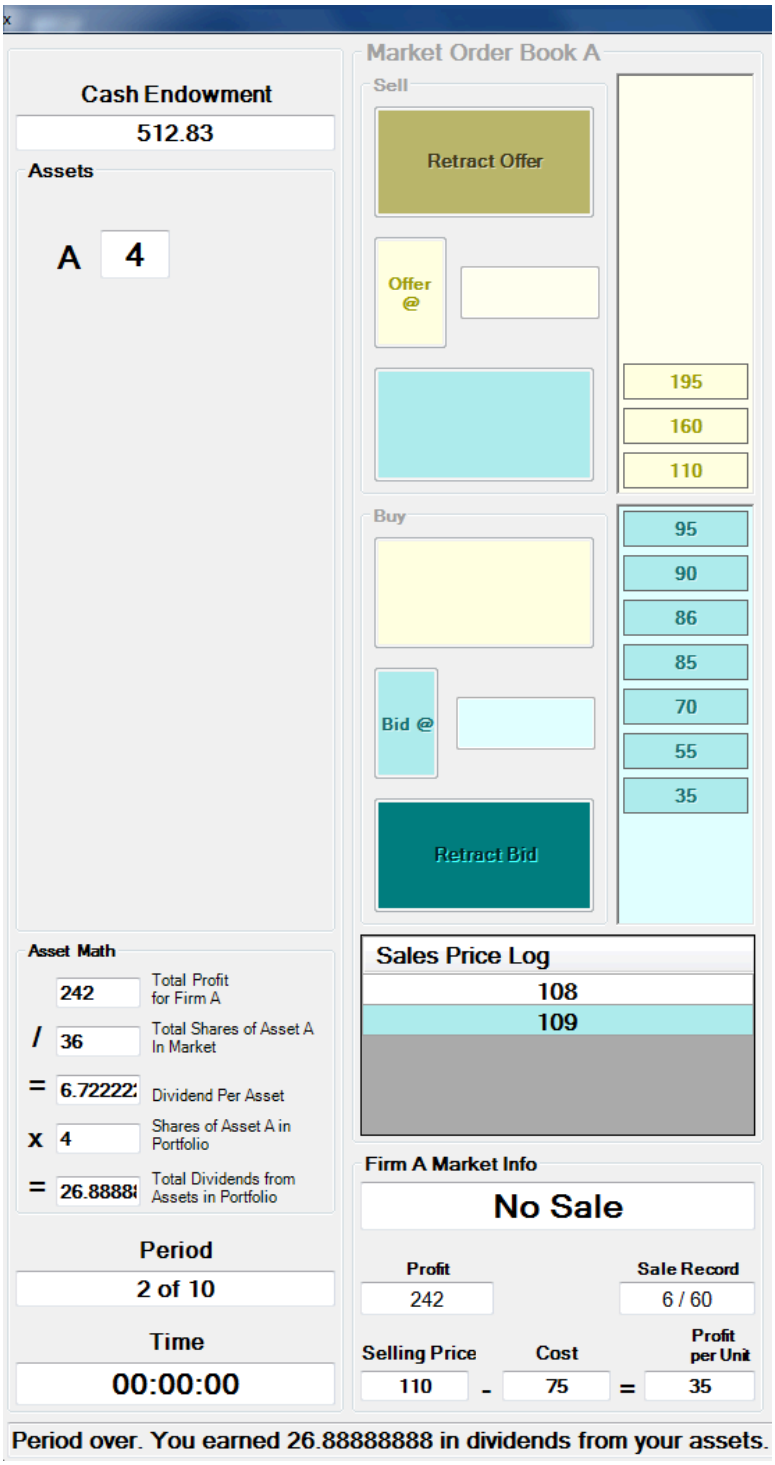


Figure B4: The Asset Market Interface at the End of a Period

Session	**Experience**	**Treatment**	α_1	α_2	R^2
1	None	*Human*	-0.10	-1.94	0.22
1	Once	*Info*	-2.12$^+$	0.95*	0.56
1	Twice	*Base*	-5.77	0.47	0.09
2	None	*Base*	0.93$^+$	0.30	0.17
2	Once	*Info*	-0.77$^+$	0.03	0.01
2	Twice	*Human*	-5.48	0.34	0.27
3	None	*Base*	-6.22	0.49	0.21
3	Once	*Human*	-5.28	-0.23	0.04
3	Twice	*Info*	-1.84$^+$	0.00	0.00
4	None	*Info*	1.81$^+$	-0.11	0.07
4	Once	*Base*	0.04$^+$	-0.12	0.07
4	Twice	*Human*	-3.98$^+$	0.21	0.17
5	None	*Info*	0.72$^+$	-0.02	0.00
5	Once	*Human*	-0.92$^+$	0.16	0.33
5	Twice	*Base*	-10.51	-0.09	0.00
6	None	*Human*	-2.84$^+$	0.10	0.02
6	Once	*Base*	-7.40	0.74*	0.76
6	Twice	*Info*	-6.40	0.14	0.04
7	None	*Base*	9.28$^+$	-0.16	0.02
7	Once	*Info*	0.66$^+$	-0.02	0.00
7	Twice	*Human*	-0.19$^+$	0.07	0.04
8	None	*Human*	-2.92$^+$	0.10	0.10
8	Once	*Info*	-3.46$^+$	0.21	0.16
8	Twice	*Base*	-4.73	0.46*	0.35
9	None	*Base*	1.33$^+$	-0.02	0.00
9	Once	*Info*	1.07$^+$	0.51	0.23
9	Twice	*Human*	-2.04$^+$	0.35	0.28
10	None	*Base*	0.44$^+$	0.07	0.16
10	Once	*Human*	1.32$^+$	0.25*	0.62
10	Twice	*Info*	0.70	0.81*	0.52
11	None	*Info*	-5.92	0.58	0.14
11	Once	*Human*	-7.24	0.07	0.00
11	Twice	*Base*	-7.13	0.17	0.08
12	None	*Human*	-4.66	1.35*	0.69
12	Once	*Base*	-4.05	0.96*	0.70
12	Twice	*Info*	-6.20	1.14*	0.49
13	None	*Info*	4.15$^+$	0.32*	0.44
13	Once	*Base*	2.58	0.34*	0.51
13	Twice	*Human*	0.98	0.38	0.21

$^+$ denotes significantly different from $-\sum d_t/T$ at $p < 0.1$.
* denotes significant at $p < 0.1$.

Table B1: Walrasian Price Adjustment by Market

Session	**Experience**	**Treatment**	RAD	RD	Duration	Turnover
1	None	*Human*	0.769	0.695	0.333	2.361
1	Once	*Info*	0.627	0.611	0.778	1.389
1	Twice	*Base*	0.558	0.538	0.667	2.056
2	None	*Base*	0.399	0.210	1.000	3.583
2	Once	*Info*	0.531	0.357	1.000	3.611
2	Twice	*Human*	0.441	0.331	0.889	4.500
3	None	*Base*	0.739	0.609	0.889	2.278
3	Once	*Human*	0.580	0.565	0.889	1.639
3	Twice	*Info*	0.500	0.435	0.778	1.278
4	None	*Info*	0.675	0.621	1.000	7.888
4	Once	*Base*	0.719	0.688	1.000	5.139
4	Twice	*Human*	0.731	0.719	0.889	4.528
5	None	*Info*	0.617	0.519	1.000	4.639
5	Once	*Human*	0.658	0.577	1.000	5.389
5	Twice	*Base*	0.526	0.473	0.444	5.389
6	None	*Human*	0.474	0.305	0.889	3.500
6	Once	*Base*	0.357	0.277	0.667	2.944
6	Twice	*Info*	0.206	0.097	0.667	2.833
7	None	*Base*	1.037	0.646	1.000	6.638
7	Once	*Info*	0.863	0.850	1.000	4.667
7	Twice	*Human*	0.865	0.865	1.000	5.500
8	None	*Human*	0.393	0.184	0.889	3.500
8	Once	*Info*	0.499	0.296	0.889	5.444
8	Twice	*Base*	0.444	0.253	0.889	5.500
9	None	*Base*	0.503	-0.199	1.000	4.833
9	Once	*Info*	0.519	0.115	0.889	4.972
9	Twice	*Human*	0.459	0.098	0.778	3.167
10	None	*Base*	0.825	0.821	1.000	8.389
10	Once	*Human*	0.788	0.788	0.889	8.389
10	Twice	*Info*	0.751	0.751	0.889	4.972
11	None	*Info*	0.382	0.160	0.333	2.278
11	Once	*Human*	0.195	-0.195	0.444	1.611
11	Twice	*Base*	0.227	-0.227	0.333	1.028
12	None	*Human*	1.214	1.214	0.666	4.194
12	Once	*Base*	1.171	1.171	0.778	2.333
12	Twice	*Info*	0.866	0.866	0.667	1.889
13	None	*Info*	0.591	0.419	0.889	6.333
13	Once	*Base*	0.563	0.487	0.889	6.528
13	Twice	*Human*	0.590	0.533	0.444	6.083

Table B2: Mean of Deviation, Duration, and Turnover by Market