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Shengle Lin

Economic Science Institute, Chapman University
1 University Dr, Orange, CA 92866

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Abstract

Gradual information diffusion model predicts that as private information travels across the population, pricing accuracy would improve and asset prices would exhibit momentum as a result. In laboratory markets I investigate the market's aggregation capacity in response to varying proportions of informed traders as a consequence of information diffusion. The results demonstrate that pricing errors are high when private information is dispersed and that, as the information spreads, the market gradually revise the errors and manifest momentum. Analysis suggests that aggregation under dispersed information conditions is hampered by three factors: equilibrium multiplicity, slow arrival of myopic traders, and anonymous trading.

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Abstract

Gradual information diffusion model predicts that as private information travels across the population, pricing accuracy would improve and asset prices would exhibit momentum as a result. In laboratory markets I investigate the market's aggregation capacity in response to varying proportions of informed traders as a consequence of information diffusion. The results demonstrate that pricing errors are high when private information is dispersed and that, as the information spreads, the market gradually revise the errors and manifest momentum. Analysis suggests that aggregation under dispersed information conditions is hampered by three factors: equilibrium multiplicity, slow arrival of myopic traders, and anonymous trading.

"*It was six men of Indostan, to learning much inclined, who went to see the Elephant. Though all of them were blind, that each by observation might satisfy his mind. The first approached the Elephant, and, happening to fall against his broad and sturdy side, at once began to bawl: 'God bless me, but the Elephant is very like a wall!' ……. And so these men of Indostan, disputed loud and long, each in his own opinion, exceeding stiff and strong. Though each was partly in the right, they all were in the wrong!*"

- John Godfrey Saxe[1], 1873

Would the market price converge to wisdom when market participants are imperfectly (and differently) informed? While traditional theories emphasize the market's capacity of correctly aggregating dispersed information regardless of how information is stored in the economy, recent empirical evidences suggest that mispricing would last for prolonged time under such conditions. In particular, asset price continuation has been repeatedly found to be responding to changes in information locality, commonly referred to as gradual information diffusion.

Hong and Stein (1999) provide a seminal model of information diffusion in relation to changing pricing accuracy. The model assumes that when different investors hold different private information, they respond only to what they know and totally fail to infer from market activities about what others may know or not know. Asset prices, being the population weighted average of all information groups' expectations, are thus biased. Investors would only revise their inaccurate evaluations after more information is passed along to them. When private information diffuses slowly across the investing public, asset prices will correct their previous errors and drift toward the intrinsic value. Hong and Stein (2007) goes further by incorporating the gradual-information-diffusion model into a general framework called "disagreement model", where information diffusion, limited attention and heterogeneous priors can be combined to understand a broad range of stylized facts. Recent empirical findings have backed up this story. It is reported that the varying proportion of informed traders to the whole investor population can impact prices substantially, absent changes in the fundamental.

This research is meant to investigate two questions: 1) Does information aggregation fail when information is dispersed in the economy, and the prices exhibit continuation as a

[1] The Poems of John Godfrey Saxe, 1873, Boston: James R. Osgood and Company, pp: 77-78

consequence of information diffusion? 2) If yes, what micro-level factors might have hampered perfect rational equilibrium from emerging?

The first question has been investigated by Bloomfield, Taylor and Zhou (2009). They run laboratory experiments on a single-asset market and find that: when pieces of new information regarding the dividend of the asset are disseminated across the subjects gradually, asset returns exhibit positive autocorrelation. While the results are encouraging, multiple joint hypotheses have been involved. The findings are also limited to macro-level price patterns without detailed reference to how private information and market prices are assimilated on an individual basis. The second question remains uninvestigated.

The experiment test in this paper directly tests the linkage between gradual-information-diffusion and momentum with no auxiliary hypothesis and brings the scope down to the individual investor level. The following innovations are made: (1) the design involves a market with two complementary assets and the market has no aggregate consumption risk, and hence assets should be priced at risk-neutral level conditional on strictly private information; (2) the realizations of information events are drawn from a rich set of paths and packed the underlying distribution completely, thus avoiding that "splashy results" get more attention (Fama, 1998); (3) the market as a whole hold complete information at all time, ensuring a stable fundamental; (4) each experiment is run for 5 times for the same group of subjects in addition of sufficient training and practice, thus controlling for learning effect; (5) return distribution and the information generating process are simplified and readily understandable; and (6) additional loans are given out to traders to enhance liquidity.

The results confirm that information diffusion alone is sufficient to generate the asset price momentum. Subjects respond primarily to their own private information and behave in myopic fashion. Little evidence supports the success of investors using the market prices to update their beliefs under dispersed information conditions.

The study generates three novel perspectives with regard to why the classical perfect aggregation equilibrium does not emerge (and consequently information diffusion generates momentum in prices):

(1) Equilibrium Multiplicity

There exist multiple equilibria given dispersed information, though only one equilibrium is correct; information diffusion reduces the number of false equilibria, forcing pricing accuracy to improve. The multiple equilibria explanation is consistent with the equilibrium multiplicity models of Grossman and Stiglitz (1976) and Angeletos and Werning (2004), which are built under conditions where no individual party have perfect information on the fundamental.

(2) The Relative Arrival Rate of Informed and Uninformed Traders

Wile privately informed traders can quickly close out mis-priced offers given their private information, those who are not enlightened by the ongoing arbitrage activities do not arrive simultaneously – the scattered arrival of myopic traders leads to prolonged asset mis-pricing. While the stochastic arrival of uninformed trades is consistent with the passive characterization of uninformed traders in early literatures, little literature has emphasized that the scattered arrival of preys poses a new limit of arbitrage. The relative arrival rate of informed and uninformed investors is accordance with the empirical findings of Vegas (2008).

(3) Anonymous Trading

Wile private information is dispersedly held by multiple parties, the market book does not reveal who offers what, thus making it difficult to track each party's transaction history and to make correct inferences about their private information. Market transparency has informational value, a point that has been emphasized by Foerster and George (1992).

The findings suggest that the market mechanism faces key micro-level challenges in aggregating diverse information that is not centrally stored, and the momentum and drift anomalies can solely be driven by gradual information diffusion process.

The paper is organized as follows. The first section reviews empirical, theoretical and experimental literature related to the topic; the second section presents the experimental design; the third section presents the results; the fourth section analyzes the data and probes into the causing structural factors in asset mis-pricing. The last section concludes briefly and addresses relevant implications.

I. Literature

A. Empirical Studies

Recent studies suggest that the relative proportion of informed traders to the whole investor population can impact prices substantially, absent changes in the fundamental.

A convincing example features Huberman and Regev's (2001) case study[2] of EntreMed's stock performance. On May 3, 1998, New York Times carried a front-page story on recent breakthroughs in cancer study and reported extensively on a biotechnology firm, EntreMed. The next day, the stock price of EntreMed soared from $12 to $52. However, the report was no new news, because the scientific journal Nature carried the same substance of the report five months earlier. Though following the Nature report, the stock price of EntreMed experienced positive move, but not as in large magnitude as it did after the New York Times announcement. This episode seems to suggest that the proportion of investors receiving new information can affect how much the new information would be incorporated into price.

Numerous recent cross-section studies that prices are biased when private information does not cover the whole population and the growing proportion of informed investors will result in the momentum phenomenon.

Hong, Lim and Stein (2000) find that the profitability of momentum strategies declines sharply with firm size[3] and, holding size fixed, momentum strategies work better with low analyst coverage. The paper contends that stocks followed by less analysts should, all else equal, be ones where firm specific information moves more slowly across the investing public[4]. The mispricings create profit space for momentum strategies to work. While the conclusion still rests on the assumption that analyst coverage is a proxy for the level of information publicity, Schmitz (2008) provides evidences that this may well be the truth. Based on an event study of a unique dataset of 300, 000 corporate news in the media in Germany, he finds that companies with lower abnormal media coverage indeed experience slower information transmission across different investor groups.

Bolmatis and Sekeris (2007) sort portfolios other proxies of information publicity (proxies include the ages of stocks since IPO and number of non-trade days in a year) and find that portfolios that tend to be 'neglected' by the market experience higher momentum. They argue that assets plagued with information problems can be mis-priced for sustained periods of time.

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[2] Hong and Stein (2007) cites the same case.
[3] Bhushan (1989) find that analyst coverage is negatively correlated with firm size.
[4] Hong, Lim and Stein (2000) also find that the effect of analyst coverage is greater for stocks that are past losers than for past winners.

The proportion of informed investors is found to be relevant in post earning announcement drift (PEAD), too. Vega (2006) studies public news data in Dow Jones Interactive in combination with regular data in CRSP and TAQ, and find that public announcements that generate underreaction are associated with high rate of uninformed traders while public announcement that make markets more efficient are associated with high rate of informed traders. Vega concludes that whether information is public or private is irrelevant in PEAD studies; what matters is the arrival rate of informed and uninformed traders.

Moreover, information diffusion has been used to explain lead-lag effect in cross-section returns. Hong, Torous and Valkanov (2007) and Hou (2007) both argue that industries that lead the market tend to carry more information regarding future economic climate and such information is only gradually picked up by other market segments.

The above empirical findings are all pointing to the argument that the proportion of informed investors matters for pricing accuracy and the changing ratio due to information diffusion moves asset prices under the same fundamental. Yet, the concept is novel to microstructure classical theories and contradicts with early experimental studies.

B. Classical Theories and Experimental Studies

Informational research in microstructure study is concerned with how private information is impounded in the trading process. The general logic is that when the informed traders move to arbitrage on their private information, the price will move in the direction that eliminates this opportunity. The conventional wisdom states that the competition among insiders would accelerate the process. The movement would enable the uninformed traders to infer from an observed price increase that some traders in the market have favorable information (Kyle, 1985). The notion of rational expectation theory predicts that, in equilibrium, asset price will reflect all of the information held by market participants (Muth, 1961; Lucas, 1972). Dissemination of information, from informed to the uninformed, and aggregation of individual traders' diverse bits of information through the market process have received consistent support. (Hayek, 1945; Grossman 1976; Fama, 1970; Radner 1979).

Early experimental studies of informational efficiency in asset markets address two questions: the dissemination of information held by insiders to uninformed traders, and the more difficult task of market aggregation of diverse information in possession of individual traders.

Results are more consistent in former case. Plott and Sunder (1982) and others have demonstrated that information held by a group of identically informed insiders is disseminated to a group of identically uninformed traders. In the latter case, results are more mixed. Plott and Sunder (1988) find that a market that trades a single three-state asset is able to aggregate information[5]. Follow-up experiments suggest that aggregation of information in markets depend on features of markets, including rules, common knowledge, experience of traders and the number of states. (Forsythe and Lundhom, 1990; O'Brien and Srivastava, 1991; Kruse and Sunder, 1988; Eberwein, 1990; Ang and Schwarz, 1985; Hanson, Oprea and Porter, 2004). Despite of those experimental findings, a majority of theories continue to vote for frictionless markets and the informational efficiency in prices.

Unlike the early experiments that involve a limited number of states and concentrate information in one group or two, Bloomfield, Taylor and Zhou (2009) run laboratory experiments specified by Hong and Stein (1999) model where information is dispersed and the number of states are large. In their single-asset market, they find that: when news information regarding the dividend of the asset is disseminated across the subjects only gradually, momentum is a robust phenomenon. While the results confirm the theory, they could have been weakened by several issues: (1) In the single-asset market, aggregate consumption varies under different states and it is unclear how aggregate consumption risk might have changed the prices. (2) The market participants at all time except the end do not have complete information regarding the liquidating dividend, making it hard to define aggregation failure. (3) The experimental design deliberately involves 95% positive autocorrelation of news surprise over time, which could have magnified the momentum effect; the caveat is that when prices exhibit momentum, it could have been driven by the same change in the fundamental and does not necessarily suggest price inefficiency. In addition, the findings are limited to macro-level price patterns without detailed reference to what causes aggregation failure.

The purpose of the experiment test here is to test the gradual-information-diffusion and momentum relationship with no joint hypothesis that Bloomfield et al (2009) involve. Equally importantly, the analysis attempts to provide micro-level accounts for aggregation failure that bugs the whole related literature and market efficiency believers.

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[5] The dividends of the asset depend on which of the three states (X, Y, or Z) is realized; if the realized state is X, half of the participants will be privately informed that the state is "not Y", and the others were similarly informed "not Z".

II. Experimental Design

A. The Model

I develop a simplified information diffusion model originally introduced by Hong and Stein (1999). In their model, there are z equal-sized groups of differently informed investors and a single risky asset that pays a liquidating dividend of D_T at the terminal time. The dividend starts with unconditional mean of D_0 and is subject to a series of disturbances over its lifetime. The disturbances follow the same equal-variance zero-mean normal distribution and are independently identically distributed.

$$D_T = E(D_T) + \sum_{j=1}^{T} \varepsilon_j = D_0 + \sum_{j=1}^{T} \varepsilon_j, \qquad \varepsilon_j \sim N(0, \sigma^2), I.I.D. \tag{1}$$

Each disturbance ε_j is further decomposed into z equal-variance surprise terms: $\varepsilon_j = \varepsilon_j^1 + \varepsilon_j^2 + \cdots + \varepsilon_j^z$. At time t, each group knows only one surprise term of ε_{t+z-1} and the market as a whole knows all the components of ε_{t+z-1}. Each surprise term of ε_{t+z-1} will be distributed to an additional group in the next period. Therefore, over time, each information group has an incomplete yet increasingly refined knowledge of ε_{t+z-1}. The information diffusion follows a strictly one-way "rotation mechanism". In Hong and Stein (1999) model, the informed traders behave in a myopic fashion and are assumed to have identical constant relative risk aversion; as a result, the market price at time z is be represented by the average of each investors' independent expectation of the liquidating dividend, adjusted by aggregate risk aversion and the supply of the security. At time t, the market price for the asset will equal to the expected value of the asset plus the population-weighted average value of all disturbances in the market, adjusted by a risk aversion term:

$$P_t = D_0 + [(z-1)\varepsilon_{t+1} + (z-2)\varepsilon_{t+2} + \cdots + \varepsilon_{t+z+1}] / z - \theta \bullet Q, \qquad \varepsilon_i \sim N(0, \sigma^2), I.I.D. \tag{2}$$

θ is the market's aggregate risk aversion parameter, and Q is the aggregate supply of the security. As t moves forward, the surprise terms spread across the population via the "rotation" ordering. Hong and Stein (1999) assumed that investors make decisions purely on their private information, without reference to the market prices, and the average of all the individual expectations conditional on each investor's private information, is therefore affected by population weight of each disturbance.

In the experimental design, a simplified version of this model is used, but the essences of the model are kept: (1) Information is held dispersedly by multiple groups, in contrast to the one group concentration in most traditional models; (2) each piece of information is a valid and equally valuable component in determining the true value—they are not noisy signals; and (3) information travels among investors and the proportion of informed traders with regard to each piece of information grows over time. A deviation from Hong and Stein (1999) is that this paper ensures full information in the market at all time such that the fundamental is ascertained.

The design reported here involves only one disturbance consisting of four surprise terms, $SURs$, each independently and identically following a zero-mean uniform distribution:

$$D_T = D_0 + SURs = D_0 + (\varepsilon_1 + \varepsilon_2 + \cdots + \varepsilon_z), \qquad \varepsilon_i \in U\{u_1, u_2, \cdots, u_3\}, I.I.D \tag{3}$$

The investor population is divided into z groups. At Period 1, each group knows one of the surprises, and the market as a whole possesses all needed information to determine the value of surprises and the liquidating dividend at the very beginning. Starting from Period 2, each group will get to know an additional surprise per period, and the information diffuses in the same fashion as the "rotation mechanism" specified by Hong and Stein (1999). Gradually, each individual group will hold an increasingly accurate knowledge of the dividend, and each will hold some information that some other groups do not have.

B. Experimental Parameterization

In what follows, I present a simple three-period market that serves as a theoretical baseline for the experimental results. Let there be a finite number of investors; two risky assets, Security A and Security B; a riskless bond; and numerous states of the world. The bonds are infused into subjects' cash holdings at zero interest rate and need to be paid back at the end of experiment. The interest rate for holding cash is normalized to zero. Each asset pays a liquidating dividend at the end of Period 3. All payoffs are denominated in a currency called Francs (₣). Market participants are sorted into two types of six investors, with one type having more Security A than B and the other type having more Security B than A.

Table I: Market with Two Risky Assets

The market consists of two complementary assets with equal supply. Security A pays an uncertain dividend of *F X* and Security B pays *F* (120- *X*). The aggregate consumption is constant in any state. 6 subjects of type I are richer in security A holdings, while 6 subjects of type II are richer in security B holdings. To enhance liquidity, 800-Franc loans are provided to all subjects at no cost. Only security A is traded in the market.

	Dividend	Holding	
Security A	X	Type I (6 subjects):	24 units
		Type II (6 subjects):	3 units
Security B	$120-X$	Type I (6 subjects):	3 units
		Type II (6 subjects):	24 units
Cash	1	₣ 1500 (800 loan)	

The design of a market with two complementary assets is initiated by Bossaerts (2007). The payoffs of Security A and Security B are perfectly complementary to each other; that is, holding a unit of Security A and a unit of Security B will yield a fixed payoff of 120 Francs.

Initial allocation of the risk securities varies across groups, but the total supplies of the risk securities are equal; hence there is no aggregate consumption risk. Risk-averse subjects who hold more of A than of B would be willing to sell A at risk-neutral prices; the presence of an equal number of subjects with more of B than of A allows the market to clear. In principle, risk-averse subjects can neutralize risk by balancing their holdings of the complementary securities. Since the total endowments of Securities A and B summed over across all subjects are the same, everyone, in theory, can balance his or her holdings. Prices should converge to levels that equal expected payoffs and risk-neutral pricing should arise.

Absent aggregate consumption risk, the risk aversion adjustment term in Equation (2) is now removed. Bossaerts (2007) has confirmed in experiments that when aggregate consumption is constant, prices converged to expected payoffs of the securities. Similar to Bossaerts (2007), Security B is not traded in the market and thus balancing on portfolio must be carried through buying or selling Security A.

Security A pays an unconditional expected dividend of 60 Francs. The true value for security A is the sum of expected payoff plus several surprise terms

$$X = 60 + SURs\,. \tag{4}$$

The experiment has three treatments: Treatment A, Treatment B, and Treatment C. The treatments differ from each other in the number of surprise terms and the distribution of surprise terms.

In Treatment A, there are four surprise terms:

$$X = 60 + SURs = 60 + (\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \varepsilon_4)\,. \tag{5}$$

Each surprise independently and identically follows a zero-mean discrete uniform distribution:

$$\varepsilon_j \in \{-10,0,10\}, \qquad j = 1,2,3,4\,. \tag{6}$$

Therefore X can take on the value of 20, 30, 40, 50, 60, 70, 80, 90 and 100, with a mean of 60 and a central tendency toward the mean. There are a total of $3^4 = 81$ states for the realizations of X.

Treatment A markets last for 3 periods, and information diffusion follows the Hong and Stein (1999) rotation mechanism. In Period 1, each ε_j is known by 25% of the population. In Period 2, each ε_j reaches an additional 25% of the population, with each surprise covering 50% of the population. In Period 3, each ε_j reaches 75% of the population. The market is closed after Period 3, and the dividends are paid out afterward.

When compared to the standard early experiments with states as few as 3, Treatment A raises the number of states to 81. Plott and Sunder (1982) run a treatment of 11 states and find that convergence to rational expectation equilibrium becomes more probabilistic. To control for the difference in the number of states between early experimental studies and Hong and Stein (1999) study, two additional treatments are introduced: Treatment B has 16 states and Treatment C has 4 states. Treatment C uses an example model of Hong and Stein (2007), and its simplicity is comparable to Plott and Sunder (1988) design. The comparison across treatments would examine whether the increase in the number of states leads to higher pricing errors and contributes to stronger momentum.

More specifically, Treatment B only differs from Treatment A in that the surprise terms are drawn from a discrete uniform set of two possible numbers:

$$\varepsilon_j \in \{-10,10\}, \qquad j = 1,2,3,4\,. \tag{7}$$

Therefore X can take on the value of 20, 40, 60, 80 and 100, with a mean of 60 and a central tendency toward the mean. There are a total of $2^4 = 16$ states for the realizations of X.

In Treatment C, there is only two surprise terms, with each surprise drawn independently and identically distributed from a discrete uniform set:

$$\varepsilon_j \in \{-20,20\}, \qquad j = 1,2. \tag{8}$$

Therefore X can take on the value of 20, 60, and 100, with a mean of 60 and a central tendency toward the mean. There are a total of $2^2 = 4$ states for the realizations of X. Subjects in Treatment C are divided into two groups and the treatment lasts only one period. One group knows one surprise and the other group knows the other surprise. Treatment C is taken from Hong and Stein (2007) and is the closest to the early experiment studies. In Plott and Sunder (1988), there are 3 states X, Y and Z, with one group knowing "not X" and the other group "not Y", thus combining the two pieces of information guarantees the state being Z. In Treatment C, combining the two ε's will determine a unique value for the asset value.

The three treatments will investigate the full spectrum of the number of states in affecting information aggregation. Six experiments of Treatment A, two experiments of Treatment B, and two experiments of Treatment C were run in the laboratory. Each experiment was repeated for five independent sessions, thus generating a total of 10 × 5 = 50 sessions of market datasets. See Table II.

Table II: Experimental Treatments

The disturbance for the dividend is the sum of a number of surprises. Each surprise is drawn from a discrete uniform set; consequently, each treatment corresponds to a different number of possible states for the security. Treatments A and B last for three periods for each market, and information diffuses over time. Treatment C has only one period and information is static. Six experiments are run for Treatment A, two are run for Treatment B, and two are run for Treatment C. In each treatment, the market session is repeated five times for the same subjects, with a new set of information realizations each time.

	# Surprise Terms	Uniform Set	# States	# Periods	# Experiments
Treatment A	4	{–10, 0, 10}	81	3	6
Treatment B	4	{–10, 10}	16	3	2
Treatment C	2	{–20, 20}	4	1	2

C. Predictions of Experimental Results

The market for security B is not open, and the investigation focuses on the price formation in the Security A market only. However, Security B offers a hedge against holdings on Security A and the structure arrangement eliminates aggregate consumption risk. In principle, Security A must be priced at risk-neutral levels conditional on private information and enables private information to be clearly expressed at the expected prices. This market structure offers the advantage of circumventing risk preference complications and focusing on information referring on the part of investors.

Hong and Stein (1999) predicted that investors will value Security A at the expected mean of the dividend, conditional on their respective private information, and investors' valuations are not affected by the information embedded in the market prices. As a result, market price would be set within the confines of each party's respective valuation. For simplicity, Hong and Stein (1999) assumed that the average of all individual valuations will prevail as the market price.

In Treatment A, each surprise is known by 25%, 50%, and 75% of the population for the three periods respectively. On the basis of the Hong and Stein (1999) model, the price in period t in Treatment A should be

$$P_t = 60 + t \bullet (\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \varepsilon_4)/4 = 60 + \frac{t}{4} \bullet SURs, \qquad t = 1,2,3. \tag{9}$$

The risk adjustment term is dropped because in the experimental environment, the absence of aggregate risk ensures risk-neutral pricing. If the surprise term is nonzero, the market price would always be deviant from the true value. The deviation decreases over the periods, resulting in momentum (drift) in prices of Security A. The possible price path for each possible surprise term is plotted in Figure 1. The price paths show clear patterns of drift and momentum. This is the major prediction of the Hong and Stein (1999) model.

Given Equation (9), the change in market price from the previous period is:

$$\mathrm{M}_t = P_t - P_{t-1} = \frac{1}{4} \bullet SURs, \qquad t = 2,3. \tag{10}$$

Therefore, if the surprise term is positive, price should exhibit positive momentum; if the surprise term is negative, price should exhibit negative momentum; and if the surprise term is zero, price should not exhibit any momentum.

Treatment B and Treatment C are compared to Treatment A to test how the number of states can potentially impact pricing accuracy. The two treatments are necessary because traditional experiments on information markets have much fewer states than this simple design, not to mention the original Hong and Stein (1999) model. If the factor matters, pricing error across in Treatment A and Treatment B should be ranked as follows:

$$\Delta_t^A > \Delta_t^B, \qquad t = 1,2,3. \tag{11}$$

Treatment C is unique, since there exist only two news surprises and the markets last only one single period. In Treatment C, each surprise term is known to 50% participants and the proportion of informed traders with regard to each news surprise is comparable to period 2 in Treatment A and Treatment B.

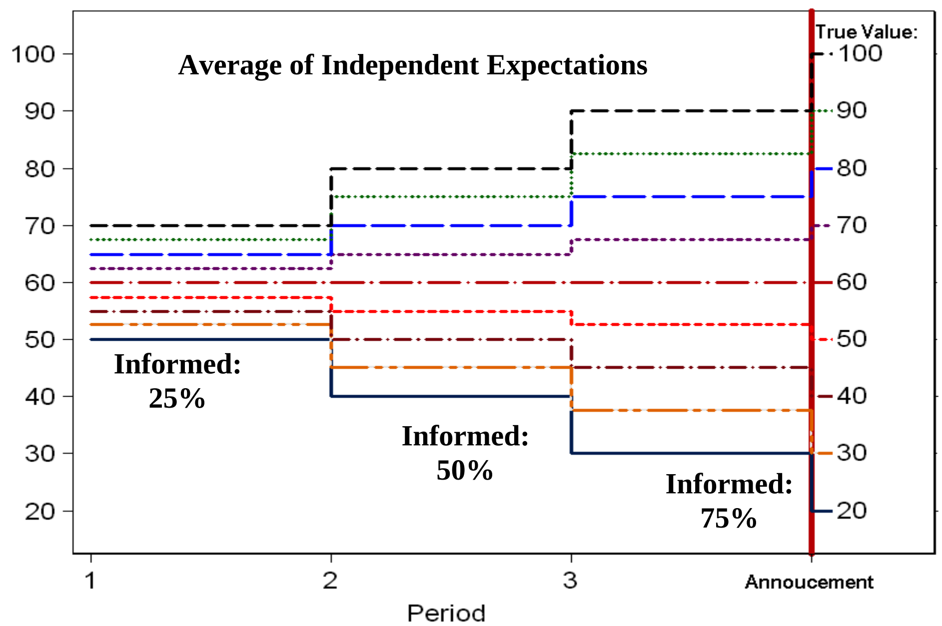


Figure 1. Predicted price paths based upon myopic information averaging. The path represents the average of all the individual expectations, predicted by Hong and Stein (1999). In period 1, each surprise term is known to 25% population. In period 2, each surprise term is known to 50% population. In period 3, each surprise term is known to 75% population. The average of independent expectations would always deviate from true value. As the ratio of informed traders grows over time, the price converges to the true value. Whenever surprise is non-zero (and true value is above 60 or below 60), predicted price will display momentum.

D. Implementation

Experiments were conducted in the Economic Science Institute laboratory at Chapman University. One hundred twenty students were recruited through an online recruiting system. A total of 10 experiments were conducted, with 6 experiments for Treatment A (81 states), 2 experiments for Treatment B (16 states), and 2 experiments for Treatment C (3 states). Twelve subjects participated in one experiment. Recruited subjects had no previous experience with the experiment and were allowed to participate only once. Experiments were held between April 2009 and September 2009, and each lasted approximately 2.5 hours including instruction, quiz, practice and actual experiment sessions.

In each experiment, subjects participated repeatedly in 5 consecutive but independent market sessions. Their earnings were accumulated over the session and were converted to U.S. cents at a ratio of 5:2.

In a typical experiment, subjects waited in a reception room until a sufficient number had arrived. Twelve subjects were then taken into the laboratory room and seated at computers behind partitions so that they could not see each other's screens. A strict no-talking rule was enforced as soon as subjects entered the laboratory. Subjects were given identical instructions that gave detailed information on the environment and rules of the institution and provided experience with the interface. There was a single core of instructions common to all treatments.

On completing the instructions, subjects were given a self-grading computerized quiz that consisted of six questions. When a subject submitted an incorrect answer, the computerized quiz automatically reminded the subject to try again. Once a correct answer was received, the logic behind the quiz was explained again. Subjects were allowed to ask questions for clarification throughout the instructions and quiz. Typically, instructions and quizzes lasted a total of 25 minutes. Finally, subjects were given a practice session. The practice session lasted three periods, and each period lasted a prolonged duration of 5 minutes. Subjects were ensured understanding and familiarity with the trading interface. During the practice session, an exemplar information news rotation mechanism was also included. No earnings were accounted for in the practice session.

During experiments, subjects are not told the exact dividend value until the trading session is over. Subjects can trade their holdings of Security A for cash in an anonymous, continuous, open-book exchange system. They can submit both market orders and limit orders.

After the practice session, the experiment proceeded into the real market sessions, and at the end of a session, the four draws for the news item were revealed in public, dividends were paid out, and earnings were displayed. Subjects earned an average of $46.5 over five consecutive sessions, in addition to the $7 show-up fee.

III. Results

In Figures 2a and 2b, price results from six experiments of Treatment A are exhibited (A1–A6). Each experiment runs for five repeated sessions, and three trading periods per session. Figure 3 plots the Treatment B results with two experiments (B1, B2), again five repeated sessions per experiment and three periods per session. Figure 4 plots the Treatment C results with two experiments (C1, C2), five repeated sessions per experiment and only one period per session[6].

In what follows, Result 1 studies whether prices exhibit momentum, and if so, whether it is driven by information diffusion. Result 2 studies whether pricing accuracy across treatments is affected by the increased number of states. Result 3 measures the accuracy of inference about the true value on the individual basis and presents evidence on whether investors fail to extract significant information from market prices.

[6] All experimental data are available at: http://esi2.chapman.edu/data/

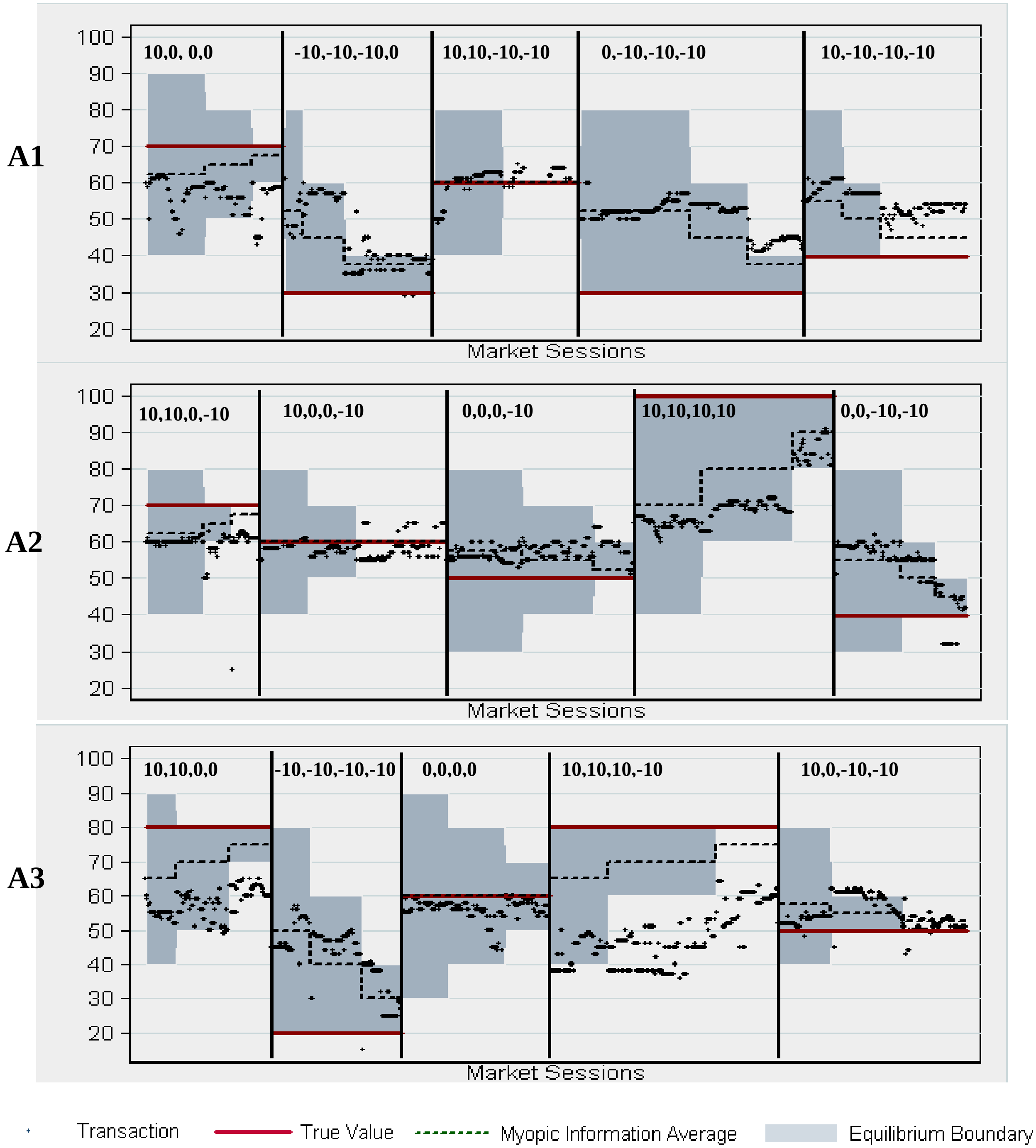


Figure 2a.Transaction prices for Experiment A1, A2 and A3. Experiment A1, A2 and A3 from Treatment A are reported. Each experiment has 5 market sessions, divided by vertical solid lines in the figure. The realizations of the surprised terms are marked on the appropriate session. Each market session has 3 periods in which information diffuses gradually. A unpaid practice session in each experiment to help subjects familiarize with the trading program is not reported. The solid horizontal line indicates the true dividend value for the period. The dashed stepstair lines represent the myopic average pricing predicted by Hong and Stein (1999). All transactions are reported. Each dot represents a unit of trade. The shaded area represents equilibrium range (See section 4A for definition).

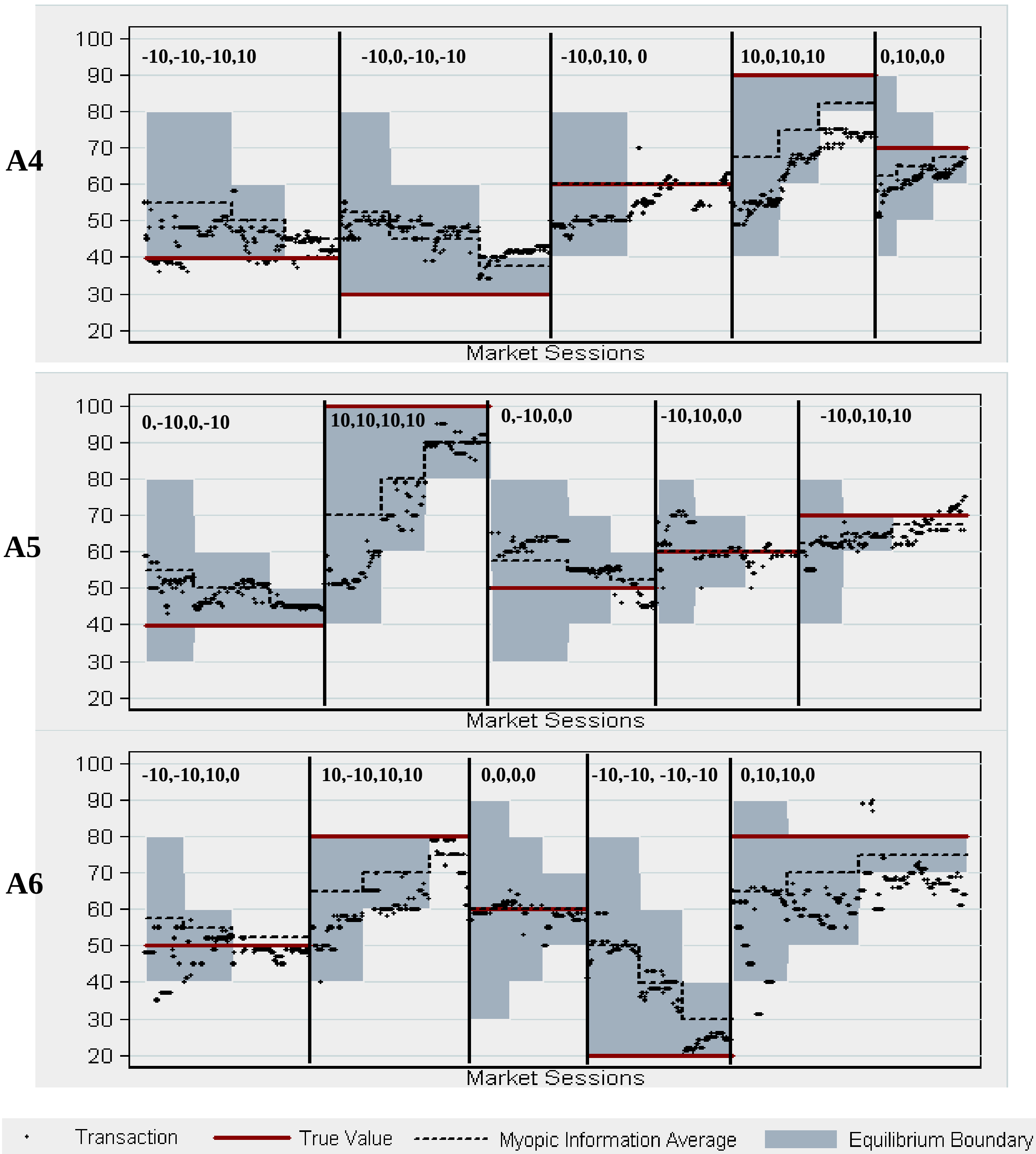


Figure 2b.Transaction prices for Experiment A4, A5, and A6. Experiment A4, A5 and A6 from Treatment A are reported. Each experiment has 5 market sessions, divided by vertical solid lines in the figure. The realizations of the surprised terms are marked on the appropriate session. Each market session has 3 periods in which information diffuses gradually. A unpaid practice session in each experiment to help subjects familiarize with the trading program is not reported. The solid horizontal line indicates the true dividend value for the period. The dashed stepstair lines represent the myopic average pricing predicted by Hong and Stein (1999). All transactions are reported. Each dot represents a unit of trade. The shaded area represents the equilibrium interval. (See section 4A for definition).

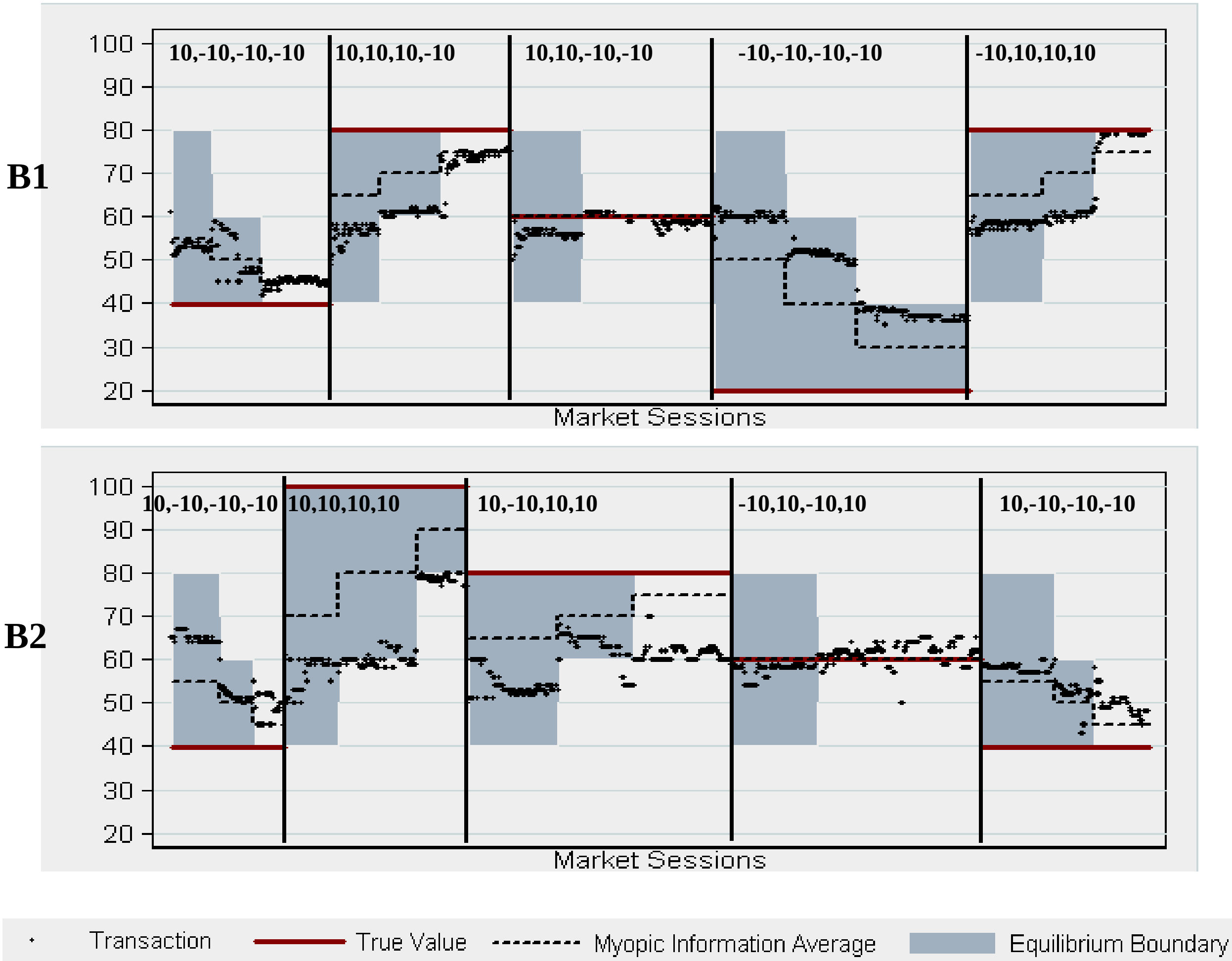


Figure 3.Transaction prices for Experiment B1 and B2. Experiment B1 and B2 from treatment B are reported. Each experiment has 5 market sessions, divided by vertical solid lines in the figure. The realizations of the surprised terms are marked on the appropriate session. Each market session has 3 periods in which information diffuses gradually. A unpaid practice session in each experiment to help subjects familiarize with the trading program is not reported. The solid horizontal line indicates the true dividend value for the period. The dashed stepstair lines represent the myopic average pricing predicted by Hong and Stein (1999). All transactions are reported. Each dot represents a unit of trade. The shaded area represents the equilibrium interval. (See section 4A for definition).

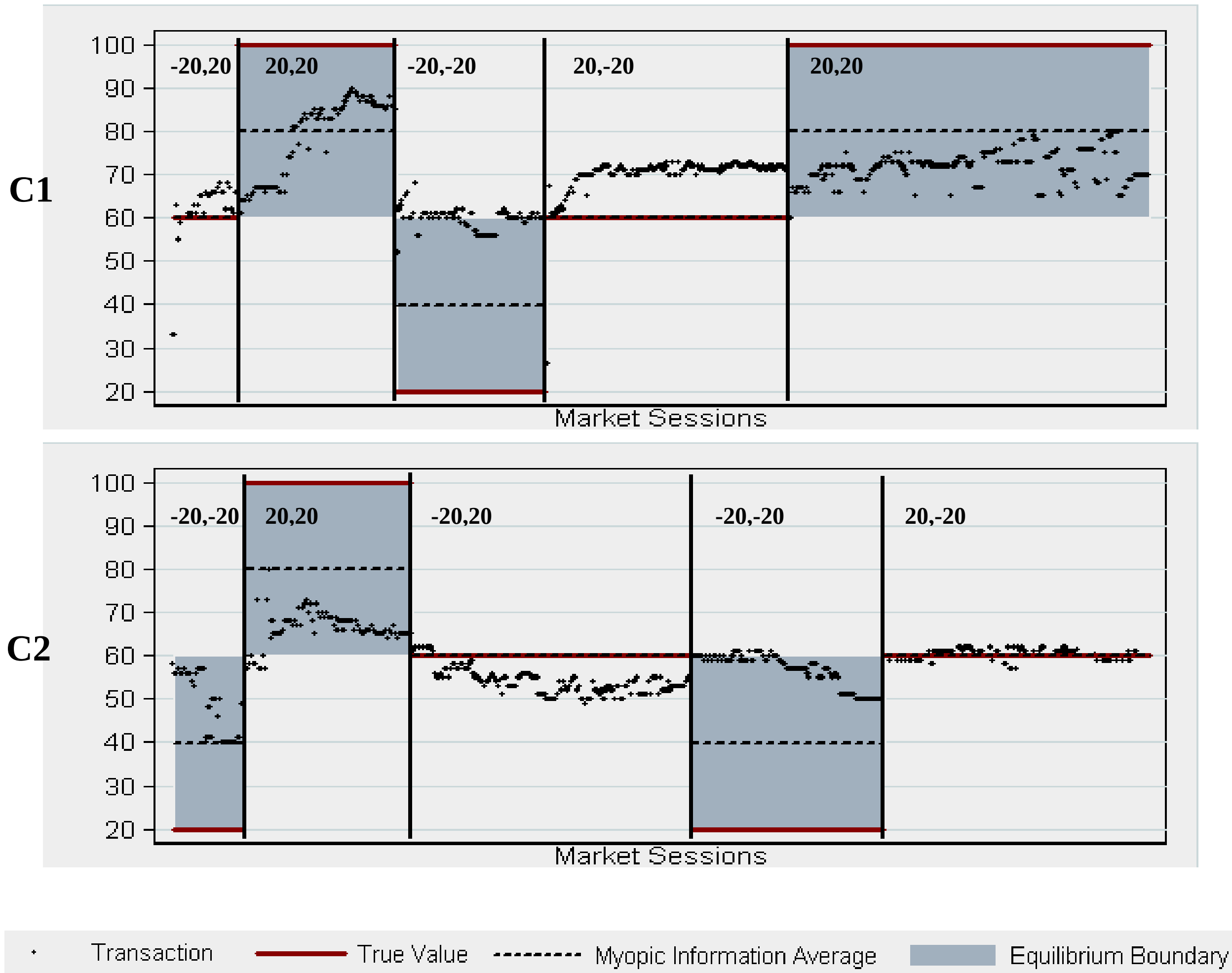


Figure 4.Transaction prices for Experiment C1 and C2. Experiment C1 and C2 from Treatment C are reported. Each experiment has 5 market sessions, divided by vertical solid lines in the figure. The realizations of the surprised terms are marked on the appropriate session. Each market session has only 1 period in which information location is static. A practice session in each experiment to help subjects familiarize with the trading program is not reported. The solid horizontal line indicates the true dividend value for the period. The dashed horizontal lines represent the myopic average pricing predicted by Hong and Stein (1999). All transactions are reported. Each dot represents a unit of trade. The shaded area represents the equilibrium interval. (See section 4A for definition).

A. Result 1: Price time series exhibit momentum toward intrinsic value as a consequence of information diffusion.

A major prediction laid out in Section II is that when the sum of surprises is smaller than zero, prices would converge to the true value from above and exhibit negative momentum; when the sum of surprises is greater than zero, prices would converge to the true value from below and exhibit positive momentum; and when the sum of surprises is zero, prices would exhibit no drift. The prediction is confirmed exactly in Figure 5. The average deviations from true value across 3 periods are plotted for each of the 40 market sessions, with 30 sessions from Treatment A (six experiments × five sessions) and 10 sessions from Treatment B(two experiments × five sessions). Seventeen sessions have a realization of positive surprise, and prices in these sessions exhibit strong negative momentum. Fifteen sessions have a realization of negative surprise, and prices in these sessions exhibit strong positive momentum. Eight sessions have a realization of zero surprise, and prices in these sessions manifest no momentum. The systematic distinctions across 3 cases are readily visible.

To look at the deviation from true value in a unified way, an indicator for pricing error is defined as the absolute percentage price deviation from true value for a period:

$$\Delta_{k,t} = \left|P_{k,t} - D_T\right| / D_T, \qquad t = 1,2,3 \tag{12}$$

Table III summarizes the pricing errors for the three periods in both Treatment A and Treatment B. The average pricing error is 39% for Period 1, 32% for Period 2, and 18% for Period 3. The pricing errors across two adjacent periods are significantly different from each other, suggesting a sizable improvement of pricing accuracy over time. The improvement perfectly coincides with the information diffusion in each period. For any two adjacent periods in a market session, the only change that occurred is that each surprise term reaches more audience, all other factors unchanged. Therefore information diffusion is the only driving factor for the improvement in pricing accuracy and, consequently, price momentum. Since information is complete at all time, it is clearly established in the results here that higher information “density” is associated with higher pricing accuracy.

Table III: Errors across periods in Treatment A and Treatment B

Error for a transaction is computed as the percentage deviation from the true value in the period. Treatment A and B have 3 periods for each session. Two adjacent periods have the same sets of private information in the economy and only differ in who knows what. Treatment C has only one period and the pricing errors are not included in this table.

	Ratio of informed traders	Mean	Observations	Std. dev.	Mean comparison	
Period 1	25%	0.39	2279	0.43	$t = 5.4$, $p < 0.0001$	
Period 2	50%	0.32	2210	0.34		$t = 16.9$, $p < 0.0001$
Period 3	75%	0.18	2305	0.20		

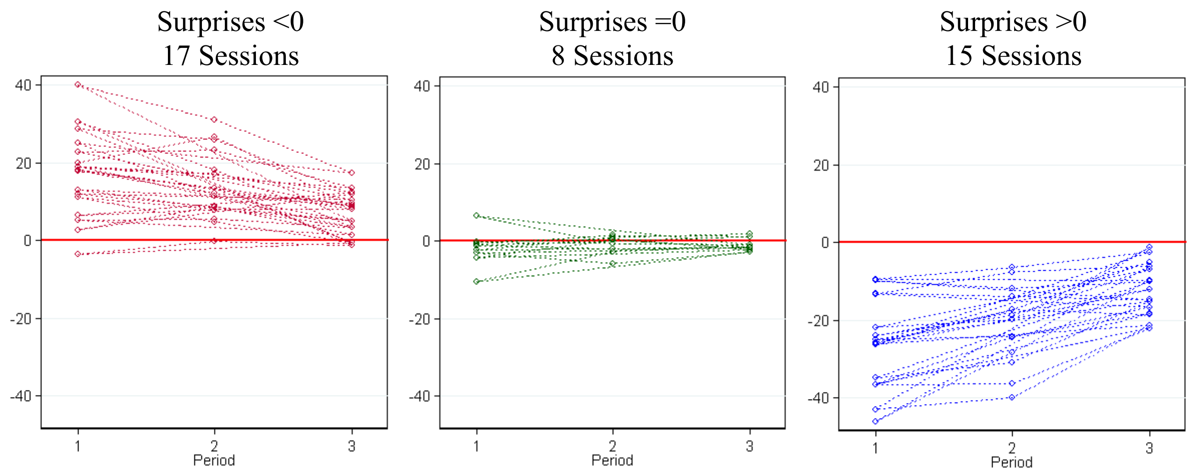


Figure 5. Average deviation from true value for a trading period. The deviation of mean price in a period from its true value is reported for a total of 40 market sessions in treatment A and treatment B. 17 sessions experience negative surprise, 15 sessions experience positive surprises and 8 experience no surprise. The average price deviations from true value for each period are linked by a dashed line and displays the directional movement. Unlike risk-averse based explanations, underpricing and overpricing both exisit.

B. Result 2: Pricing accuracy does not improve as the number of states is reduced.

Treatment A differs from Treatment B in the number of states for the liquidating dividend. Plott and Sunder (1982) show that, when the number of states is increased from 3 to 11, information aggregation in the market becomes unstable. It is naturally conjectured that Treatment A should have a higher pricing error than Treatment B. However, Table IV suggests no such evidence and indicates some sign of the opposite conclusion. For the same period, a market in Treatment A experienced less average errors than a market in Treatment B, though the differences are not statistically significant. Treatment C experiences higher errors than both Treatment A and Treatment B. Figure 6 provides box plots for the average errors in the three periods for each treatment and confirms that Treatment B experiences slightly higher error. Treatment A and Treatment B differ only in the numbers of states and consequently the possible realizations of true value, as the boundaries of possible true value are both 20 and 100.

Periods in Treatment C differ from periods in Treatments A and B in two ways: First, it only has four realizations of the states determined by two surprise terms; second, the surprises are given out to two groups, rather than four groups, in the very beginning. As a result, Treatment C lasts for only a single period. It is similar to Period 2 in Treatments A and B in the sense that each surprise term has reaches 50% population. However, the pricing errors in Treatment C seem to be the largest among the three treatments. This evidence suggests that the determinacy of pricing accuracy is hardly related to the number of states or the level of complexity in the environment. This puzzle will be addressed in Section IVA.

Table IV: Comparison of Pricing Errors across Treatments

The average pricing errors in a trading period of treatments A and B are listed on the left; the average pricing error of Treatment C is listed on the right. Wilcoxon Rank Sum test is used to compare the statistical difference of pricing errors in Treatment A and Treatment B.

	Treatment A			Treatment B			Mean comparison	Treatment C		
	Mean	Obs.	Std. dev.	Mean	Obs.	Std. dev.	Two-sample Wilcoxon rank sum test	Mean	Obs.	Std. dev.
Period 1	0.35	30	0.37	0.48	10	0.56	$z = -0.69$, $p = 0.49$			
Period 2	0.30	30	0.31	0.35	10	0.44	$z = -0.56$, $p = 0.57$	0.64	10	0.79
Period 3	0.15	30	0.14	0.21	10	0.25	$z = -0.59$, $p = 0.55$			

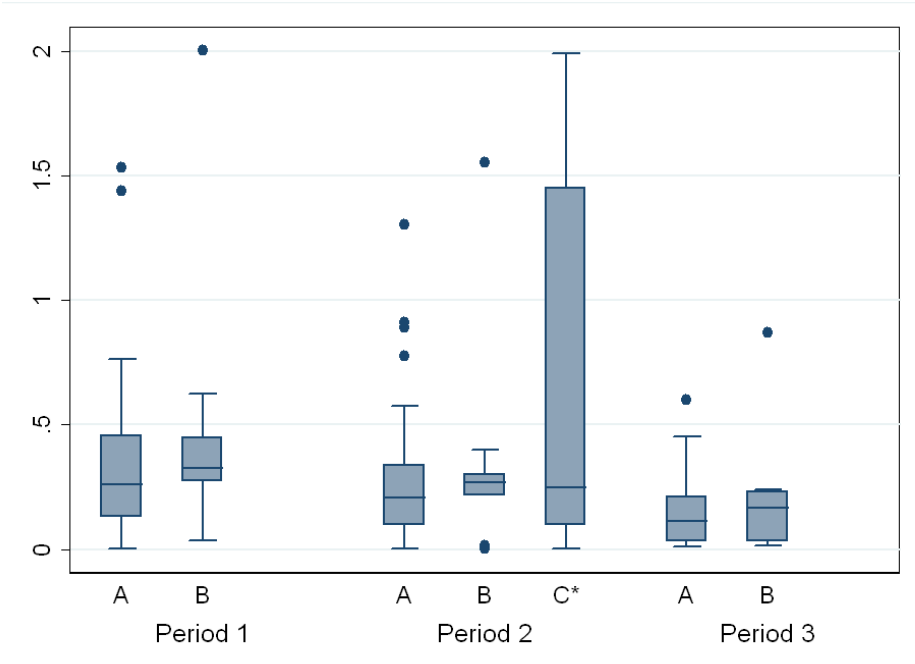


Figure 6. Box plots for pricing error across treatments. Pricing error for a period is plotted, sorted on period number and treatment identity. Treatment C is listed in the Period 2 category, because each piece of private information is revealed to 50% population, equivalent to period 2 of treatment A and B.

C. Result 3: Individual investors fail to decipher market activities and behave in a myopic fashion.

The previous two results addressed aggregate market pricing accuracy. Result 3 examines how well each individual is informed by the market price. To do so, a subject's valuation of the security has to be identified. While no direct subjective measurement exists, a subject's valuation can be approximated. A proxy mechanism called *separating price method*, introduced by Rockenback (2004), is used next.

From the experimental data, it is impossible to directly tell what a subject's exact valuation is, but buying and selling activities should reveal their preference. An investor who follows his or her own valuation V_i buys the security whenever the security price is lower than V_i, and sells the security whenever its price is higher than V_i. For price V_i, the investor is indifferent between buying and selling the security. From these observations, a separating price can be identified that best explains the investment decision of a subject in a trading period by applying the following procedure: consider that subject i made K transactions within a period, and denote the transacted prices as J_k. Suppose that $V_i \in \{20,21,...,100\}$ is the candidate separating price. The investment decision of investor i in the period violates the assumption of the separating price if he or she buys the security $J_k > V_i$ or sells the security $J_k < V_i$. In case of violation ($\omega_k = 1$), I calculate the squared deviation as the magnitude of violations:

$$\Gamma_k = (J_k - V_i)^2 \bullet \omega_k, \qquad k = 1,2,\cdots,K, \qquad \omega_k \in \{0,1\}. \tag{13}$$

The candidate price V_i that best separates between buying and selling activities for investor i is the price that minimizes the sum of squared deviations:

$$V_i = \arg\ \min\ V_i \in \{20,21,\cdots,100\} \sum_k \Gamma_k (V_i). \tag{14}$$

It is possible that more than one price has the smallest sum of squared deviations. As one can easily verify, this can only happen for a connected price range. Because there is no good reason to assume that the "true" separating price is at a specific location in that range, V_i is defined as the middle point of the range. The examination here is restricted to Treatment A and Treatment B, and uses 682 observations of individual separating prices V_i out of a total of 960 observations (= 12 subjects × 8 experiments × 5 sessions × 3 periods), with the rest irretrievable for the reason that subject either buys only or sells only in a period.

Once V_i is derived, the valuation is compared to the true value D_T and one's private information projected mean, $subj\_mean_i$. To evaluate how much an individual improve one's valuation over his own private information, an indicator of inference accuracy is generated:

$$\lambda_i = \frac{V_i - subj\_mean_i}{D_T - subj\_mean_i}. \tag{15}$$

If $V_i = D_T$ and λ_i is 1, that means the subject obtains perfect foresight; if $V_i = subj\_mean_i$ and λ_i is zero, that means the subject is completely myopic; if λ_i is greater than 1, that means the subject over extrapolates; and if λ_i is smaller than zero, that means the subject is not informed by the market price at all and is too conservative.

Table V summarize the inference accuracy for Treatment A and B. In Period 1, subjects were extremely cautious with an average inference accuracy ratio less than 0. In Period 2, inference effectiveness is significantly improved yet the average ratio is close to 0. Only in Period 3 can some positive sign of correct inference be observed. Again, there are significant improvements from Period 2 to Period 3. Across all three periods, the average inference effectiveness ratio is 0.12, which is much closer to total ignorance of market price than to perfect information extraction.

Figure 7 plots a histogram for the inference accuracy and the distribution almost centers around myopic zero inference sampling over all trading periods.

Table V: Price inference accuracy across periods in Treatment A and B

Note: Inference accuracy is measured on subjects' valuations relative to the position of one's own private information projected mean and the true dividend value. A ratio of zero indicates complete myopic, and a ratio of 1 indicates perfect foresight.

	Mean	Observations	Std. dev.	Mean comparison	
Period 1	–0.21	259	0.93	t = 2.93,	
Period 2	0.05	206	0.97	p = 0.002	t = 5.62,
Period 3	0.59	217	1.13		p < 0.001
Pooled	0.12	682	1.06		

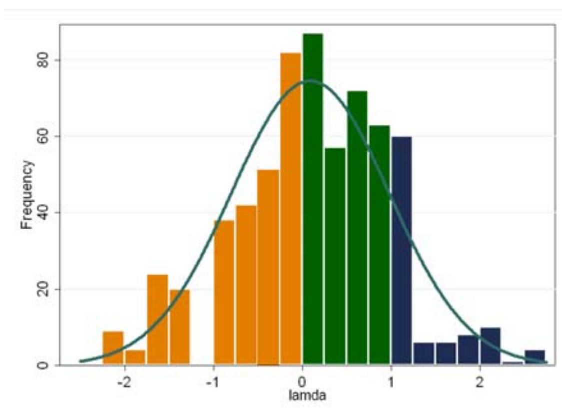


Figure 7. Inference accuracy distribution for Treatment A and B. The histogram for inference accuracy indicates a relative symmetric distribution centering around a mean of 0.11. The level is closer to compete myopic (λ =0) than perfect (revealing λ =1).

IV. Analysis

The preceding results clearly suggest failure of information aggregation, a fact that contrasts with the conventional notions of perfect information revelation and findings in some of the early experimental literature. The results pose puzzles: What factors are relevant in determining the accuracy of aggregation? Result 1 clearly suggests that when information is highly dispersed, aggregation fails; and when information diffuses, pricing accuracy improves. Why would information "density" per capita matter for market price efficiency?

In what follows, I will present three explanations: (1) multiple equilibria exist given dispersed information, and information diffusion reduces the number of false equilibria and pricing accuracy naturally improves; (2) though competition among insiders can quickly close out mispriced offers, these mispriced offers do not arrive simultaneously, the dispersed arrival of uninformed traders leads to prolonged asset mispricing; and (3) the market book does not reveal who offers what, thus making it difficult to track an informed party's activities and to make inferences.

A. Equilibrium multiplicity and the stability of false equilibria

Multiple equilibriums in dynamic expectations models have been ubiquitous in macroeconomic studies, in which how people coordinate their beliefs affects real production (Black, 1974). The existence of nonunique equilibria dominates a wide range of theories including currency crises, bank runs, and financial bubbles and crashes; rather, the debate focuses on what causes the market to select one equilibrium over another. Driskill (2006) offers the literature survey on such selection criteria.

With regard to financial market information aggregation, Grossman and Stiglitz (1976) first endogenize public information by allowing individuals to observe financial prices and show that equilibrium can be established where the prices do not reflect true worth of the assets due to noisy supply shocks. Angeletos and Werning (2006) use a similar framework where agents can observe the endogenous public information, aka, the financial prices and demonstrate that equilibria multiplicity is ensured when individuals observe fundamentals with small idiosyncratic noises.

Multiple rational expectation equilibria are relatively new to the classical theories on information aggregation. As will be discussed, market prices can settle down on any candidate equilibrium that is compatible with the information distribution in the economy, and a selection criterion may exist in favor of some equilibria over the fully revealing equilibrium.

In the experimental environment, multiple equilibria are defined as prices that are compatible with all individuals' private information. Under such equilibria, no individual will have absolute confidence to attack the status quo prices. Only one equilibria reflects the true value of the asset, while the rest of equilibria reflect situations where each individual hold mistaken beliefs about the information held by others and the mistaken beliefs are mutually compatible. This occurs when different parties are differently informed, similar to the idiosyncratic noises in individual parties' private information in the model of Angeletos and Werning (2006). The experiment design here, based upon Hong and Stein (1999), is an exact example of the scenario.

In Treatment A, the news surprise has four terms, each held by one group (25% of the population). The first group with the knowledge of ε_1 can ascertain that the dividend is within the interval $[\varepsilon_1 + 30, \varepsilon_1 + 90]$. Define the intersection of individual groups' intervals as *equilibrium interval*. It can easily be noted that the equilibrium interval can cover more than one equilibrium. In fact, any possible state within the intersection can be an equilibrium. Following is a simple example: Suppose that the four surprises are 10, 10, 10, and -10, and thus the true value is 80. The three groups with the knowledge of 10 can ascertain that the dividend is within [40, 100], whereas the group with the knowledge of -10 can ascertain that the dividend is within [20, 80]. Thus the equilibrium interval is [40, 80]. Now any price at 40, 50, 60, 70, or 80 does not contradict with any information group's private information and can sustain all groups' beliefs. If the market initially assumes the dividend to be 40, the groups with the knowledge of 10 will assume that all the rest of the realizations are -10, whereas the group with the knowledge of -10 will assume that the other three realizations have a sum of -10. Once the price of 40 established, there is no trigger that induces any party to change its belief. Indeed, Experiment A6 Session 2 Period 1 confirms for this example that most transaction prices falls between the boundaries of possible equilibriums (See Figure 2b.). The patterns can be observed in the price time series plots of all treatments, where the intersections are marked out in the shaded area (See Figure 3, Figure 4 and Figure 5); 70.2% of transactions are within the range. Note that prices falling out of the boundary range are not rare, which will be explained in the next.

Table VI: Feasible GLS regressions on pricing error

The mean pricing error for a trading period is regressed on the equilibrium range for 130 periods, after controlling for experimental treatment dummy and information coverage ratio proxy. The trading periods in Treatment C are considered as "Period 2", since each piece of information is also known by 50% population

Independent variable	Pricing error
Equilibrium range	0.018 (6.85***)
Treatment(=B)	0.16 (2.32**)
Treatment(=C)	0.37 (3.21***)
Period(=2)	0.36 (3.76***)
Period(=3)	0.53 (4.06***)
Constant	–0.54 (–3.75***)

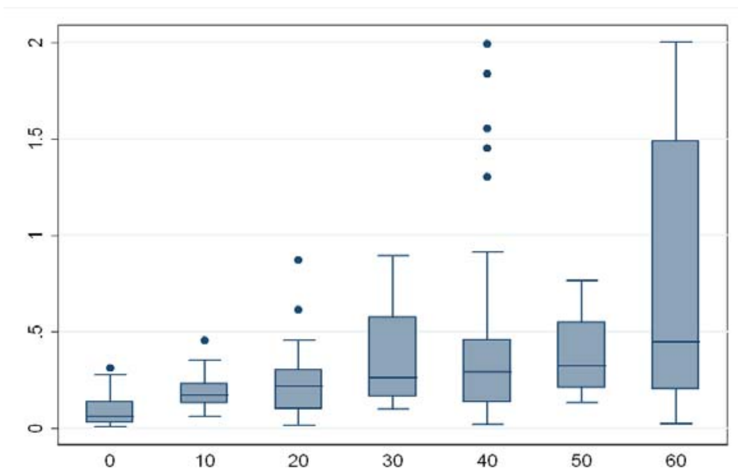


Figure 8. Pricing Error across varying equilibrium ranges. The box plot for pricing errors for each level of equilibrium range from all periods is presented. A range of zero means that only one equilibrium exists.

If the above logic is at play, then the number of possible equilibria will be positively correlated with pricing errors. Define the length of the equilibrium interval as *equilibrium range*. Since more equilibria lead to larger equilibrium range, equilibrium range can be used as a proxy. To test this, pricing errors for a period are regressed on equilibrium range in a period.

Table VI reports the regression results based on observations from all treatments and indicates that the pricing error in a period is significantly positively correlated with the equilibrium range, after controlling for experimental treatment and period effect. Figure 8 graphs the box plots of pricing error for each level equilibrium range. As is shown clearly, pricing error steadily increases when equilibrium range grows.

B. Scattered arrival of myopic traders and the persistence of out-of-equilibrium prices

The analysis in Section IIIA offers an understandable explanation for how prices may not land on the true value due to equilibrium multiplicity. However, it remains a question why the out-of-equilibrium-range prices persist. Out-of-equilibrium prices pose obvious arbitrage opportunities. Why are such opportunities sustainable? As long as an out-of-equilibrium limit order exists, the party that knows for sure that it is a safe transaction should act immediately. In Kyle (1985), informed insiders should in theory instantly close out such opportunities. However, the experimental results indicate broad violations of the theory, because 29.8% transactions[7] are out of equilibrium range. (See Figure 2, 3, 4)

To find out the cause, a microscopic view of price formations is necessary. In Figure 10, the trading activities in Experiment A3, Session 1, Period 3 are plotted as an example. Each buying or selling transaction is coupled with a range plot of the actor's private information interval. The true value for the period is 80, as determined by four surprise terms of 10, 10, 0 and 0.

In period 3, the four information groups will each know 3 surprise terms as {10,10,0}, {10,0,0}, {0,0,10} and {0,10,10} respectively. Therefore, there are two different private information ranges for all subjects: two groups with the interval [60, 80] and the remaining groups with the interval [70, 90]. According to Kyle (1985), the price should converge to 80 quickly. The market prices hover around 63 and almost persist for the whole duration of the trading period. At the price of 63, it is a safe buy for the groups with interval [80, 100]. Indeed, they were buying the security throughout. No problem is found on the buy side. However, it is shown that subjects with the private information interval [60, 80] were continuously submitting limit orders around 63 throughout the first two-thirds of the period. Only in the end did some of these subjects become buyers for the same price level. In this case, the groups with interval [60, 80] seemed to have learned little from the market at all and continuously submitted myopic transactions. As is shown, the reason why price lingers around an off-equilibrium level is not that arbitragers do not take away safe gains immediately, but because the myopic traders arrive in scattered and prolonged fashion.

[7] About half of the out-of-equilibrium-range transactions occur when there is only one equilibrium for the trading period.

This finding is highly consistent with the PEAD study of Vegas (2008), who reports that public announcements that generate underreaction are associated with the higher arrival rate of noise traders, while public announcements that make markets more efficient are associated with higher arrival rate of informed traders. Vegas (2008) utilizes a proxy variable for the presence levels of informed traders in market activities, the probability of information-based trading (PIN) , a measurement initiated by Easley and O'Hara (1992). The example here directly exposes the market book and private information held by each information group, thus identifying that the continuing arrival of myopic traders as the reason for persistent disequilibrium prices.

To identify the myopic traders in all periods, the following definition is made: If a trader made a selling (buying) transaction at a price that is within his own private information interval but below (above) the common interval of all groups, the transaction would count as a myopic trade. Figure 9 draws the frequency of myopic trades at each second of a 2-minute period, sampled from a total of 130 periods. The plot demonstrates that myopic trades arrive evenly over time, and there was no clear sign of declining in myopic trades over time.

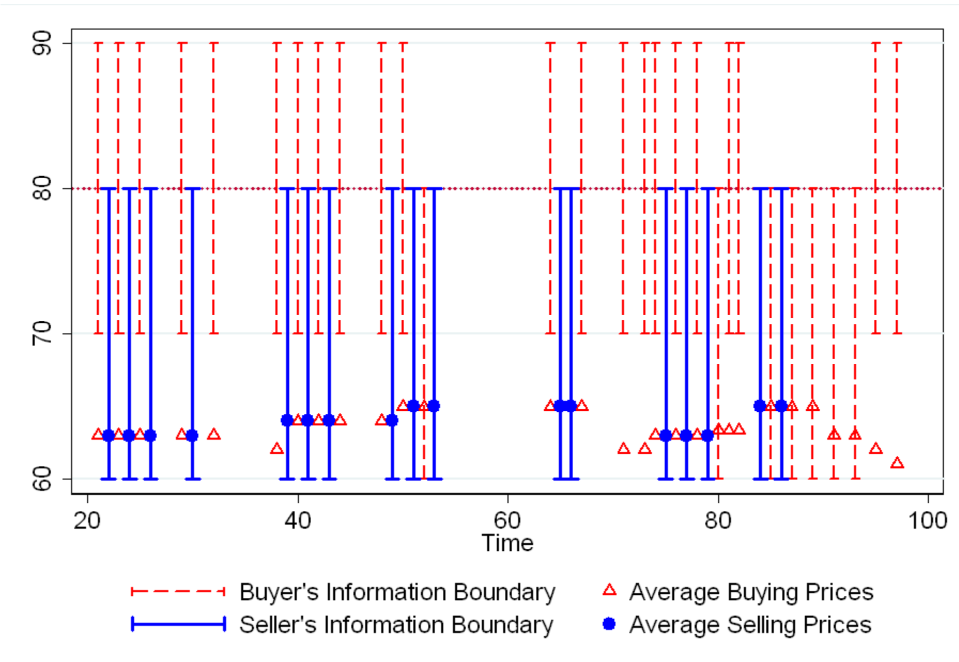


Figure 9. Buyers' information, sellers' information and market orders in period 3 of Experiment A3, Session 1. The market orders in Experiment A3-Session 1-Period 3 are reported, together with the actor's private information interval. Adjacent trades for the same subject are merged and only the average is shown. A total of 46 orders are reported here. All orders below price 60 are considered as noisy trading and are dropped for saving space.

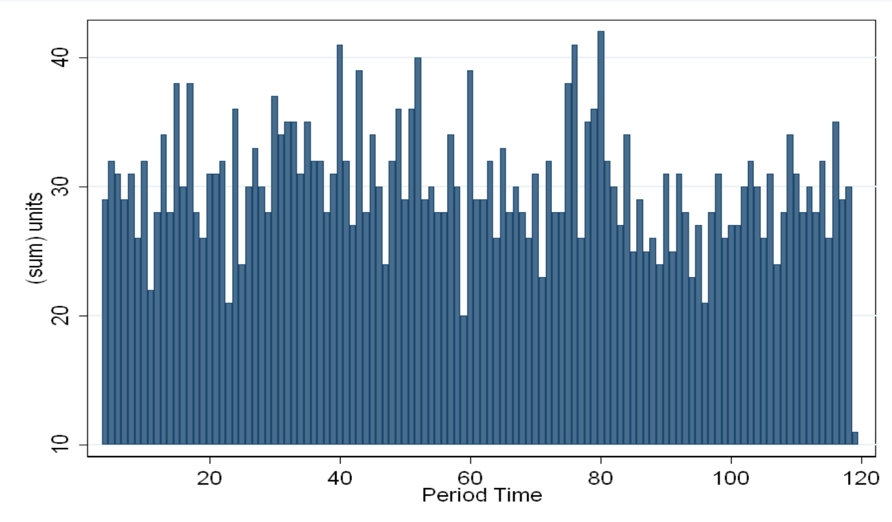


Figure 10. Frequency of myopic transactions within the time of a trading period. The vertical axis reports the frequency of myopic trades (not noisy trade) in each second of a period over a sample of 130 periods. Each period lasts 120 seconds. If a trader made a selling (buying) transaction at a price that is within his own private information interval but below (above) the common interval of all groups, the transaction would count as a myopic trade.

One potential explanation for this observation is that myopic trades induce more myopic trades, as Grossman and Stiglitz (1976) emphases that wrong price itself can pass noise to observers. The mispricing created by myopic trades in the beginning might other traders to believe that the price is at a reasonable level and affirm their actions. Taking the example again, the groups with interval [60, 80], after seeing transactions at 63, may form belief that the dividend was 60, which is compatible with their own private information.

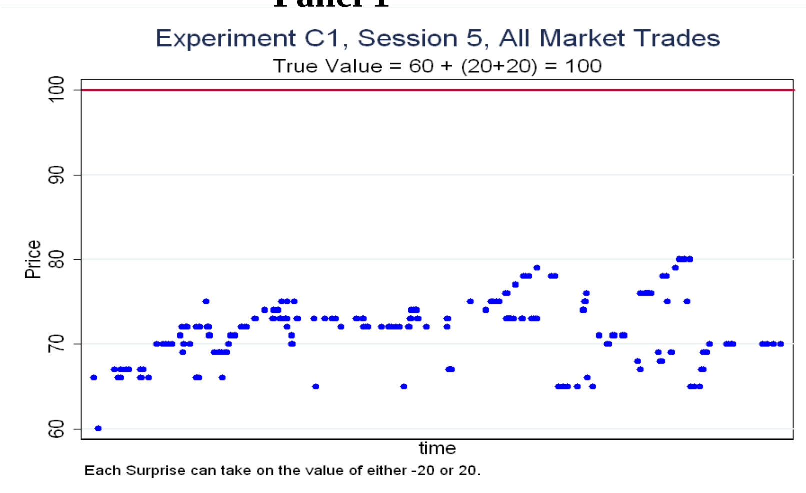
C. Anonymous Trading and Market Transparency

One assumption underlying classic theories of information aggregation is that the uninformed party can observe the activities of the informed parties (Kyle, 1985). In reality, market transparency is very limited. Market transparency is defined (see O'Hara, 1995) as the ability of market participants to observe information about the trading process. Researches have suggested that it can affect the informativeness of the order flow and hence the process of price discovery. In most stock exchanges, information regarding prices, quotes, volumes and time is generally revealed to all participants. However, the open-book trading system does not expose the identities of traders. Forster and George (1992) show a model that once the anonymous trading assumption is relaxed, market makers can track the magnitude and direction of large trades (net buyer or net seller) and extract valuable information and reduce adverse selection costs.

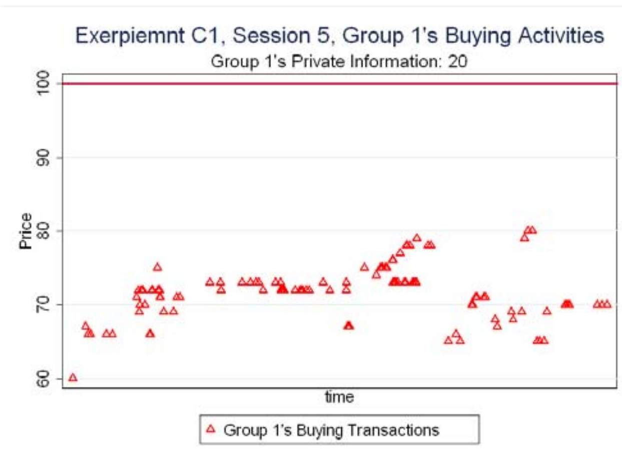
Under Hong and Stein (1999) type environment, anonymity becomes particularly important. When different pieces of valid private information are located in the hands of multiple groups, it is challenging to differentiate who submitted what. In the anonymous experimental design laid out above, each group of investors are motivated to solve the task of accurately inferring three separated pieces of the private information held by three other groups. The market book does not list the identity of any of the three groups, not even one's own group. The job of figuring out who is the buyer and who is the seller for the past transaction is almost impossible. While the experiment does not have an additional treatment of full transparency, the analysis below suggests this is a valid factor as well.

Figure 10 presents all transactions in Experiment C1 Session 5 Period 1 in a Panel 1. Recall that the two news surprises can either take on values of -20 or 20 in Treatment C. The true value is 100 and the two surprises are: 20 and 20. Most transaction prices lie between 60 and 80. By observing merely the aggregate trading activities in Panel 1, an individual cannot be absolutely confident that the true value is 100. The logic is simple: the individual with the first signal of 20 can ascertain that the value is either 60 or 100, however, he cannot know whether the person who buy at a price, say 70, is having the same signal or the other signal; if the former is true, a price of 70 is plausible since the asset can pay either 60 or 100 condition on the buyer's private information; if the latter is true, a price of 70 implies the buyer receives the other signal as 20 and the asset value must be 100. The dilemma can easily be solved when one look at the buying histories for each information group as shown in Panel 2 and Panel 3 respectively. It is reasonable to assume all groups have positive private information, both being 20, because both groups are willing to consistently purchasing above 60. Without this breakdown perspective, it is difficult to conjecture that the true value is 100.

Panel 1



Panel 2



Panel 3

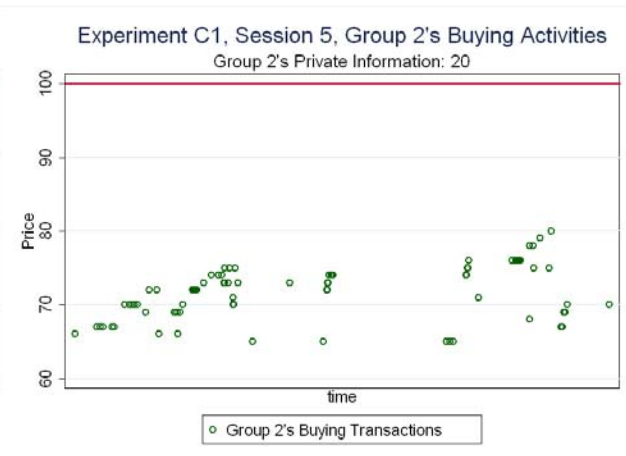


Figure 11. Transactions breakdown for each information group. The true value is 100 and the two surprises are 20 and 20. The aggregate transaction history do not tell what information the other group holds. Breaking down to each group, the transaction history tells more reliable information on what each group holds.

IV. Concluding Remarks

This paper designs a two-asset laboratory market where the aggregate consumption is constant regardless of the realization of states. For the asset of interest, the information regarding its fundamental is split into multiple pieces and the pieces are initially revealed to multiple information groups. Over time, each piece of information travels across the investor public, which is commonly referred to as gradual-information-diffusion.

In the experiments reported in this paper, gradual information diffusion in the market can move asset prices significantly, absent changes in the fundamentals. Price deviations from the true value are large when information is sparsely dispersed and errors are gradually corrected as information "density" grows. Over the course of error correction, market prices exhibit momentum.

In complete accordance with Hong and Stein's (1999) model on information diffusion and underreaction, the data indicate that prices exhibit positive momentum when news surprise is negative, negative momentum when news surprise is positive and no momentum when news surprise equals zero. The markets underestimate the size of news surprise in both positive and negative news cases. This is a vital difference from risk-based explanations, as risk aversion would only predict underpricing and thus positive momentum.

Price momentum in the absence of change in fundamentals suggests that information aggregation in market prices fails. By analyzing each trader's activities, I find that subjects are unsuccessful in inferring true value from market prices and behave almost in complete myopic fashion.

The reason for aggregation failure is not what is generally assumed - the increasing number of possible states hampers pricing accuracy. The results indicate that more states (uncertainty) does not necessarily correspond to higher pricing error. The analysis section suggests that the market mechanism faces subtle challenges in aggregating diverse information.

Three important factors are identified to be relevant in the aggregation of dispersed information:

(1) Equilibrium is not unique, though only one is correct; information diffusion reduces the number of false equilibria and pricing accuracy naturally improves. In the Hong and Stein (1999) structure, false equilibria are stable because agents can hold mistaken beliefs about what information is held by others. Angeletos and Werning (2006) present a model that when individuals know imperfectly (and differently) about the fundamental and the prices are revealed to all participants, multiple equilibria are an inevitable outcome. The results also confirm that the more equilibria there are, the higher the pricing errors emerge.

(2) Though competition among insiders can quickly close out mispriced offers, these mispriced offers do not arrive simultaneously—the scattered arrival of uninformed traders leads to prolonged asset mispricing. Consistent with Vegas's (2008) study on PEAD, market price efficiency is largely depending upon the arrival rate of informed and uninformed traders. The slow death of myopic trades creates a new limit to arbitrage.

(3) The market book does not reveal who offers what. Anonymous trading making it difficult to track an informed party's activities and to make inferences, especially when information regarding the fundamental are dispersedly held by multiple information groups. If information group identify is known to subjects, the inference about the true value will become much easier.

To sum up, this paper confirms Hong and Stein (1999) information diffusion model predictions and complement Bloomfield et al (2009) in providing more microscopic view of the information aggregation process. The experiments are carefully designed to allow maximum information expression. In addition, the results offer valuable insights for multiple equilibria literature and post earnings announcement drift studies, and refresh the experimental studies on information aggregation in markets with data uder environment of dispersed information.

As Hong and Stein (2007) point out in the synthesis, gradual information diffusion (Hong and Stein, 1999), and limited attention (Hirshleifer and Teoh, 2003), and heterogeneous priors (Harris and Raviv, 1993)become the three pillars of the "disagreement model" and form a powerful framework whereby return predictability and volume can be linked to differences in beliefs of investors. The "disagreement" model can connect to a wide spectrum of theories and empirical findings, without making stupidity assumption on the part of a single representative agent. The mere assumption is that investors have limited information processing capacity in making inferences about what information others hold, paying full attention to all information sources or forming unbiased ex ante beliefs. But investors remains boundedly rational (or reasonably savvy). The findings in this paper significantly uphold the gradual information diffusion model's position in the "disagreement" model, because the tests are run absent no influence of the other two. Besides, the strength of experimental study lies with directly testing the hypothesis of concern with no auxiliary hypotheses – information diffusion can drive price momentum, absent issues related to changes in fundamental, risk aversion, short-selling constraint, liquidity constraint, etc.

Appendix: Experiment Instruction

Thank you for participating in today's experiment. You've earned a $7 show-up bonus for participating. By carefully reading and following the instructions below, you have the potential to earn significantly more.

For every 5 experimental Francs (*₣*) you earn in the experiment, you will be paid 2 cents in cash. What you earn depends on your decisions and the decisions of others.

If you have any questions at any time raise your hand and a monitor will answer your question in private.

1. The Situation

The experiment consists of several separate market sessions. Each session has 3 periods. In a market session, there exist two types of Securities, Security A and Security B, valued at *₣*X and *₣* (120-X) per unit respectively. At the beginning, each participant will receive an initial basket of Security A, Security B and Cash. *For Example*:

	Holdings	Value
Security A	18 units	*₣* X / unit
Security B	12 units	*₣* (120-X) / unit
Cash	*₣* 1500 (*₣* 800 Loan)	

Security A can be bought or sold in the market. You buy Security A with cash, and you get cash if you sell them. Your earnings for a session will be based on your final basket holdings at the end of the 3rd period:

Total Value of the Securities you own + your final Cash – Loan

Your holdings in a session cannot carry over to next session. When a new session starts, you will receive a new set of holdings. Your payment for the whole experiment will be the sum of your earnings from all sessions.

2. The Value of the Securities

Before a session starts, a computer draws four numbers: A, B, C and D. Each number can take on the value of -10, 0 or 10 with equal chances. The numbers are drawn independently. Say, if A is -10, B has 1/3 chance of being -10.

The value of $X is the sum of these 4 numbers plus *₣* 60:

₣ X = ₣ 60 + A + B + C + D

Therefore, X may be as small as *₣*20 (=60-10-10-10-10) or as large as *₣*100 (=60+10+10+10+10). Over four draws, X tends to be closer to its average value *₣*60 than to the extreme values. Security A is worth *F* X per unit and Security B is worth *F* (120-X) per unit. Security A and Security B are complementary to each other, since holding the two together will always yield a joint payoff of *F* 120.

3. Information update on the value of Security A

Although the four numbers are determined before a session starts, the exact value of *F* X is not revealed to anyone until a session is over. However, participants will get to know one out of the four numbers in every period.

- In period 1, each participant will know ONE of the numbers. ***A**, **B**, **C** and **D** will each be known by 25% of the population.*
- In period 2, each participant will get to know a second number. ***A**, **B**, **C** and **D** will each be known by 50% of the population.*
- In period 3, each participant will get to know a third number. ***A**, **B**, **C** and **D** will each be known by 75% of the population.*

No individual will be told all four numbers until a session is over. However, the population as a whole always have the complete knowledge of **A**, **B**, **C** and **D**.

Here is an example:

Assume A=10, B=0, C=-10, D=-10, and assume all participants are divided into four groups: I, II, III, IV.

- In period 1, group I get to know 10, group II get to know 0, group III get to know -10, and group IV get to know -10.
- In period 2, group I get to know 10 and 0, group II get to know 0 and -10, group III get to know -10 and -10, and group IV get to know -10 and 10.
- In period 3, group I get to know 10, 0 and -10, group II get to know 0, -10 and -10, group III get to know -10, -10 and 10, and group IV get to know -10, 10 and 0.

4. Market Trading

You can trade Security A with other participants in the market. You buy Security A with cash, and you get cash if you sell Security A. You won't be able to buy Security A unless you have the cash. Security B is not traded throughout the experiment.

You will be able to sell Security A, even if you do not own any. In this case your holding of Security A becomes negative. When you have negative holdings of Security A:

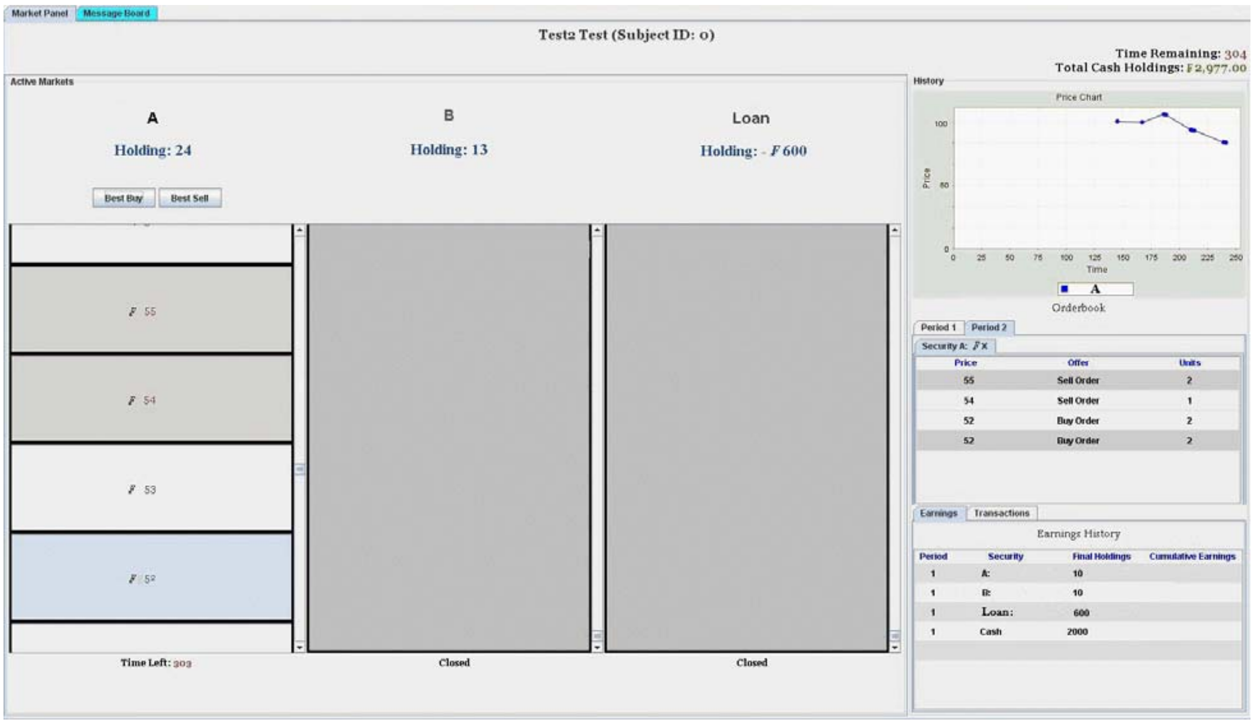
- If you purchase Security A afterwards, you can close out the negative position;
- If your holding of Security A remains negative at the end of a session, you will have to pay the value of Security A, instead of receiving it.

As long as your overall holdings will not generate negative earnings in the end, the program allows you to sell as many units as possible. (When computing your tentative earnings, the program would judge a unit of Security A at *F*50 for each positive holding, and at -*F* 70 for each negative holding.)

5. Market Interface

After all have logged in, a market interface like the one below will appear. A larger view of the image is provided to you on the print-out on your desk.

- The interface is divided into several sections:
- The upper-right corner shows a participant's Total Cash holding and the time remaining for the period.
- The left section shows the trading market for Apple. (Orange is not traded.)
- The right section consists of 3 parts: Price Chart, Orderbook, Earnings/Transaction History.



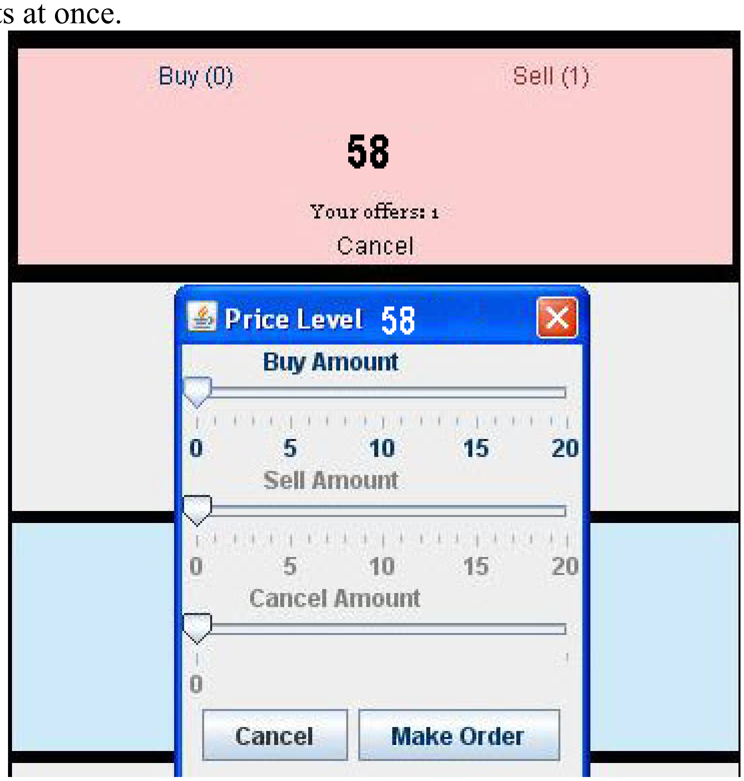
6. How to make trades?

The Active Markets panel has 3 columns. The columns correspond to Security A and Security B. At the top, you can find the numbers of units you hold. Currently, the image shows: 24 A and 13 B. Only market A is open for trade.

The A column consists of a number of price levels at which you and others enter offers to trade. Current proposals to buy are indicated in blue; proposals to sell are indicated in red. When you move your cursor to a particular price level box, you get specific information about the available offers. On top, at the left hand side, you'll see the number of units requested for purchase by participants in the market. Currently there is 1 proposal to buy at the price of *F* 56. Each time you click on the letter "Buy", you propose to buy one unit.

On top, at the right hand side, the number of units offered for sale is given. Currently there is 1 proposal to sell at the price of $58. Each time you click on "Sell", you propose to sell one unit.

At the bottom, you'll see how many units you offered, as indicated in "Your offers". Each time you hit "Cancel", you reduce your offer by one unit.
If you click on the price level number, a small window appears that allows you to buy, sell, or cancel multiple units at once.



7. History/Price Chart

The History Panel shows a visual chart of past transaction prices in the period.

8. Orderbook

The Orderbook panel lists current orders in the market and orders in the past periods. In the current period, YOUR orders are highlightened in gray. If you click on one of them, the corresponding price level box in the Active Markets panel is selected so that you can easily modify YOUR offer.

9. Earning/Transaction History

The Earning History panel shows, for each period, your final holdings for each of the Fruits and cash. Earnings are not reported until the end of a session. Your earnings accumulated over the sessions will be indicated in Cumulative Earnings. The Transaction History panel allows you to track all past occurred transactions.

10. How Trade Takes Place

If you want to buy A, click on 

, the price level of the lowest selling offer will be selected, and you may click on "Buy" to buy a unit at a time. (If you propose to buy above the lowest selling price, you will still get the lowest selling price.)

If you want to sell A, click on 

, the price level of the highest selling offer will be selected, and you may click on "Sell" to sell a unit at a time. (If you propose to sell above the highest buying price, you will still get the highest buying price.)

11. Restrictions On Offers

Before you send in an offer, the program will check your ability to deliver on promises that you implicitly make by trading fruits. It may not allow you to trade to holdings that generate negative earnings in the end. A message appears if that is the case and your order will not go through.

12. Summary

- The experiment last multiple separate sessions. Each session is divided into 3 periods.
- At the end of period 3 in a session, Security A pays ₣X, and Security B pays ₣ (120-X). The two securities are complementary in the sense that if Security A pays more, Security B would pay less; and vice versa.
- The value of ₣X is the sum of 4 numbers drawn by a computer, each being either -10, 0 or 10 and being equally likely to be chosen in every draw.
- Each participant will get to know one new number in every period. However, all four numbers are always known by the entire population.
- In each period, market is open for trading on Security A. (Security B is not traded.)

If you are ready, you may click the link below to sign up.

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