A DOUBLE AUCTION MARKET WITH SIGNALS OF VARYING PRECISION

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ABSTRACT

A computerized double auction market with human traders is employed to examine the relation of price and volume under conditions of asymmetric information. In this market, the informed traders receive higher precision signals than the uninformed traders. The relation of price and volume has been suggested as an important factor in the process of information revelation whereby information held by informed traders is transferred to uninformed traders. In contrast, the no-trade theorems suggest that trade should not occur at all between informed and uninformed traders. The results show trading volume within the informed group to be positively correlated with signal precision. In situations of asymmetric information, uninformed trading activity as measured by volume/precision correlations declines significantly as the precision of the signals of informed traders increases. However, the presence of asymmetric information does not lead to a zero trade condition for either the informed or the uninformed traders.

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In competitive market situations, prices may be less than fully revealing only temporarily. If insider traders are present in a market, insiders' information is sometimes described as "leaking" out into market prices as an invisible process, whereby all information eventually appears in equilibrium prices. While this process is not well understood, one explanation is that observing price dynamics will indicate how information is incorporated into prices over time. However, time series studies of prices often find that previous prices are often good predictors of current prices, at least of the *expected* current price, so that reaction to current information is obscured. Fama (1970) argued that when market equilibrium is stated in terms of expected prices, prices fully reflect available information. The Hayek hypothesis as defined by Smith (1982) predicts that a suitable market institution is sufficient for prices to eventually converge to the competitive price. Neither of these views serve to explain the process of price adjustment to new information. We are interested here not so much a the situation in which expectations have been formed or prices have converged, as in the temporary condition during which prices are becoming revealing, and expectations are being formed.

It is believed that when prices are less than fully revealing, factors endogenous to the trading environment influence the information relevation mechanism. These factors include the institutional structure of the market regulating the manner in which traders interact. The information revelation mechanism can be studied by observing the process of price formation. A key endogenous variable which may be due in part to the market institution is the intensity of typical trading activity. Volume or the number of trades are examples of measures of trading intensity. The importance of volume as an endogenous variable in market mechanisms has only recently been studied (see, e.g., Lang, Litzenberger, and Madrigal (1992) and Blume, Easley, and O'Hara (1994)) but the importance of volume statistics is as yet not well understood. Up to now, laboratory analysis has not much been used to describe the role of volume, or to test the recent theoretical models.

This laboratory analysis focuses on the behavior as seen in the volume of trading by asymmetrically informed traders. The experiments are designed to demonstrate how traders change their behavior based on relative differences in information. As traders change their behavior by adjusting their demands in the course of trading, prices will be directly affected. The price effect will be attributed to the fact that prices do not fully reflect all available information. While the process in which information is incorporated into prices cannot be observed directly, these experiments examine how traders react to differences in information. Traders' reactions to these conditions of asymmetric information are studied by examining market prices together with the volume of trading.

I. Review of the Experimental Literature & Relevant Theory

The experimental sessions described here extend existing experimental results on information efficiency in asset markets by focusing on how expectations are formed. The analysis tests if volume as an observable element of the trading environment is related to the formation of expectations. Since expectations are the focus, it may not be surprising that while expectations are being formed, the market may not be fully informationally efficient.[1] In fact, the experimental literature is fairly convincing in demonstrating that asset markets are less than fully informationally efficient.

Forsythe, Palfrey & Plott (1982), Plott & Sunder (1982, 1988), and Friedman, Harrison & Salmon (1984) examine the convergence of prices to various degrees of efficient equilibrium, and identify characteristics of asset markets which appear to increase the regularity of convergence of prices. Copeland & Friedman (1987, 1991) include measures of private information, and define variations of the rational expectations model for experimental asset markets which correspond to the common categories describing market efficiency. Carthew (1990) and Merys (1990) test the robustness of strong-form informational efficiency when the proportion of insider traders is increased. Friedman (1993) examines asset market efficiency for various trader privileges such as order flow information and delays in information, and finds that certain types of privileges are useful to insiders. Private values are used and information is in the form of “good” and “bad” signals. Order flow has also been studied by Schnitzlein (1994) where it was shown that insiders do tend to influence overall order flow. Complete surveys of asset market efficiency in the experimental literature are found in Sunder (1995) and Duxbury (1995).

The current study is unique in that common values contingent on a state of nature are used instead of private values to study convergence to a rational expectation equilibrium, and privileges are defined by the quality of signals insiders receive as to the value of the asset traded. While

[1] Predictions of informational market efficiency have been classified by Fama (1970) as either weak, semi-strong, or strong form efficient. Weak form efficiency suggests only public information is reflected in equilibrium prices. Semi-strong form efficiency predicts that all public and some private information will be reflected in equilibrium prices. Strong form efficiency predicts all information, public and private is incorporated into the equilibrium market price.

previous studies examined the usefulness of order flow to insiders, the current study examines if publicly available order flow information, in the form of volume statistics, might be useful to informed as well as uninformed traders. This study is also unique in that zero intelligent, robot traders, are used as liquidity traders in a common value market, and allow counterparty and order flow results to be analyzed in this context.

A. *The Theory of Trading under Asymmetric Information*

The model of trading under asymmetric information by Grossman & Stiglitz (1980) consists of a risky and a safe asset, and two groups of traders. Information is costly, and the traders who choose to purchase information become the informed traders while those who do not are referred to as uninformed. The model solves for the proportion of informed and uninformed traders in terms of a set of model parameters including the quality of the available information and uncertainty as to the value of the risky asset. The model is set in a noisy rational expectations framework.

The conclusion Grossman & Stiglitz reach is that when information is costly, prices cannot fully reflect this costly information. And secondly, an equilibrium cannot exist under rational expectations without some noise or uncertainty in the system. In their discussion of the thinness of speculative markets, especially Theorem 6, it is shown that if the cost of information is sufficiently large or small, the mean and variance of the volume of trade is zero. Alternatively, as the precision of the informed traders' information becomes very large, the mean and variance of volume of trade goes to zero.

It is the thinness of trading for certain small equities which is the focus of a subsequent paper by Blume, Easley, and O'Hara (1994) (henceforth BEO). They present a noisy rational expectations model similar to that of Grossman & Stiglitz, and focus on the role of volume under asymmetric information. Contrary to Grossman & Stiglitz, however, volume does not become insignificant but rather reaches a stable limiting distribution. The model has both informed and uninformed traders each receiving a costless signal at the start of trading. Traders are then able to trade a riskless and a risky asset based on these signals. The only distinction between the informed and uninformed traders is in the level of precision of their respective signals, and this creates information asymmetry. Whereas in the Grossman & Stiglitz model, only the informed traders could purchase a costly signal, in this model both groups of traders receive a costless signal.

While the Grossman & Stiglitz predictions of the effects of costly information cannot be compared with BEO, predictions concerning the mean and variance of trading can be compared across these two models. The Grossman & Stiglitz model predicts that the volume of trade will go to zero as the precision of the signals of the informed traders increases while the BEO model predicts that the volume of trade will not go to zero but will reach a limiting distribution. BEO argue that as the precision of signals of the informed traders increases, they take larger positions in the risky asset in order to exploit small price discrepancies. This is the first hypothesis to be tested in the current study.

A second prediction of the BEO model concerns the behavior of the uninformed traders. Initially the informed traders have an advantage over the uninformed traders because their signal is more precise. However, this advantage tends to dissipate during the course of trading as prices converge to a single equilibrium price. This assumes that equilibrium in prices occurs when the prices of the risky asset reflects the true or fundamental value of asset. In the Grossman & Stiglitz model, once an equilibrium price is reached, price becomes a sufficient statistic for all the information in the market, and the precision of the uninformed signal becomes irrelevant. The convergence of prices to equilibrium might be described as a process where precise information which once belonged only to the informed traders 'leaks out' and eventually becomes available to the uninformed traders in the form of the market price. Given a choice, uninformed traders will eventually choose the market price over their own information, hence, the equilibrium price is a sufficient statistic for all market signals.

In the BEO model, the focus is not on equilibrium prices as sufficient statistics but on the trading activity of the informed and uninformed traders. Rather than wait for price equilibrium to be reached, and information to be revealed in equilibrium prices, uninformed traders attempt to estimate the precisions of the signals of the informed traders. This is accomplished by observing trading volume, and understanding the relation between volume and price changes. The prediction of the BEO model is that uninformed traders observe trading volume and use this information to predict the precision of the informed traders' signals. In this context, price is not a sufficient statistic, and it is expected that uninformed traders change their behavior based on the observed trading volume. This is the second hypothesis to be tested.

Another possible reaction for the uninformed traders is to simply refuse to trade with the better informed traders. The no-trade theorems of Milgrom & Stokey (1982) and Tirole (1982) demonstrate the conditions under which it would be irrational to ever agree to trade with a better informed trader. While the BEO model describes how uninformed traders use volume to better estimate the precision of the informed traders' signals, these estimates will always be inferior to complete knowledge of the information of informed traders. If this is the case, then the no-trade theorem suggests that it is irrational for uninformed traders to trade with the informed traders. This forms the basis of the third and final hypothesis to be tested.

II. Experimental Design

In the experimental sessions, one group of traders is given information of higher precision than another group. The subgroup with the highest (lowest) precision information is defined as the group of informed (uninformed) traders. The experiments vary the precision of the information provided to the informed traders as well as the identity of the informed traders. Information given to traders is in form of an estimated precision of the redemption value of a risky asset. Information precision is measured by the standard deviation of the signal describing the redemption value of the risky asset.[2] Since uninformed traders are always given information which is less precise than the information given to the informed traders, it is possible that the uninformed traders may find it useful to estimate the precision of the signal of the informed trader. This would then provide an estimate of the degree of information asymmetry in the market. The uninformed traders might then decide when if at all they should limit their trade with the informed trader due to the degree of asymmetric information.

Three areas are examined in the context of the experimental sessions. One considers only the informed traders, and the other two examine the reaction of the uninformed traders to the informed traders. First, when trading with other informed traders, do the informed traders increase their trading activity as the precision of their own signal increases? That is, as the precision of the group's signal increases will the volume of trade also increase? Second, how do the uninformed traders react the situation where the informed traders have high precision signals vs. low precision signals? Third, how important is the no-trade theorem in this context? If there is a positive probability that uninformed traders are facing informed traders, will trading volume decline based on this probability?

[2] By this definition, a high precision signal is drawn from a distribution with a small standard deviation, whereas a low precision signal is drawn from a distribution with a larger standard deviation. This definition was chosen to simplify the player instructions. A more common definition which dates back at least to Fisher (1935) is to define precision as the reciprocal of variance.

A. Specifications

The design specified here is a modification of the design used by Copeland and Friedman (1987) to test the effect of sequential arrival of information in a CDA institution.[3] The design employs the same double auction software used to compare common vs. private values in Merys (1990) and to document the behavior of informed traders in Carthew (1990). The main modifications from previous designs included new specifications for the profit module, the creation of synthetic robot player modules, and the specifications for the timing and content of market signals.

Trading takes place over multiple trading sessions called trading days. The duration of each trading day is 120 seconds during which traders are allowed to submit market orders and participate in transactions. There is no limit on the number of market orders or transactions by any traders although the initial endowments of each trader are limited. Profits earned during each trading day accumulate throughout the experimental session and are paid out to participants in cash at the end of the session.

Nine experimental sessions were conducted with six human traders participating in each session. Each subject was assigned to be either an informed trader (3 traders) or an uninformed trader (3 traders) at the beginning of each period. During the course of the session, the role of each participant changed so that uninformed (informed) traders became informed (uninformed). The role of each trader was specified by a control file, and did not depend on individual traders' actions. Five sessions were conducted with inexperienced players, two with experienced players, and one with a mix of experienced and inexperienced players.[4] Five control files were created for these sessions. Three sets of 30 periods were created for inexperienced players, and each set was used twice. Two sets of 40 periods were created for experienced players.

In addition to informed and uninformed participants, synthetic traders called robots participate throughout the sessions. The activities of the robot are limited by their endowments as were the real participants. The robots do not, however, react to market generated information.

[3] The experimental design uses the Double Auction Market (DAMKT) software developed by Daniel Friedman, now at the University of California-Santa Cruz.

[4] The majority of subjects were recruited from a pool of subjects with experience in Cason & Friedman's (1996) call market institution, a similar screen based market institution. In this way, the commonality across institutions was exploited. The double auction and the call market trader screens are nearly identical, and use the same set of keys to place bids and offers. The new aspects for this study were rules of trading, the profit rules, and the information provided on trader screens. While experience with a similar institution was valuable, experience with the new environment proved to have a significant effect on trader behavior.

Their activity is confined to buying or selling at random times based on their price signal. For example, if the signal is $1.20, a robot might place an order to buy or sell at this price. This type of activity is often referred to as liquidity trading. The purpose of allowing robots is to generate a minimum level of trading activity at all times, and provide a positive incentive to trade. This lower threshold could be satisfied simply by including more real participants but using robots lowers the total cost of the experiments. Using robots has an additional benefit in that it allows for the traders with entirely consistent if not predictable behavior, and thus they serve as a useful control group in analyzing the behavior of less predictable real traders.[5]

All traders of both types are endowed with 5 shares and $25 at the beginning of each trading period. The redemption value of the shares is drawn from a truncated normal distribution with a mean value of $2.50 and standard deviation of $1.00. Values drawn outside the range $0 to $5.00 are replaced by redrawing from the same distribution. The redemption value of the shares is common to all traders. The redemption value of the each of these shares is estimated by a price signal, and these signals are unique and private information for each individual trader.

Player instructions are provided in Appendix A, and representations of players' screens is shown in Appendix B. The trading day begins with each trader receiving a private price signal. At this time the traders are not identified as informed or uninformed. For the first 20 seconds of the trading day, there is no additional information given to the traders although traders may generate market information by submitting orders and executing transactions. After the initial 20 seconds, signal precisions are sent to each of the traders' screens where signal precisions are defined as the standard deviation of the distribution from which the signal is drawn. At 120 seconds the trading day terminates, and the redemption value of the shares are posted.

Signals are also drawn from a truncated normal distribution with a mean value set equal to the redemption value of the asset, and percision determined by the trader type. Signals are drawn from a truncated normal distribution instead of a simpler uniform distribution because the long tails of the normal distribution allow uncertainty not found in a uniform distribution, and this uncertainty allows a greater potential variety of trader beliefs. Of course, reducing the precision of the draws from any distribution increases uncertainty, but this can also lead to signals which are less meaningful to all traders. The normal distribution has the nice property that when the

[5] Liquidity trading through the use of robots has only recently been investigated. It was believed that liquidity trading was necessary to provide a profit incentive for traders since otherwise the market is a true zero-sum game. In other common value experiments such as Merys (1990) and Carthew (1990), traders were paid a fixed amount at the end of the session. While traders as a group might receive the same amount with robots or with fixed payments, robots allow individual real traders to compete for bonus profits and thereby provide profit incentives during each period of a session. Schnitzlein (1994) also employs computer generated trades to represent noise (liquidity) trading.

precision of the draws is reasonably high, signals will tend to be useful for the trader in the majority of cases while only occasionally will there be a misleading outlier signal. An outlier could be considered simply a case of bad luck for the trader.

Traders' profits for each trading day are based on the redemption value of the asset revealed at the end of the trading period. The redemption value is the same for each type of trader, informed and uninformed. Total profits for the period are calculated at the end of each period by taking the difference between the value of shares purchased or sold and the redemption value for that period. For example, if the redemption value was $1.20, and if trader bought (sold) of shares at $1.10 ($1.30) then profits would be $.10 for each share purchased (sold). In addition, traders may earn profits by buying (selling), and then reselling (repurchasing) these same shares at a higher (lower) price within the trading day.[6]

A bonus of 25¢ is paid to each trader at the end of each period as additional incentive. This bonus is added to a trader's the profit or loss to arrive at the total for the particular trading day. The contribution to trading profits range between $5.00 and $10.00 depending on the completed number of periods for the session. The details of this calculation, and the total profits for all previous trading days are displayed on the traders' "interim trading screens". These screens appear for 20 to 30 seconds between each trading period. The profits displayed on these screens are private. Each trader can track their own profit performance but not the profit performance of other traders in the session.

The experimental design does not lead to a zero sum game as in most common value environments. Profits are earned from other real traders as by convention, and additional profits may be earned by trading with robot traders or through the trading bonus. Since losses by robot traders are expected, these losses represent a transfer to real traders. The transfers from robots create a positive sum game for the real traders.

The mean difference between a trader signal and the asset worth ranges from less than one penny to about 17¢ below the asset worth. The maximum difference is $1.43 for trader 5 in control file Set I. The difference between the mean signal which represents the aggregate trader information, and the asset worth is less than 5¢, and over the five sets averages less than 2¢. The average value of the asset worth is $2.37 over the five sets. The distribution from which the asset

[6] Valuing initial endowed shares at each traders' signal was also considered. This would confuse, however, the calculation of profits since some shares would be valued according to private values and others according to common values. This method may also invite traders to succumb to the sunk cost fallacy as traders may be forced at times to begin a trading period in a losing position. A similar problem arises when risk averse traders are endowed with random endowments of a risky asset. Some traders will immediately be at a disadvantage relative to other traders because they are exposed to greater market risk (transaction risk as differentiated from price risk).

worth is common knowledge to all traders. The average asset worth is above traders' prior estimate of $2.50 in two sets, and below the prior estimate in the remaining three sets.

B. Informational Efficiency & Testable Hypotheses

Trader performance might best be estimated by how well traders use the information provided to them. This can be done on an individual trader level where the relevant information is the trader's individual signal, and on a more aggregated level where the relevant information includes the information provided to all traders. Several questions can be explored: 1) how well do traders aggregate their own private information with the information available from observing the market. 2) how closely do transacted prices follow the true worth of the asset. 3) do informed and uninformed traders use information in the same way.

The first two questions allow this market to be characterized as a private information (PI) or rational expectations (RE) model. The third question considers strategic trading behavior where informed traders might wish to keep their superior information out of the hands of the uninformed traders. The method of analysis is to examine the how closely transaction prices for individual traders match the information known to be available to the same trader. The difference between the transaction price and private information is summarized by using the mean absolute deviation (MAD). The statistics are computed for the difference between the transaction price and aggregate information, and between the true worth, information, and price. If transaction prices more closely match the aggregate market information as opposed to private information, then this market can be characterized as a market exhibiting rational expectations.

To satisfy what may be considered necessary requirements of a rational expectations market, traders must be capable of updating their prior beliefs with new private information (after the arrival of private signals), as well as aggregate their own private beliefs with observed market information as it becomes available. It will be assumed that the method traders use to update their own beliefs can be described by Bayes theorem. In addition, since private signals provided to traders are drawn from a normal distribution and each trader's prior is from a known normal distribution, the result of applying Bayes theorem will result in a updated signal which is also normally distributed.[7] If the trader had access to the private signals and precisions of all other

[7] See for example DeGroot (1970) for an discussion of natural conjugates. Judge, Hill, Griffiths, Lutkepohl, and Lee (1982, Chapter 4) show why the normal distribution used as a prior distribution is a natural conjugate prior. It is assumed that the fact that the distribution is truncated has an little effect for this situation.

traders, these signals could be combined as to form a composite signal, $\hat{s}$ as

$$\hat{s} = \frac{\sum_{i=1}^{N} s_i \rho_i}{\sum_{i=1}^{N} \rho_i}$$

where s_i is the signal of the i'th trader, and ρ_i is the inverse of the variance of the signal. Note how this calculation uses the inverse of the variance of each signal to weight the contribution of each signal in the overall result. A trader's prior could also be included in this calculation.

An efficient use of information might result in a two tiered natural ordering of spreads. On the first tier, an individual trader’s transaction prices should be closer to the common prior updated by a private signal than to either the common prior or private signal alone. When this is true it will be said that the individual trader uses private information efficiently. On the second tier, the aggregation of all trader signals might be closer than the individual signals of traders are to actual transaction prices. That is, the difference between aggregate information and transaction prices is smaller than the difference between private information and transaction prices. When this occurs it implies that transaction prices are indeed reflecting available information in the market, and the market can be considered informationally efficient.

In this market a high degree of informational efficiency does not necessarily imply that traders are transacting close to the true value of the asset. This is because the true value of the asset follows an i.i.d process during the course of the sessions, and the signals given to traders only approximate the location of the asset each period. It would require a large number of traders (assuming one signal for each trader) for the aggregation of signals to equal the true worth of the asset by the law of large numbers. In this market there are only six traders, too few to expect the aggregation of their signals to equal the true worth of the asset.

When robot trades are considered the situation is improved. Even though robots have no 'market intelligence' in that they blindly bid or ask according their signal and robots actions are indistinguishable from real traders, robot actions can provide information to the real traders. When there are no market orders, a robot bid or ask is simply the signal given to the robot. When orders are present, a robot order may improve the existing orders or transact with the existing orders. Only when robot orders improve an existing market order is the robot signal revealed to other traders. In a transaction involving robots, the robot signal is not revealed because the transaction takes place at the existing market price. Therefore more information regarding robot signals is revealed by robot orders than by robot transactions. The ability of the real traders to use the information from the robot actions can then measured by comparing actual transaction prices to the true worth of the asset. If the MAD for transaction prices to the true worth of the asset is smaller than the MAD for transaction prices to the aggregate information in the market, then it will be inferred that robot information is used by the real traders.

In addition to an analysis of the informational efficiency in this market specification, the three hypotheses introduced in the overview are tested. The first hypothesis examines the reaction of the informed trader to an increase in the precision of the informed group's signal. The variance of each trader's signal can be associated with the degree of certainty of each trader's belief. BEO suggest that while a greater dispersion of beliefs tends to increase volume, as beliefs become more certain, volume also increases as traders are more confident in taking larger positions to exploit small price discrepancies.

A situation where precision is poor, reflecting diverse beliefs might be described as one where two traders might disagree on the value of an asset, and both assume their own belief is correct while their opponent's belief is incorrect. While trade may not be mutually beneficial, by trading each trader is allowed to rationally act on personal beliefs. Whether these personal beliefs are correct or not is another matter.

Increasing precision can lead to two dynamic effects: 1) traders can become more confident of their own beliefs and trade increases. 2) traders' own beliefs may resemble more and more the common belief and overall trade decreases. That is, beliefs may converge as overall precision increases. These contrary predictions of trading activity lead to the first hypothesis to be tested: for informed traders, trading volume is similar in periods where low variance signals are provided as in periods where high variance signals are provided. The alternative hypothesis is that trading volume within the informed group increases with signal quality. Correlation coefficients are used to test this hypothesis.

There are real limits, however, to an ever increasing degree of precision within the group which still allows for positive quantities of trade. This is partially due to the fact that prices are only allowed to change in 1¢ increments in this market so if the precision of the group is on a finer scale than 1¢, then there can be no more trade as everyone will agree on the current price to within 1¢. More realistically, the rewards to trading at very small profit margins will at some point not be worth the trader's effort. This effort to transact can be considered a type of transaction cost.

It is expected that within a trading period, over time the second of these two effects will dominate and trade will decline as beliefs converge. A Probit model is used to examine trade between various types of counter-parties over time but within a period. If beliefs do converge over time, and converge faster for the informed traders, then it would be expected that informed traders would trade less with other informed traders over time. The Probit model will predict the probability of observing an informed trader trading with another informed trader based only the elapsed time for the trading period and the elapsed time for the session. The model is specified as

$$Pr(Y = y \mid X = x) = F(\alpha + \beta(Period) + \gamma(Seconds)),$$

where X is the counterparty, Y is the initiating trader, period refers to the number of the trading period within the session, and seconds refers to the time elapsed since the beginning of a trading period. The function F is the cumulative normal distribution function, identifying this model as a Probit model. The model is estimated separately for each type of initiating trader. If convergence of beliefs is faster for the informed traders than for the uninformed traders, then the gamma parameter should be negative and statistically significant for informed traders and insignificant for uninformed traders.

A second hypothesis examines the behavior of the uninformed traders in the presence of informed traders. Uninformed traders are always at a disadvantage when trading against informed traders with high precision signals. If the precision of the informed traders is known (or could be estimated), uninformed traders might trade less when the degree of asymmetry of information is large, and they are at the greatest disadvantage. BEO suggest that uninformed traders use endogenous trading statistics to estimate the precision of the informed group. One such statistic is trading volume. This leads to a testable prediction. Given that the precision of the informed traders is not common knowledge, uninformed traders may be unable to determine the signal precision of the informed traders. Alternatively, uninformed traders may reduce their trading activity as measured by volume in periods when the precision of the informed traders is high. Measures of correlation between the volume of trade for the uninformed traders vs. the precision of the signal of the informed trader are used to test this hypothesis.

The third hypothesis examines a no-trade situation. The Milgrom and Stokey (1982) no-trade theorem proves under general common value conditions that it is irrational for less informed traders to accept trades with better informed traders because the lesser informed trader should expect to lose. In this experimental environment, each trader is told (by way of a message sent to the trader's screen) if they are in the informed or uninformed group, and the implications of their group assignment are clearly explained to each trader. Informed traders are always given signals drawn from a distribution with a small variance about the true asset value, where as the uninformed traders are given signals drawn from a distribution with a larger variance about the true value.

If the no-trade theorem were applied rigorously, the uninformed traders might simply refuse to trade, and wait until a later period when they become informed traders. This would be rational if the signal of the informed trader were always superior to the signal of the uninformed trader. In these experiments, however, this is not necessarily the case. The difference between the informed and the uninformed trader is based on the distribution from which signals are drawn. The mean of these distributions is the same, only the variance differs. It is therefore possible for uninformed traders to receive on occasion better signals (closer to the true asset value) than the informed traders. The signals of the informed traders are only superior to those of the uninformed traders in a statistical sense. That is, the distribution of signals for the informed traders stochastically dominate the distribution of signals for the uninformed traders as predictors of the true asset worth.

This feature of the signal generation process leads to possible reasons why uninformed traders might not refuse to trade during a period. Since the uninformed traders need not trade every period, they might be selective and trade only when they believe their signals are at least as good as the signals of the other traders; or they believe they will trade with a robot. It is also possible that uninformed traders ignore their signals and look at market prices and volume, and these data provide sufficient information to participate in trades. This explanation would place the uninformed traders in the role of technical traders or arbitrageurs. Another possible reason is that there is simply too much uncertainty by both types of traders, and the overall uncertainty in the market swamps the effects of the asymmetric information. Since there are only a small number of traders, implying a small number of signals of each type, the advantage for the informed traders may not have been fully recognized.

The null hypothesis is that the asymmetric information present in the market does not necessarily lead to a zero trade condition, and per capita trade volume is the same for both types of traders. The alternate hypothesis is that the volume of trade for the uninformed traders will be significantly lower than the volume for the informed traders. As a consequence, the majority of trade observed will occur between the informed traders and the robot (liquidity) traders. An analysis of the distribution of trades will serve to test this hypothesis.

III. Results

A. Analysis of Trading Activity

An overview of the traders' actions is provided by Table I. The level of trading activity is measured by the volume statistic. The mean volume is the average number of transactions for each period of an experimental session. The smallest values are seen in the experienced sessions. The highest value is seen in experiment 12, which also had the highest average profit per period for the informed traders. Absolute volume is computed for each type of trader as the sum of the shares bought and sold. This measure of shares transacted gives a more detailed idea of trader activity across trader types than the aggregate volume measure.

Trade profit is the average trading profit per period for each type of trader. For example, in experiment 9, informed traders earned on average 25¢ for each completed transaction. In each session, robots serving as liquidity traders on average lost on each transaction. The average profits for the uninformed traders varied from a loss of 17¢ to a profit of 4¢ depending on the session. The number of transactions is computed as the number of players times the number of periods in a session. For example, there were 3 informed traders in experiment 9, and 30 periods in the session giving a total of 90 observations. For each of these observations, there may have been many transactions.

There were two experienced sessions, and due to the larger number of periods per session, observations from experienced sessions comprise about 31% of total observations. The average volume for experience sessions is 9.0 vs. 13.6 for inexperienced sessions. The average absolute volume is 2.2 for experienced sessions vs. 3.4 for inexperienced sessions. Pervol is defined as the ratio of absolute volume over total volume. For each type of session the average of this ratio is .25. This value may be used as a measure of the degree of participation of individual players. The value of this ratio is large enough to infer that each player regardless of experience had sufficient opportunity to participate in transactions. Net volume is defined as the difference between shares bought less shares sold. The minimum for each level of experience is -5 indicating that the initial endowment of 5 shares was a binding constraint for at least one trader who might have wanted to sell more shares.

The Kruskal-Wallis nonparametric rank test in Table II takes as the null hypothesis that the distributions of the descriptive statistics are the same across the three types of players. For each case, homogeneity is rejected. In Part B, informed and uninformed traders are compared using the Wilcox rank-sum test, and only the netvol measure cannot be rejected as being the same across the two groups tested. This might be interpreted as implying that netvolume as a measure of volume is not a refined enough measure to distinguish between the two groups, and other measures of volume should be used. Part C considers experience as a distinguishing factor, and with the exception of the netvol and the profit measure, homogeneity can be rejected. As to the result for the profitability measure, it is somewhat of a surprise that experience does not lead to higher profits while the way in which those profits are earned does change with experience. This leads one to believe that other factors such as trading volume are are important factors for describing trading activity, especially how traders learn from experience.

The main tool for period-by-period analysis are correlation coefficients which are used to describe precision/volume and profit/volume relations.[8] In Table III, measures of trading volume are compared with the precision within a trader's group (IPRC), and with the precision outside a trader's group (OPRC).[9] These same volume measures are also tested against total trading profit for the period. It can be seen in the first three parts of the table that increasing precision has little or no effect on aggregate volume for the combined group of traders, or across levels of experience. Absolute volume, the sum of shares bought and shares sold, however, does show statistically significant measures of association with precision. Absolute volume is positively correlated with an increase in traders own precision, and negatively correlated with an increase in the precision of the opposing group. This result is significant at the .01 level for experienced traders, and for the combined experienced/inexperienced group, but not statistically significant for the inexperienced traders. The correlation between absolute volume and opposing group precision is strongest (-0.17) in the experienced group and statistically significant at the .01 level. As precision increases in the opposing group, the traders own absolute volume decreases. The results

[8] The Spearman correlation coefficient is reported rather than the more common Pearson coefficient because it could not be assumed that the relation between the variables tested was linear. The Spearman coefficient tests more generally that the variables are mutually independent against a positive or negative correlation between the variables. The Pearson and Spearman correlation coefficients tended to be similar except in some cases where there were large outliers, especially when the profit variable was involved.

[9] The variable IPRC is the inverse of the standard deviation of the signal of a trader's own group (informed or uninformed), while OPRC is the inverse of the standard deviation of the signal of the opposing group of traders. These results are based on trading period data and not transaction data. Individual transaction counterparties are therefore not identified. These correlation results are due to the presence of the two types of traders in the market.

for absolute volume are statistically significant at the same or higher level when absolute volume is considered in proportion to aggregate volume (PerVolume).

As might be expected, profitability is positively correlated with traders' own level of precision, and statistically significant at the .01 level. Profitability is also positively correlated with absolute volume (and PerVolume) although not strongly. These results can be interpreted as implying that when traders have more precise signals, they tend to trade more and earn higher profits.

An additional dimension is added to the correlation analysis in the second part of Table III. While still considering experience as a factor, we now add informativeness and examine each of the resulting four combinations of factors (informed/inexperience, uninformed/inexperienced, informed/experienced, and uninformed/experienced). The relation of traders' own precision (10¢ vs. 25¢) and volume measures is not statistically significant for the informed/experienced group. Volume measures do not appear to change as informed traders receive better signals. This relation will be examined in more detail in a following subsection (Hypothesis 1). For the profit measure, however, the relation is statistically significant at the .05 level and positive. For the informed/experienced group, profit is also positively correlated with all measures of volume. This result is significant at the .01 level.

For the uninformed/experienced group of traders, the correlation between the opposing group's precision (10¢ vs. 25¢) and volume measures is negative and statistically significant at the .01 level. For this group, profit is also negatively correlated with all measures of volume. This relation is also significant at the .01 level. It is interesting to note that for the uninformed/experienced traders, volume shows a stronger negative correlation with the opposing group precision than with trading profits.

Experience appears to have a large effect on the actions of the uninformed traders. For the uninformed traders, the correlation between absolute volume and the precision of the informed traders is positive and statistically insignificant for the inexperienced group, while it is negative and statistically significant for the experienced group. As was mentioned previously, profit measures do not capture the experience effect. For the uninformed traders, the correlation between volume measures and profitability is always negative and statistically significant regardless of experience. For the informed traders, the positive correlation between absolute volume and profit increases with experience, and is always statistically significant at the .01 level.

Besides trading period data, individual transaction data are also examined. Transaction data shows that real traders represent over 80% of total activity as measured by event data (place order to buy or sell, cancel order, buy, sell), with robots representing the remaining 20%. Real traders initiated on average 73% of the transactions for all sessions; while in experienced sessions, real traders initiated on average 61% of transactions. Tables IV focuses on the trading match-ups, and especially the group identity of the initiating party of a transaction. While all types of traders are allowed to act as market makers by submitting simultaneous bid and ask orders, the initiating party of a transaction must choose to act upon either the buy side or the sell side. Whereas the market maker may be indifferent between the buy and sell side, the initiating party must show a preference. For this reason, the initiating party is singled out in the analysis

Real traders initiating transactions with other real traders represents 56% of the total transactions; real traders initiating transactions with robots represents 17% of the total activity; robots initiating transactions with real traders represents 25% of the total activity; and robots initiating transactions with other robots represents only 2% of the total activity. When robots are excluded, informed traders initiating transactions with other informed traders represents 21% of the total transactions; informed traders initiating transactions with uninformed traders represents 27% of the transactions; uninformed traders initiating transactions with informed traders represents 33% of the transactions; and uninformed traders initiating transactions with other uninformed traders represents 18% of the total activity.

B. Analysis of Informational Efficiency

The results measuring the informational efficiency in this market specification are shown in Tables V. Trades initialized by robots are excluded, while trades with robot counterparties are included. Using only private information consisting of the common prior and a private signal, the results in Part A suggest that traders approximate Bayesian updating of beliefs. Each trader's private information enhanced by Bayesian updating (PI(Bayes)) more closely reflects the realized transaction price than private information comprised of the trader's signal without Bayesian updating (PI(S)).

There appears to be a significant difference between the informed and uninformed use of information. The informed trader spreads (PI(S) and PI(Bayes)) are less than the uninformed trader spreads for each session, and the difference between the two information measures (PI(S) vs. PI(Bayes)) as reflected in the spread to the transaction price is greater for the uninformed traders than for the informed traders. Knowing the common prior distribution seems to be more useful to the uninformed traders than to the informed traders in estimating transaction prices. The informed signal is within a penny of the PI(Bayes) estimate of the transaction price, while for the uninformed it is closer to 5¢.

The results for the aggregated information from all real traders is presented in Part B. Aggregated information is closer than private information to actual transaction prices. The mean absolute deviation (MAD) measure indicates that transaction prices (P) are closest to aggregate information, followed by private Bayes updated information (B), followed by individual signals (S) which do not take into account signal precisions. For trades initiated by informed traders, the difference from aggregate information to transaction price is consistently *higher* than the difference from aggregate information to their own private information. While for uninformed traders, the difference from aggregate information to transaction price is consistently *lower* than the difference from aggregate information to their own private information. The same results hold if the true asset worth replaces the measure of aggregate information. This is because aggregate information closely approximates the asset worth in each period.

This difference between the informed and uninformed traders might indicate that informed traders initiate trades when price differs from the aggregate estimate relative to their own estimate while uninformed traders initiate trades when price is relatively closer to the aggregate estimate. That is, informed traders may trade even when price differs from the aggregate signal, an estimate of price, because their own private information is superior to the aggregate estimate. Uninformed traders initiate trades which depend more heavily on the aggregate signal than they do their own private information.

It should be noted that from the above analysis, the profitability of these trades cannot be inferred. The spreads reported are for the initiating party to a transaction, and while the spread between price and aggregate information is the same regardess of who initiates the trade, profitability is found to differ greatly. As was mentioned before, the profitability of a trade depends on the type of counterparty (informed, uninformed, or robot), but also on the direction of trade. Initiators to transactions tended to earn lower profits than the counterparties to transactions.

C. Inferential Data Analysis

Of the three hypotheses presented here, two deal directly with precision/volume relations, and the third examines predictions of the no-trade theorem. The first hypothesis looks at the behavior of informed traders only. The second looks at the behavior of the uninformed traders in relation to other groups of traders. The last looks again at the behavior of the uninformed traders and in relation to the no-trade theorem, considers the rationality of this group of traders.

Hypothesis 1. *Volume/Precision Relation for Informed Traders*

H_0: Volume for informed traders transacting with informed traders (trade within the informed group) is similar in periods where low variance signals are provided as in periods where high variance signals are provided.

H_1: Trading volume within the informed group increases with signal quality.

Trading volume within the informed group is found to be positively correlated with signal precision; therefore reject H_0 in favor of H_1. The strength of this correlation decreases with experience, and with trader experience the correlation coefficient appears to loses its statistical significance. The probability of an informed trader completing a trade with another informed trader also declines with time. It should be noted that the trading environment included other trader types (uninformed and robot traders) with lesser quality signals, so that even if all informed traders held consistent beliefs and could not trade among themselves, there might always be other types of traders available. The data shows, however, that trading among informed traders represented a sizable percentage of total trade by the informed group (12% of all trading in Table IV). Therefore there should be some evidence of within group effect.

Correlation coefficients for the informed traders matched against all other types of traders lead to the conclusion that the quality of the signal within the informed group had no significant effect on absolute volume. The correlation coefficient for experienced informed traders is -0.07 and is not significantly different from zero (Table III).

When informed trading activity was segregated according to counterparty type on a transactions level, however, it is seen that for informed traders trading against other informed traders, volume increased with precision (Table VI). This correlation is positive and significant for the inexperienced traders, and positive but insignificant for the experienced traders. A contingency table tests if the proportion of trading between informed and uninformed counterparties is the same across precision level. The Chi-Square test rejects homogeneity of proportions across precision at the 0.03 level. The data show that at the high precision level, informed traders in fact increase the proportion of their trades with other informed traders.

Over time, it becomes less likely that informed traders find other informed traders as counterparties. Assuming that trading during a period leads to price convergence, the beliefs of traders will converging to a common belief over time, and this may occur faster for informed than for uninformed traders. A Probit analysis gives some support to this proposition (Table VII). It is seen that probability of informed traders completing a trade with another informed trader declines with time. The Probit model defines a trade between informed traders as a binary dependent variable, and the number of the trading period and time within the trading period as explanatory variables. For inexperienced and experienced traders, the intercept is estimated as 0.69 (standard error 0.04) with a coefficient on elapsed time in ten second increments of -0.04 (standard error 0.01). In the later part of trading periods, trade is more likely between uninformed traders, or for uninformed traders initiating trades with informed traders.

Hypothesis 2. *Uninformed Trading Activity*

H_0: The trading volume for uninformed traders within a period does not depend upon the level of precision of the informed traders' signal.

H_1: Uninformed traders reduce their trading activity as measured by volume in periods when the level of precision of the informed traders has increased.

Uninformed trading activity as measured by volume/precision correlations declines significantly as the precision of the informed traders increases; therefore reject H_0 in favor of H_1. Correlation coefficients indicate (Table III) that for all traders trading activity measured by volume (AbsVolume) is positively correlated (0.08) with traders' own precision, and negatively correlated (-0.08) with the precision of the opposing group of traders. These result is statistically significant at the .01 level for the experienced traders, but statistically significant for the inexperienced traders only for the level of precision within the traders' group.

For the uninformed traders only, the correlation between absolute volume (or percent volume) and the precision of the informed traders is positive yet insignificant for the inexperienced group, while it is negative (-0.22) and statistically significant for the experienced group. In fact, for the uninformed/experienced group, volume shows a stronger negative correlation with the opposing group precision than with trading profits.

By observing trading activity, uninformed traders in some way estimate the precision of the informed group, and using this information change their own behavior. The profitability of this strategy is clear from examining the strong positive correlations between precision and profits for the informed traders. Since trading environment is close to a zero sum trading game, profits for the informed traders must come either from uninformed traders or robot traders.

How the uninformed traders become aware of the precision of the informed traders is unclear, and it may require some type of learning. BEO do not specify a specific learning mechanism, and we do not propose one here. The inferred result, however, is that uninformed traders alter their trading behavior by reducing their trading activity when the precision of the informed traders present in the market is high.

Hypothesis 3. *The No-Trade Theorem*

H0: The asymmetric information present in this market does not necessarily lead to a zero trade condition for either the informed or uninformed traders.

H1: As the no-trade theorem would predict, the trading activity of the uninformed traders will be lower than for the informed traders due to informed traders having more precise trading information. The majority of trading observed will occur between the informed traders and the robot (liquidity) traders.

The high level of trading activity between the informed and uninformed groups is higher than the level expected if uninformed traders acted to avoid informed traders. The no-trade theorem does not predict the observed trading levels; therefore we cannot reject H0.

The no-trade theorem suggests that the uninformed traders should not participate in trades since their expected return from trading is on average negative (Table I). Even though uninformed traders might earn positive profits when matched against robot traders, robots are indistinguishable from informed traders so there is impossible for the uninformed traders to know which type of trader they are matched against. Even when robot trades are included with other types of trades, the uninformed traders consistently lost on average 5¢ per trade. Trader experience does not appear to alter this behavior. The behavior of the uninformed traders in these experiments therefore does not coincide with the predictions of the no-trade theorem.

Trade between the informed and uninformed represents 56% of total trading. Uninformed traders initiating trade with informed traders accounts for 19% of all transactions, and uninformed traders initiating trades with other uninformed traders accounts for 10% of total trade activity (Table IV). The average profit for an uninformed trader initiating a trade with an informed trader (-0.17), another uninformed trader (-0.13), and a robot (+0.05) suggests that unless the counterparty to a trade is a robot, trades initiated by uninformed traders will be unprofitable. The observed percentage of uninformed initiated trades having robots as counterparties is only 22% of trades initiated by uninformed traders.

While the predictions of the no-trade theorem are not supported in this experimental design, if the number of traders of each group was large, it is expected that the failure of the no-trade theorem would be less in evidence.

IV. Conclusions

The experiments described in this study test current theories regarding the role of volume in assets markets in the presence of uncertainty and asymmetric information. The design utilized a common value, continuous double auction market. The main treatment variables were the level of information precision, and the precision ratio across informed vs. uninformed traders. Along with the human traders, zero intelligent, robot traders were used as liquidity traders.

The results support the rational expectations trading model of Blume, Easley & O'Hara (1994) in that for the informed traders, trading volume was found to be positively correlated with precision. Furthermore, the uninformed traders reduce their trading as the precision of the informed traders' signal is increased. Since the uninformed traders do not know the precision of the signals of the informed traders, this suggests that they make inferences on the basis of market observables. The results also run counter to the predictions of the no-trade theorem in this setting. A possible explanation for this result is the structure of the signal generating mechanism and the presence of robot (liquidity) traders.

Future experiments may vary the number of informed traders, or the number of robots in each session to test the rebustness of these results. The time-series property of the redemption value might also be modified to better compare these results with field observations. At present the redemption value is drawn from a normal distribution, and these draws are independent from period to period. A moving average representation might provide a comparison to test for the robustness of the results generated from a simple i.i.d process for the true value vs. more complex price generating mechanisms. An extension of the current design might allow asset shares to accumulate over time while the total asset stock might be exposed to supply shocks as a source of noise in the system.

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Appendix A

Instructions for Players

1 Welcome

This is an experiment in the economics of market decision making. Funds have been provided by the National Science Foundation and the Board of Studies in Economics at this university. These instructions have been written to explain clearly how the experiment will work, and if the instructions are followed you can earn a considerable amount of money which will be paid to you in cash at the end of the session today. If you have any questions about the instructions or how the experiment works please ask.

In this experiment we create a market for a fictitious good called an **asset**. You as **traders** will have an opportunity to buy or sell shares of this asset using your computer. These are decision you will make on your own to allow yourself the greatest reward. Out of fairness to you and your neighbors there will be no talking with your neighbors once the session begins. Do not discuss your information or how you make your decisions at any point during the experiment.

We will all log into the program together and when everyone is ready the session will begin. There will be 25 to 40 periods of 120 seconds each during the experiment session. Each period is called a **trading day**. At the beginning of each trading day you will be given 5 shares of the asset and $25 of cash to use during the trading day. Each new trading day is signaled by a tone and a clock in the upper right corner of your screen will indicate how much time is left in the trading day. For example, there are 5 seconds left in the trading day in Chart 1. At the end of each trading day your **profits** will be calculated for you and will be displayed during an intermission of 30 seconds. After the intermission a new trading day begins and you will be given 5 new shares and $25 cash. Shares and cash from one trading day cannot be used in later trading days. Shares must be redeemed at the end of each day and cash expires. Each trading day is independent of earlier trading days and only your profits (or losses) accumulate from day-to-day.

2 How to Earn Profits

As a trader you can buy shares of the asset from any other trader willing to sell to you. Likewise you may sell shares of the asset to any trader who wishes to buy from you. No trader knows the true value of each share until the end of the trading day, so during the trading day you must estimate how much each share is worth. The true value of the asset is called the **redemption value**, and this is the amount each share of the asset is worth. The redemption value is drawn each trading day from a normal distribution truncated between $0 and $5.00 rounded to the nearest penny with a mean value of $2.50. The redemption value is drawn independently for each trading day and all values for the session have been selected in advance by the computer.

There are three ways to earn profits. (i) If you sell shares to another player, your profit at the end of the trading day will be calculated as the selling price **P** less the redemption value **R** for each share sold. Profit = (P - R) for each share sold. For example, if you sell 2 shares at $2.00 per share during the trading day and the redemption value is $1.50, your profit for that day would be (2.00 - 1.50)*(2) = 1.00 dollars. If you had sold shares for less than $1.50 you may lose money on the trade (earn negative profits).

(ii) If you buy shares from another player, your profit at the end of the trading day will be calculated as the redemption value **R** less the cost of the shares purchased **C** for each share purchased. Profit = (R - C) for each share purchased. For example, if you buy 3 shares at $1.00 per share during the trading day and the redemption value is $1.10, your profit for that day would be (1.10 - 1.00)*(3) = 0.30 dollars. You can also loss money on a transaction by paying more for shares than they are worth. That is, if your cost is greater than the redemption value you will lose money on the trade.

(iii) You also have the ability to sell shares during the trading day and then later decide to buy them back at the new market price. It does not matter if you buy the same shares back or different ones since all shares are identical. If you sell shares and then buy them back within the same period, your profits are calculated based on the selling price **P** and the purchase price (or cost) **C** only. For example, if you sold 2 shares at a selling price of $2.00 per share and then bought then back at $1.75 per share your profit for these transactions would be $0.25 per share. Profit = (P - C) for each share transacted. The order of the transactions does not matter. You might buy first then sell latter or sell first and buy latter.

You can trade as often as you like during the trading day as long as you have cash or shares to trade. After each trading day your trading profits are calculated and added to your overall total. The value of the asset revealed at the end of the trading day is worth the same amount to each player. A bonus of 25¢ will be added to your trading profits after each trading day. After the last trading day, your total profits are calculated and you will be paid this amount in cash ($US Dollars). Recall that the cash you use during the day expires at the end of each trading day and this cash does not contribute to your profits.

3 How to Buy and Sell

All commands needed to buy or sell are found in boxes at the bottom of each trader's screen. Inside each box is a description of the command and a special market key. To enter a **bid** to purchase shares at a specific price, type the desired price and then hit the bid key which is the **p** key on the keyboard. For example, the four keystrokes "125p" indicates that you wish to purchase shares at $1.25 per share. Do not use a decimal point as all values are in penny terms. After you enter a bid, it will appear on your screen as shown in Chart I and it will also appear on all other trader's screens. The asterisk to the left of 'your price' indicates that of all of the traders, you have the best bid. This also makes your bid the 'market price'. If you change your mind, you can revise your bid by first canceling your bid by hitting the **u** key, then entering a new bid as described above.

To enter an **ask** to sell shares at a specific price, type the desired price and hit the ask key which is the **q** key on the keyboard. For example, the four keystrokes "250q" indicated that you wish to sell shares at $2.50 per share. Again do not use decimal point. If you wish to cancel or revise your ask, first cancel your ask by hitting the **r** key, then enter a new ask.

You may also accept an outstanding market ask or bid from another player rather than enter a new bid or ask. If another trader is willing to sell at the market ask price shown on the screen, you may purchase these shares by **accepting the best ask**. Buying shares in this way is done by hitting the **i** key on the keyboard. Similarly if another trader is willing to buy shares at the market bid price shown on the screen, you may sell your shares by **accepting the best bid**. Selling shares in this way is done by hitting the **e** key on the keyboard. Accepting the best bid or best ask is immediate and cannot be canceled if you change your mind.

Your current holdings of shares are also shown at the bottom of the screen for both your net share position and your net position in cash. Each trader begins the trading day with 5 shares and $25 cash. As you trade, these holding will be adjusted to reflect your activity. Your cash and share balances are adjusted for all transactions, including transactions where you buy (sell) and then sell (buy) shares within the trading day. Your share and cash positions show your net positions. For example, on Chart 1 if you began with 5 shares and buy an additional 2 shares then sell 3 shares, your net position in shares will be 4 shares as shown.

4 Additional Help

To help you estimate the end-of-day redemption value of the asset, a **price signal** is given to each trader at the start of each trading day. In Chart 1 this price signal is $1.97. This price signal is only estimate of the redemption value of the asset and may not reflect the actual asset redemption value. Each trader receives a unique price signal and it would be rare that two traders would receive the same signal. These signals are drawn each trading day from a normal distribution about the true redemption value. That is, the mean value of the distribution of signals for each trading day will be the redemption value for that trading day.

A normal distribution or sometimes known as a bell curve is shown in Chart 2. Note that the distribution is symmetric about the mean value The mean value is the highest point on the curve and also the most likely value to chosen from a random draw. Most of you will be familiar with normal distributions from seeing the results of exam scores. Often with large classes when exam scores are plotted on a graph with exam scores shown along the horizontal axis and the number of students receiving that score on the vertical axis, the resulting graph displays a distinct bell curve shape. Most scores will fall close to the mean test score while there will be a few very high and a few very low scores. The same will be true for the price signal you receive. Most signals will fall close to the true redemption value of the asset while a few signals will fall somewhat above the true redemption value and a few signals will fall somewhat below the true redemption value. On Chart 2 the mean value is 69 and each observation represents a student's score. It can be seen that most exam scores are close to 69 while a few fall somewhat to either side of 69.

After 20 seconds of the trading day have passed you will also be given a number which will be known as a **precision** indicator. This precision indicator will tell you on average how close your signal is to the true redemption value of the asset. For example, you receive a price signal of $1.97 and later your receive a precision indicator of $0.50. There is about a 68% chance that your price signal falls within $0.50 of the true redemption value. That is, you can be reasonable sure that the redemption value is between $1.47 and $2.47. About 32% of the time the redemption value will fall outside of this range.

Sometimes half of all traders have signals with a greater precision than the signals of the rest of the traders. The traders with the best signals will be known as **informed**. In some sessions this will be indicated on the screen by the **informed** indicator. This indicator may tell you that there are insiders present in the market or it will tell you that you yourself are an insider for this trading day. There are three possible precision values {10¢, 25¢, and 50¢}. If you are an informed trader, you will receive a precision which is better than the uninformed traders. Sometimes all traders will be uninformed and all will receive the same precision indicator.

A second indicator is the **volume** indicator which keeps track of the number of shares which have been traded within the trading day. At times the volume indicator will be blank although you can always keep track of shares on your own since all transactions are shown as they take place. There are three parts to the volume indicator. The first is is 'volume' which keeps track of the total number of trades for current trading day. The second is 'last' which is the direction of the last trade during the trading day. The direction of trade refers to how the last trade was initiated. If a buyer accepts the best offer the direction is 'bought', and conversely, if a seller accepts the best bid the direction is 'sold'. The third part, 'net' is a running total of 'bought', counted as a positive unit, and 'sold', counted as negative unit. For example, the order of the previous five trades was {bought, sold, sold, bought, sold} which gives a net value of -1.

In addition to the real traders present in the room there will be **robot** traders buying and selling at random times during the trading day. It will be impossible to distinguish real from robot traders during a trading day. Each robot will begin the trading day with 5 shares and $25. At predetermined random times during the trading day a robot may post a bid or offer at its price signal, or accept an outstanding market bid or offer.

Between each trading day you will be presented a summary of the activity which occurred during the previous trading day. Traders who show a losing position of more than $18 will be considered bankrupt, and will not be allowed to continue. All traders receive a minimum of $5 for participating. Good luck. Be sure to ask questions if there is anything that you do not understand, or if you are suspicious that the program is not running correctly.

Appendix B

Market and Interim Screens

```
Double Action Market 2.0          Trader Name                   Time left:  0:24
Experiment prac:  Day #2          (Trader #7)
                Market Type:             B
        Signal    90   Group (Uninformed or Informed)
         3.26     +/- 25      Informed



                                  * VOLUME | LAST | NET *
                (Trader #7)           6    BOUGHT   2
      Your   Market
      Price  Price
Asks:  4.00   2.94
Bids:         2.25

Ticker Tape:   2.90  2.50  3.31  3.00  2.65  2.94

===>
+------+ +------+ +------+ Holdings:                +------+ +------+ +------+
|  Q   | |  E   | |  R   |        Cash   Shares     |  U   | |  I   | |  P   |
|      | |Accept| |      | Start:  25.00   5.00     |      | |Accept| |      |
| Ask  | | Best | |Cancel| Change:-14.65  +5.00     |Cancel| | Best | | Bid  |
|      | | Bid  | | Ask  | Now:    10.35  10.00     | Bid  | | Ask  | |      |
+------+ +------+ +------+                          +------+ +------+ +------+
```

```
Double Action Market 2.0          Trader Name                   Time left:  0:57
Experiment prac:  Day #2          (Trader #7)                          (Interim)
Trrns     Qty Price Worth Prof.                         DayProfit Quo     Total
-------------------------------                         -----------------------
 1 B U   1.00 2.94  3.30  0.36                           1    0.00    0.25    0.25
 2 B U   1.00 3.00  3.30  0.30                           2    1.85    0.25    2.10
 3 B U   1.00 3.31  3.30 -0.01
 4 B U   1.00 2.50  3.30  0.80
 5 B U   1.00 2.90  3.30  0.40








==============================================================================
Total Trading Profit:                            1.85  T    1.85    0.50    2.35
Trading Commission:                              0.25
Total profit, day # 2                            2.10
Accumulated Profit, days  1 -  2                 2.35
```

Table I

Descriptive Statistics: Mean Value

Exp	Type	Nobs	Volume	AbsVolume	Trade Profit
9	Informed	90		2.97	0.25
	Uninformed	90		2.61	-0.00
	Robot	60		2.73	-0.37
	All	240	11.1	2.78	0.00
10	Informed	75		2.71	0.16
	Uninformed	75		2.32	0.03
	Robot	50		2.46	-0.27
	All	200	10.0	2.50	0.00
11	Informed	90		4.92	0.07
	Uninformed	90		4.49	-0.01
	Robot	60		3.02	-0.09
	All	240	17.1	4.28	0.00
12	Informed	90		5.00	0.37
	Uninformed	90		4.59	-0.17
	Robot	60		3.05	-0.31
	All	240	17.4	4.36	0.00
14	Informed	90		2.79	0.19
	Uninformed	90		3.10	0.04
	Robot	60		2.70	-0.34
	All	240	11.5	2.88	0.00
15*	Informed	120		1.91	0.25
	Uninformed	120		1.84	-0.14
	Robot	80		2.30	-0.17
	All	320	7.9	2.88	0.00
16*	Informed	120		2.74	0.21
	Uninformed	120		2.21	0.04
	Robot	80		2.60	-0.38
	All	320	10.0	2.51	0.00
17	Informed	105		3.01	0.26
	Uninformed	105		2.74	-0.14
	Robot	70		2.94	-0.18
	All	280	11.6	2.89	0.00
All	Informed	780		3.19	0.22
	Uninformed	780		2.92	-0.05
	Robot	520		2.71	-0.26
	All	2080	11.9	2.97	0.00

Notes: *Experienced Players. Volume is the total number of transactions during the period. Absolute volume is the per capita sum of purchases and sales in each period. Trading profit does not include a 25¢ commission paid to all traders at the end of each trading day. The number of observations is computed as (the number of players) x (the number of periods in a session).

Table II

Nonparametric Hypothesis Tests

	Variable	Test	Nobs	Test Statistic	P-value
A.	Informed vs Uninformed vs Robot				
	AbsVolume	K-W	780,780,520	12.0	.00
	NetVolume	K-W	780,780,520	42.7	.00
	PerVolume	K-W	780,780,520	18.2	.00
	Bought	K-W	780,780,520	22.4	.00
	Sold	K-W	780,780,520	43.7	.00
	Profit	K-W	780,780,520	270.1	.00
B.	Informed vs Uninformed				
	AbsVolume	Wcx	780,780	3.11	.00
	NetVolume	Wcx	780,780	-0.27	.79
	PerVolume	Wcx	780,780	4.21	.00
	Bought	Wcx	780,780	2.62	.01
	Sold	Wcx	780,780	2.67	.00
	Profit	Wcx	780,780	7.51	.00
C.	Experienced vs Inexperienced				
	AbsVolume	Wcx	480,870	-10.42	.00
	NetVolume	Wcx	480,870	-0.77	.44
	PerVolume	Wcx	480,870	-2.89	.00
	Bought	Wcx	480,870	-7.55	.01
	Sold	Wcx	480,870	-5.91	.00
	Profit	Wcx	480,870	-1.05	.29

Notes: The null hypothesis suggests no difference in the distributions described by each of the sample variables. Two-sample comparisons use the normal approximation to the Wilcoxon (Wcx) rank-sum test. Multiple comparisons use the Chi-square approximation to the Kruskal-Wallis (K-W) test for k independent samples and $k-1$ degrees of freedom.

Table III

Correlation Analysis
(Spearman)

	IPRC	Volume	PerVolume	AbsVolume
A. All Players				
IPRC	-	0.00 (.84)	0.10 (.00)	0.08 (.00)
OPRC	-0.90 (.00)	0.00 (.84)	-0.11 (.00)	-0.08 (.00)
Profit	0.20 (.00)	0.04 (.08)	0.02 (.34)	0.04 (.09)
B. Experienced Players				
	IPRC	Volume	PerVolume	AbsVolume
IPRC	-	-0.03 (.47)	0.15 (.00)	0.11 (.01)
OPRC	-0.90 (.00)	-0.03 (.47)	-0.18 (.00)	-0.17 (.00)
Profit	0.26 (.00)	0.09 (.06)	0.07 (.11)	0.09 (.04)
C. Inexperienced Players				
	IPRC	Volume	PerVolume	AbsVolume
IPRC	-	0.02 (.48)	0.07 (.03)	0.07 (.04)
OPRC	-0.90 (.00)	0.02 (.48)	-0.07 (.04)	-0.04 (.21)
Profit	0.16 (.00)	0.03 (.37)	0.00 (.90)	0.02 (.48)

Notes: Nonparametric Spearman correlation coefficients are reported for each variable pair. P-values for test of a zero coefficient are shown in parenthesizes. IPRC is the inverse of the players own precision while OPRC is the inverse of the precision of the other type of traders. For example, if the player is in the informed group (uninformed) then OPRC is the value for the uninformed (informed) traders for the period.

Table III (continued)

Correlation Analysis
(Spearman)

		IPRC	Volume	PerVolume	AbsVolume
D.	Informed/Inexperienced				
	IPRC	-	0.10 (.02)	-0.01 (.78)	0.06 (.25)
	Profit	0.08 (.07)	0.08 (.09)	0.14 (.00)	0.16 (.00)
E.	Uninformed/Inexperienced				
		IPRC	Volume	PerVolume	AbsVolume
	OPRC	-	0.11 (.02)	0.03 (.56)	0.07 (.17)
	Profit	-	-0.02 (.63)	-0.16 (.00)	-0.13 (.01)
F.	Informed/Experienced				
	IPRC	-	-0.15 (.02)	0.02 (.72)	-0.07 (.27)
	Profit	0.14 (.03)	0.17 (.01)	0.22 (.00)	0.26 (.00)
G.	Uninformed/Experienced				
		IPRC	Volume	PerVolume	AbsVolume
	OPRC	-	-0.15 (.02)	-0.17 (.01)	-0.22 (.00)
	Profit	-	-0.01 (.86)	-0.14 (.03)	-0.12 (.07)

Notes: Nonparametric Spearman correlation coefficients are reported for each variable pair. P-values for test of a zero coefficient are shown in parenthesizes. IPRC is the inverse of the players own precision while OPRC is the inverse of the precision of the other type of traders. For example, if the player is in the informed group (uninformed) then OPRC is the value for the uninformed (informed) traders for the period.

Table IV

Tabulation of Trading Activity

EXP	ii N	ii PCTN	iu N	iu PCTN	ui N	ui PCTN	uu N	uu PCTN	ALL N	ALL PCTN
9	36	20	51	28	70	39	24	13	181	100
10	38	29	35	27	31	23	28	21	132	100
11	71	21	84	25	122	36	60	18	337	100
12	71	21	83	24	119	34	72	21	345	100
14	31	16	62	33	51	27	44	23	188	100
15	26	18	33	23	58	41	26	18	143	100
16	50	25	62	31	61	31	26	13	199	100
17	46	22	64	30	63	30	39	18	212	100
ALL	369	21	474	27	575	33	319	18	1737	100

EXP	ii PCTN	ir PCTN	iu PCTN	ri PCTN	rr PCTN	ru PCTN	ui PCTN	ur PCTN	uu PCTN	ALL PCTN
9	11	11	15	11	4	9	21	11	7	100
10	15	12	14	13	2	10	12	11	11	100
11	14	7	16	12	1	9	24	6	12	100
12	14	8	16	12	1	6	23	7	14	100
14	9	12	18	10	1	13	15	10	13	100
15	8	4	10	23	3	19	18	6	8	100
16	12	11	15	16	1	15	15	7	6	100
17	11	7	16	17	3	13	16	8	10	100
ALL	12	9	15	14	2	11	19	8	10	100

Notes: The percentage of trade between trader type is tabulated. For example, trade initiated by an informed trader and completed with another informed trader is abbreviated by ii. Trade initiated by an uninformed trader and completed with an informed trader is abbreviated by ui. Trades involving robots are abbreviated by r.

Table V

Transaction Price Analysis

Mean Absolute Deviaions - All Transactions

A. Private Information

		Informed & Uninformed		Informed Traders		Uninformed Traders	
Exp	Nobs	PI(S)	PI(Bayes)	PI(S)	PI(Bayes)	PI(S)	PI(Bayes)
9	253	0.37	0.35	0.29	0.28	0.45	0.42
10	189	0.41	0.37	0.28	0.27	0.57	0.49
11	402	0.36	0.34	0.28	0.28	0.44	0.40
12	427	0.29	0.28	0.19	0.19	0.36	0.36
14	262	0.38	0.36	0.22	0.22	0.55	0.49
15	176	0.44	0.39	0.35	0.34	0.51	0.42
16	271	0.28	0.25	0.22	0.22	0.35	0.30
17	274	0.36	0.33	0.25	0.24	0.47	0.41
All	2254	0.35	0.33	0.25	0.25	0.45	0.41

B. Aggregate Information

	Informed & Uninformed			Informed Traders			Uninformed Traders		
Exp	AI-S	AI-B	AI-P	AI-S	AI-B	AI-P	AI-S	AI-B	AI-P
9	0.29	0.28	0.23	0.12	0.11	0.25	0.45	0.43	0.21
10	0.27	0.25	0.28	0.09	0.09	0.24	0.49	0.44	0.33
11	0.27	0.24	0.25	0.11	0.12	0.26	0.41	0.36	0.25
12	0.28	0.27	0.19	0.10	0.10	0.19	0.43	0.42	0.20
14	0.31	0.28	0.21	0.09	0.09	0.21	0.53	0.48	0.22
15	0.41	0.35	0.27	0.11	0.11	0.32	0.62	0.52	0.24
16	0.25	0.22	0.20	0.15	0.14	0.18	0.40	0.32	0.23
17	0.29	0.26	0.23	0.12	0.13	0.23	0.46	0.41	0.22
All	0.29	0.26	0.23	0.11	0.11	0.23	0.46	0.41	0.23

Notes: The mean absolute deviation by trader type where trader type is determined by the initiator of the transaction. Private information in the form of signal only (PI(S)) is compared with private information where traders include the common information prior estimate of the true worth, and improve their private information through the use of Bayesian updating (PI(Bayes)). Aggregate information (AI) reflects the combined signals, precisions, and common prior for all traders. Private signal (S) is the private information for the trader initiating the transaction, and (B) is the private Bayes updated information signal. The actual transaction price is abbreviated by (P).

Table VI

Correlation Analysis
(Spearman)

	SII	SIU	SUU
A. All Players (without Robots)			
IPRC	0.11	-0.07	0.08
	(.07)	(.25)	(.17)
B. Experienced Players Only (without Robots)			
IPRC	0.09	-0.19	-0.24
	(.45)	(.09)	(.03)
C. Inexperienced Players Only (without Robots)			
IPRC	0.14	-0.01	0.20
	(.10)	(.87)	(.01)

		ii	iu	Total
Frequency	0.04	187	167	354
Percent		16.77	14.98	31.75
Row Pct		52.82	47.18	
Col Pct		29.17	35.23	
	0.1	454	307	761
		40.72	27.53	68.25
		59.66	40.34	
		70.83	64.77	
	Total	641	474	1115
		57.49	42.51	100.00

Statistic	DF	Value	Prob
Chi-Square	1	4.616	0.032

Notes: Trading volume on a transactions level is shown for informed traders against other informed traders (SII), against uninformed traders (SIU), and for uninformed traders trading with other uninformed traders (SUU). IPRC is the inverse of the trade initiating group's precision. The contingency table compares informed traders trading with informed traders (ii) and informed traders trading with uninformed traders (iu) across precision levels (25¢ and 10¢).

Table VII

Counterparty vs. Time Analysis

	Variable	DF	Estimate	Std Err	ChiSquare	Pr>Chi
A.	All Traders					
1.	Model: ii = period seconds					
	INTERCPT	1	0.6860	0.0449	233.91	0.0001
	PERIOD	1	-0.0048	0.0017	7.74	0.0054
	SECONDS	1	-0.0433	0.0050	75.15	0.0001
2.	Model: iu = period seconds					
	INTERCPT	1	0.6572	0.0463	201.07	0.0001
	PERIOD	1	-0.0060	0.0018	11.12	0.0009
	SECONDS	1	0.0111	0.0052	4.59	0.0322
3.	Model: ui = period seconds					
	INTERCPT	1	0.4644	0.0462	101.10	0.0001
	PERIOD	1	0.0045	0.0018	5.96	0.0147
	SECONDS	1	0.0152	0.0052	8.48	0.0036
4.	Model: uu = period seconds					
	INTERCPT	1	0.8042	0.0566	201.79	0.0001
	PERIOD	1	0.0141	0.0024	35.07	0.0001
	SECONDS	1	0.0423	0.0067	40.26	0.0001
B.	Experienced Players Only					
1.	Model: ii = period seconds					
	INTERCPT	1	0.6897	0.1229	31.49	0.0001
	PERIOD	1	-0.0094	0.0042	5.13	0.0235
	SECONDS	1	-0.0411	0.0141	8.49	0.0036
2.	Model: iu = period seconds					
	INTERCPT	1	0.5240	0.1250	17.59	0.0001
	PERIOD	1	0.0026	0.0043	0.36	0.5508
	SECONDS	1	-0.0076	0.0145	0.28	0.5970
3.	Model: ui = period seconds					
	INTERCPT	1	0.5080	0.1292	15.46	0.0001
	PERIOD	1	0.0054	0.0046	1.41	0.2349
	SECONDS	1	0.0211	0.0152	1.91	0.1671
4.	Model: uu = period seconds					
	INTERCPT	1	0.8107	0.1709	22.52	0.0001
	PERIOD	1	0.0085	0.0065	1.71	0.1905
	SECONDS	1	0.0963	0.0234	16.90	0.0001

Notes: A Probit model is estimated to explain the probability of traders from one group initiating trades with traders in the same or a different group. For example, Model I. uses time to explain transactions where informed traders initiated trades with other informed traders (ii). Similarly in Model II., time explains when informed traders initiated trades with traders from the uninformed group (iu). The second set of results employ the same models reestimated using observations from experienced sessions only. Seconds are measured in ten second increments. Period refers to the trading period number.