Informational price cascades and non-aggregation of asymmetric information in experimental asset markets

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Abstract

We report on experimental markets for a contingent claim asset that eight subjects traded for nine periods before the state was revealed. There is an informative binary signal that arrives after each of the first eight trading rounds. In our baseline treatment the realization of the signal is public information, and in another treatment, market participants are randomly sequenced and receive the signal as private information. In the latter case, we observe zero information aggregation and prices lock in on home grown norms, which we call informational price cascades. We test the fragility of the price cascades in two further treatments. First, we break the monopoly on each signal by revealing it to two subjects, and then we increase that number to four. It is only when we inform four participants, or one-half of the market, that cascades fail to form and information starts to aggregate in the market.

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1 Introduction

Ideally asset markets perform important functions such as directing capital to the greatest wealth creating opportunities, facilitating the efficient sharing of risk, and the accurate incorporation of diverse and relevant information into market prices. This last function is commonly referred to as information aggregation and has theoretical foundations in the hypotheses of rational expectations (Lucas, 1972) and efficient markets (Grossman, 1976). Traditional tests of whether information aggregates in financial markets have relied upon indirect inferences usually in the form of testing for profitable trading strategies based on public information. However, since the market's information set is never available to the researcher, it is not possible to directly test for information aggregation using real market data.

Controlled laboratory experiments do not suffer from this issue, and therefore are well suited to evaluate information aggregation. One strand of literature (Plott and Sunder, 1988; Forsythe and Lundholm, 1990; Camerer and Weigelt, 1991; Barner, Feri, and Plott, 2006) finds strong support favoring information aggregation with short lived assets traded in continuous double auctions. A second strand of literature conducts experiments on variations of the rational herding model developed by Bikhchandani, Hirshleifer, and Welch (1992), with the theoretical prediction that individuals would ignore their private information resulting in informational cascades. Several experimental studies (Anderson and Holt, 1997; Celen and Kariv, 2004; Kubler and Weizacker, 2004; Goeree, Palfrey, and Rogers, 2007; Alevy, Haigh, and List, 2007) confirm the theoretical prediction that information fails to aggregate in the form of cascades and herding. A key institutional feature in these studies is a market maker who exogenously sets a constant price for the asset. Avery and Zemsky (1998) reformulate Bikhchandani, Hirshleifer, and Welch (1992) model with a market maker who adjusts this price according to Bayes rule. They show that this change results in full information aggregation and no information cascades.[1] Subsequent experimental studies (Sgroi, 2003; Cipriani and Guarino, 2005, 2009; Drehmann, Oechssler, and Rider, 2005) confirm this prediction and report greatly reduced herding and informational cascade formation, and thus high levels of

[1] The prediction of full information aggregation occurs only under some conditions.

information aggregation.

We report on asset markets experiments that synthesize these two strands of literature; we adopt the asset and corresponding information structure of Bikhchandani, Hirshleifer, and Welch (1992) and we use the continuous double auction for trading. While accommodating flexible prices, our setting differs from Avery and Zemsky (1998) and related experiments as it adheres to the principle of decentralized information (Hurwicz, 1972). A trader's portfolio holdings and adjustments, information regarding dividends, and her identity when taking market actions are all private information. Consequently, traders can only learn from the observation of public market data such as contract prices and limit orders in the open book. Replacing social learning by observing the actions of others with learning solely from the observation of anonymous market actions leads to a dramatic change in the informational efficiency in the market.

The most dramatic change is that we observe *zero* information aggregation when information signals are private information. In our first set of experiments, we consider two between-subject treatments: public information in which each signal is observed by all traders, and private information in which each signal is revealed to one trader (with traders taking turns at being this insider.) In the private information treatment, there is no information aggregation, and how this aggregation failure manifests itself is surprising. Within an experimental session, trades quickly lock into a single price and subsequent contract prices rarely substantially deviate. We refer to this phenomenon as an informational price cascade because the lock-in price has zero correlation with the fundamental value of the asset and there is evidence that arriving private information does not get incorporated into the market. The persistence of these informational price cascades is quite strong; within a session, these price norms carry across the conclusion of one asset's life to a new market repetition in which subjects' endowments are reset and a new - but identical - contingent asset is traded. However, while the value at which prices cascade is session specific, different price norms emerge in different sessions.

Despite market prices failing to incorporate newly arrived private information, we don't observe accompanying strong herding in terms of trader's asset portfolio adjustments. Some subjects do adjust the number of assets they hold conditional upon their private signals and increase their earnings, but there is great variance in these two measures. One might suspect that insiders will wait before acting on their private signals, but that is only half the story. Forty-four percent of the time an informed trader participates in one of the first two trades that occurs after she receives her private signal, while about thirty percent of the time, the informed trader does not make a contract in that period. So how is it these portfolio adjustments do not lead to information leaking into market prices? The sequential arrival of asymmetric information to the market creates a longer lived asset (in discrete time), than of those traded in the typical continuous double auction information aggregation experiments. In studies such as Plott and Sunder (1988), assets typically live for one trading period and all asymmetric information regarding it's value is endowed to traders prior to the period. In contrast, our markets start with a common prior for asset value and over the course of trading, a sequence of eight informative signals are received. This creates an asset that lives for nine-periods with no dividends other than its terminal value. This creates opportunities for traders who are not informed to trade and create noise – which they do – despite strong theoretical reasons they should not (Milgrom and Stokey, 1982; Tirole, 1982). These noise traders allow informed traders to exploit their private information without perturbing a market price norm.

An obvious question is how robust are the informational price cascades we report? Motivated by models of partial aggregation such as Diamond and Verrecchia (1981), Kyle (1989), Holden and Subrahmanyam (1992), and Foster and Viswanathan (1996), we make two important modifications in the experimental design for the private treatment. First, we create a new treatment where each signal is given to two subjects. By doing this, we remove the information monopoly held by the informed trader. We do not find any effect of removing this monopoly on information aggregation. In another treatment, we give each signal to four subjects. We find partial aggregation in this treatment, supporting the prediction in some of the above models about the importance of the fraction of informed traders being an important determinant of aggregation.

The paper proceeds with a description of the experimental design and protocols. We also develop the hypotheses to be tested in this section. Then. we present the data analysis from the public and private information treatments in which we establish the zero aggregation and price cascade results, and we provide extensive robustness checks on the statistical analysis. In the penultimate section, we present the results of our two and four person informed trader sessions which demonstrate the generic nature of price cascades and suggests under what conditions they can be broken. We conclude with further discussion of how our results inform various literatures and highlight possible directions for additional study.

2 Experimental design

We present the experimental design in two parts. In the first sub-section, we introduce the asset, the structure of market signals, and their effect on fundamental value. We also describe our implementation of the double auction trading institution, and our experimental protocols. In the second sub-section, we present our four treatments regarding the information structure of market signals. Then, we discuss relevant models and the major hypotheses they provide.

2.1 Asset structure, market institution, and protocols

Consider a simple asset a that lives for nine periods and possesses no value other than a final dividend $d(a)$. Market participants hold a common prior that this final dividend is either zero or one dollar with equal probability. To test for information aggregation, we introduce informative, but imperfect, signals about the dividend value before periods two through nine. Each signal is an independent realization of the following probability experiment. If the dividend is one dollar, the signal is a draw from an urn containing eight red ($\mathcal{R}$) chips and four($\mathcal{B}$) black chips. On the other hand, if the dividend is zero, the signal is a draw from an urn with four red chips and eight black chips. Thus, the probability of drawing a red chip conditional on a one dollar dividend is two-thirds, $\Pr(\mathcal{R}|d(a) = 1) = 2/3$, and the probability of drawing a red chip conditional on a zero dollar dividend is one-third, $\Pr(\mathcal{R}|d(a) = 0) = 1/3$. For any sequence of realized signals, the Bayes rule calculation for the posterior probability that $d(a) = 1$ reduces to $1/\left(1 + 2^{-k}\right)$, where k is the number of $\mathcal{R}$ less the number of $\mathcal{B}$ signals. For the relevant values of k, Table 1 provides the corresponding posterior probabilities that $d(a) = 1$, or in other words, the conditional expected value of the dividend, $E\left[d(a)|k\right]$. For our purposes, the fundamental value of a at every point in time is its expected value given conditional all realized signals up to that point.

We populate the market for the asset a with eight traders, endowing each trader with five dollars of currency and five units of the asset. For all nine periods in the life of the asset, traders have the opportunity to buy and sell the asset amongst themselves via a continuous double auction. During a market period, traders can take the following actions: submit bids to purchase, submit asks to sell, make market sales (agreeing to sell at the current highest bid), and make market buys (agreeing to purchase at the current lowest ask). While these actions are for a single unit, traders can submit multiple bids and asks, and make multiple purchases and sales within a period. When a market period closes, all remaining bids and asks expire.

There are several rules regulating a trader's actions. The bid-ask spread is the difference between the current lowest ask and the current highest bid, and any new bid or ask must reduce this spread. Specifically, a trader can submit a bid at anytime; however, her new bid must exceed the current highest bid. Likewise, a trader can freely submit an ask, on the condition it reduces the current lowest ask. Successfully submitted bids and asks are stored in a public bid-ask queue. A trader can freely retract one of her bids (asks) from the queue as long as it is not the current highest (lowest) one. Whenever a trader submits a bid, her available currency is temporarily reduced by the amount of the bid. In the same vein, when a trader submits an ask, the number of her available units is temporarily reduced by one. We do not allow short sales by prohibiting asks and market sales when a trader does not have an available unit. Similarly, we prohibit bids and market buys without sufficient available currency.

A trade occurs when either the current lowest bid is accepted by a market sale, or the current lowest ask is accepted by a market buy. Subsequently, the associated bid or ask is removed from the bid-ask queue, and the corresponding temporary adjustments to the available currency become permanent. The contract price is then added to a sequential list of current period prices which is displayed to all traders.

The only element of the microeconomic system (Smith, 1982) we have yet to specify is the knowledge each trader possesses about the market signals, and this is our treatment variable. Prior to describing our treatments, we give the common set of experimental protocols. We conducted all of our sessions in the National University of Singapore (NUS) Department of Marketing's Behavioral Research Computer laboratory.[2] We executed the continuous double auction trading mechanics using the Marketlink software application for running market experiments (Cox and Swarthout, 2006), publically available at the Econport website (http://www.econport.org). We augmented the computerized trading procedures with hand-run protocols to induce the various information treatments.

We recruited participants through e-mails to the undergraduate majors in the NUS Department of Economics and undergraduate majors and Master of Business Administration students from the NUS School of Business. Participants were told the experiment would last approximately two and a half hours, given a ten Singapore dollar payment for showing up on time, and also privately paid any monies earned in the experiment. All amounts in the experiment, and this description, are in Singapore dollars. There was no conversion between experimental and local currencies as is often done. Each subject participated in only one session.

Every experimental session had eight subjects. A session started with a public reading of the instructions, followed by a practice market consisting of three trading periods (the earnings from which subjects were not paid). Subjects then participated in a sequence of three markets for which they earned money. Each of these markets consisted of nine 90 second trading periods. Prior to period one, the subjects could observe us toss a coin that determined the asset's dividend value and the composition of the urn. However, the outcome of the coin toss was not shown to the subjects. After period nine, we announced the realized dividend value, and a subject's earnings for that market was her final currency balance plus the number units of the asset she held at the conclusion of trading, multiplied by the dividend value. All subjects had common knowledge of this structure. Note, that there was no carry over of currency or asset units across markets, and a subject started each market with a new endowment. A subject's total payment was the show-up fee and the sum of her earnings in the three markets.

[2]This laboratory is especially designed to conduct research experiments with individual computers housed in privacy carrels that prevent subjects from viewing each other's computer screens and also discourage communication between subjects.

2.2 Informational treatments and major hypotheses

Our experimental treatments concern how signals were disseminated to the subjects. The following list provides the treatments and the implementing protocols. Note that the relevant protocols were common knowledge to all subjects within a treatment and fully disclosed in the publicly read instructions.

1. **Public Information (PUB)**: All subjects publicly observe every signal. Prior to trading in periods two through nine, a single chip was drawn at random in view of the subjects. The color of the chip was shown to all traders and then returned to the urn. After the value of the dividend was announced, at the conclusion of market period nine, we allowed subjects to verify the contents of the urn.

2. **Private Information (PVT)**: We used the same protocols as the PUB treatment with the following modifications. In each market, subjects were randomly and anonymously ordered one through eight to determine the sequence of informed traders. Prior to trading in periods two through nine, the color of the randomly selected chip was only revealed to that period's informed trader. To preserve anonymity, an envelope was distributed to every subject. The informed trader's envelope contained a slip of paper with the color of the selected chip written on it, and all other envelopes contained a slip of paper with the printed word 'None.' The envelopes were recollected after the subjects inspected the contents.

3. **Private Information with Two Informed Traders (2SIG)**: This treatment follows the same protocols as the PVT treatment except that we revealed each signal to two subjects rather than one. The subjects were formed into four anonymous and randomly ordered pairs. The ordered pairs took turns being the informed trader pair for periods two through five. Within a pair, the two subjects did not know each other's identity. Then, for periods six through nine we generated a new random set of pairs. Thus, a subject knew that she would observe one of the first four signals, and then observe another signal from the set of the last four signals. Further, she knew that when she observed a draw from the urn, exactly one other subject simultaneously observed the same draw.

4. **Private Information with Four Informed Traders (4SIG)**: This treatment was the same as 2SIG except that four subjects rather than two observe each draw. In this case the eight subjects were divided into random groups of four for the market period pairs two/three, four/five, six/seven, and eight/nine. Thus a subject knew she observed the draw once in each of those pairs of market periods.

We adopted a between subject experimental design: each experimental session was exposed to a single information treatment. Table 2 provides details regarding our experiment design such as the number of sessions per treatment and the acronyms will use for each treatment.

Before discussing some of the motivations and hypotheses generated by the differences between these treatments, let's consider some of the constants. First, the set of feasible allocations is the same across the four treatments: the same number of traders each endowed with five units each of currency and assets. Second, the total information content of the market does not vary as there are exactly eight independent draws from the urn with identical timing. With a constant set of feasible allocations and information structure, the rational expectations equilibrium is the same for every market in all treatments.

2.2.1 Rational expectations versus informational cascades

In terms of hypotheses development, we will progress from full revelation of all information in a rational expectations setting to successively lower degrees of information revelation. In our setting, the rational expectation equilibrium is that, for every possible history of signal realizations, the equilibrium price equals the expected dividend and excess demand for the asset is zero. Implicit in the zero excess demand condition is that each market participant calculates the expected dividend conditioning upon all market signals observed by any market participant, not just the signals she observes. Radner (1979) showed that such fully revealing equilibrium are generically rational expectations equilibrium in finite state settings like ours. Moreover, the core idea that competitive equilibrium prices in commodity markets incorporate all relevant information no matter how sparsely held in the economy was first championed in Hayek (1945). Later, Grossman (1976) extended it to the case of uncertainty and assets. These ideas are the basis of our first hypothesis.

Hypothesis 1. *Rational Expectations Equilibrium: Market prices equal the fundamental value as defined by all realized market signals.*

There are two effects governing the price dynamics in the rational expectations equilibrium. First, whenever a market participant observes a new market signal, the resulting change in value results in a perfectly correlated change in price. Second, there is price efficiency such the price level always equals the market fundamental value, and there is no opportunity to increase expected earnings through trade. A market outcome can fail to be price efficient - and thus failing to implement a rational expectation equilibrium - but still be informationally efficient, which we define as the above correlation being exactly equal to one. For example, consider a market dynamic in which price adjustments are exactly one-half of any change in fundamental value. While this would fail price efficiency, there still remains a clear one-to-one mapping between the path of market prices and the sequence of realized signals. So from observing the public market data, we could infer all of the signals regardless of whether it is privately received or publicly received. So, our second hypothesis relaxes the assumption of price efficiency and only addresses information efficiency.

Hypothesis 2. *Correlation efficiency: The correlation between market prices and fundamental value is one.*

Next, we relax the above efficiency concept even further, by recognizing that the market prices of assets may be influenced by trader's biases in judgement (Hirshleifer, 2001). In particular, the rational expectations equilibrium for our experiment relies heavily on the assumption that conditional probabilities are updated according to Bayes rule when market signals are realized. Past experimental studies have shown that asset prices generated in markets are not immune to evaluation errors such as base rate fallacy (Ganguly, Kagel, and Moser, 2000) or the representative heuristic (Camerer, 1987). For our next hypothesis, we suppose that whatever systematic judgment errors subjects make, they are the same in all our treatments. This allows us to consider the PUB treatment as our baseline, and if information aggregates when it is asymmetric, then market prices should all follow the same data generating process.

Hypothesis 3. *Comparative efficiency: Pricing Dynamics are the same in all treatments.*

From a theoretical standpoint, the above hypotheses essentially modify the full information rational expectations hypothesis to one in which participants are allowed to deviate from rationality in terms of how they use information to update their beliefs and the corresponding impact this has on equilibrium prices. However, it assumes that such judgement biases have no effect on the ability of the market to aggregate diffuse information.

Next, motivated by the seminal paper on rational herding by Bikhchandani, Hirshleifer, and Welch (1992), if individuals do not act according to their signals, then the market price will not reveal any information and the prices will be in the form of an informational cascade. To the extent that cascades are present, this would also imply that information aggregation will be significantly lower in the private treatment relative to the public treatment. In fact, with a cascade, information aggregation should be zero subsequent to the onset of a cascade.

Hypothesis 4. *Informational Cascade: Prices in the private treatment will be in the form of informational cascades where prices do not reveal any information.*

While the the model by Bikhchandani, Hirshleifer, and Welch (1992) was developed to explain rational herding, the model by Avery and Zemsky (1998), strive to make the model more fitting to that of a traditional asset market by allowing the price to adjust in a way that reflects the information that can be inferred by an outsider from its holder. In this case, the result that they obtain is that prices again become fully revealing and we would recover the rational expectations equilibrium. Thus, if the mechanism of flexible prices makes actions fully revealing of signals, we would not see any cascades and therefore, this would imply that one of hypotheses 1, 2, or 3 should hold.

2.2.2 Partial Aggregation hypotheses

Purely from a theoretical standpoint, the hypotheses developed above have two extreme predictions, either full aggregation or no aggregation. In this sub-section, we briefly survey models that would imply partial aggregation. A seminal paper by Diamond and Verrecchia (1981) predicts the result of partial aggregation of prices in an environment where there are multiple sources of uncertainty, namely information and noise about endowments. While the above paper does not formally model the mechanism of the market, another seminal paper by Kyle (1985)does and obtains the result that a monopolist informed trader with perfect information about an asset's liquidation value would trade patiently in such a manner that prices only partially aggregate information. However, this paper's market structure does not exactly match the experimental setting in this paper, one of the important differences being that the insider has perfect information on the asset's liquidation value.

However, in another model that is closer to the experimental setting in this paper, Kyle (1989) considers informed rational traders with imperfect information about an asset's final value, non-informed rational traders, and pure noise traders who trade a risky asset by simultaneously submitting excess demand functions, from which market clearing prices and allocations are determined. The Bayes-Nash equilibrium generates prices that only partially aggregate information. A key insight is that informed traders dampen their net excess demand, which has the effect of under revealing their information but also creates the opportunity for excess returns. More over, there is a comparative static result which states the greater the number of informed traders, the more price incorporates that information. Likewise, Foster and Viswanathan (1996) develop a multi-period version of the model developed in Kyle (1985) and find that insiders would trade patiently with over many periods with partial information revelation. In our setting, this suggests the following hypothesis.

Hypothesis 5. *The relative ranking of information aggregation from lowest to highest is PVT, 2SIG, and 4SIG.*

In contrast to the above, Holden and Subrahmanyam (1992) generalize the Kyle (1985) model along the dimension of studying the effect of multiple insiders. This is a multi-period model in which the realization of asymmetric information occurs prior to the market (unlike our sequential information realizations). In the equilibrium, if more than one trader observes a signal (where the signal, as in Kyle (1985) is fully revealing of the assets final value), insiders compete away the informational rents and the market price fully reveals the signal. This suggests any lack of information aggregation we observe in our PVT treatment should return when we break the monopolies on the draws from the urn. To the extent that this result is applicable to our experimental setting, this would imply the following.

Hypothesis 6. *Informational Monopoly: there is less than full information aggregation in the PVT, but full aggregation in both 2SIG and 4SIG.*

3 Empirical analysis of prices cascades

In this section, we present analysis of the PUB and PVT data and test our first four hypotheses. We start with a presentation of contract prices and paths of fundamental value for a typical PUB and a typical PVT experimental session. Figure 1 is a 2×3 array of graphs, with rows corresponding to experimental sessions and the columns to the three market sequence within a session. In this figure, the top row corresponds to one of the PUB sessions, PUB4, and the bottom row to one of the PVT sessions, PVT6. The horizontal axis of each market graph measures time, the vertical lines indicate market period closings. A dot represents a contracts by its time stamp and price (the vertical axis value.) The step function tracks the fundamental value given realized urn draws and as is calculated according to Table 1. At the top of each period, we give the total number of trades within that period. In Figures 2-5, we provide similar figures for all sessions of the PUB and PVT treatments.

Consider session PUB4 in the first row of Figure 1. Trading in Market 1 starts with a possible bubble. In the first three periods there are several trades exceeding the maximum possible dividend of one dollar. It turns out the dividend in this market is zero, every signal was black, and the fundamental value correspondingly decrements each period. While the adjustments of prices track this value, the actual level of transaction prices approach fundamental value only around Period 7. This is consistent with other studies that generally document that subjects do not perfectly update according to Bayes rule (Grether, 1980; Camerer, 1987; Charness and Levin, 2005). In Markets 2 and 3, as the subjects gain experience, we find successively smaller and shorter duration bubbles, which is consistently found in other experimental studies (Smith, Suchanek, and Williams, 1988; Dufwenberg, Lindqvist, and Moore, 2005; Haruvy, Lahav, and Noussair, 2007). Subsequently, the trends of prices and values are similar, although with some noise.

The PVT6 session, second row of Figure 1, has markedly different price dynamics. In Market 1, prices almost always exceed fundamental value, but never exceed one dollar. More importantly, there is no obvious responsiveness of prices to value. As the markets progress, the transactions lock in to a trading price unrelated to the value, and fail to adjust to subsequent changes in value. We refer to such a price lock-in as an informational price cascade. Consistent trading at such a home grown price norm makes it very difficult to for market participants to infer the private - but valuable - information observed by others. Also, it is quite remarkable how this price cascade, and those in other sessions, span across market incidences even though it is common knowledge that endowments are reset and asset dividends are drawn anew. Inspection of the data in the Figures 4 and 5 will confirm these informational price cascades arise in almost all sessions for the private treatment.

The PVT6 session is also interesting because it is one of the few instances in which the price cascade breaks and information appears to flood back into the market. Consider the last trading period of Market 3. Here, the period's informed trader had already taken as long a position in the asset as her budget constraint allowed before observing a Black signal. The trader appears to panic, quickly selling units at prices below the established norm. Thus, despite only have observed the one piece of information, the trader has possibly speculated on a disproportionately large decrease in fundamental value.

3.1 Univariate analysis of price-fundamental value relationship

We proceed to quantify the informational efficiency, or the apparent lack off, suggested by visual inspection of the data. As implied by Hypothesis 2, a basic indication that prices incorporate information should be a positive correlation between price and fundamental value. Table 3 presents simple univariate correlations of fundamental value and each trade price stratified by treatment and market repetition. This correlation is computed incorporating all trades within each trading period and computing its correlation to the fundamental value in the given period, where the fundamental value is determined by the prior dividend probabilities and any realized draws from the urn.

The correlations are virtually zero in the PVT sessions, while strictly positive and quickly increasing in the PUB sessions. In the public sessions, the correlation between value and traded prices rises from 0.29 in Market 1 to 0.88 in the final market. The hypothesis that the correlation is zero is soundly rejected in all the markets. In contrast, the PVT market correlations are not insignificantly different from zero in Markets 1 and 3, and negative in market 2. Further, the correlations are not growing across the markets. These correlation computations support the general notion that prices in the PUB treatment respond to signals whereas prices in the PVT treatment do not.

Figure 6 presents this correlation on a period by period basis within each market for all sessions in each treatment. We take the mean, median and closing price for each period to compute the correlations with value across sessions within a treatment. Thus, for this figure, correlations are computed based on a single price statistic per trading period per session.[3] In the first period, the fundamental value is always one-half, hence there is zero variance in the first period fundamental value. Cosequently, the correlation in the first period is always zero. Clearly after period four, with all three measures of price, the correlations of value and price in the PUB treatment display a strongly increasing pattern, and by Market 3, the correlations approach one. In contrast, the correlations in the PVT treatment are close to zero and do not display any distinct trend. In fact, as the number of periods increase (i.e., number of signals increase), the correlations often decrease, sometimes becoming negative. Unlike in the PUB sessions, Market 3 does not show any faster or greater degree of convergence relative to Market 1.

Result 1. *Hypothesis 2, and information aggregation, fails in the PVT treatment; the correlation between price and value is zero However, in the PUB treat the correlation approaches one in the latter stages of a session.*

The presented correlation measures capture the degree to which prices adjust with changes in fundamental value; however, they do not inform to how well prices match the fundamental value. We refer to ability of prices to accurately reflect fundamental value as price efficiency. We would like an objective measure of the difference in the price efficiency between the PUB and PVT treatments. To this end, we define two metrics of pricing inefficiency in this market.

First, we define pricing inefficiency as the absolute value of the deviation of price from

[3] In the PUB and PVT treatments, there were 216 periods in total across all sessions and markets (total of eight sessions for each treatment with nine periods per market and three markets per session). Out of this, there were no trades in five and six periods in the PUB and PVT treatments respectively.

value expressed as a percentage of value. With perfectly price efficient markets, this should equal zero and larger values would imply greater degrees of inefficiency. This measurement gives some idea of the relative inefficiency of the PVT treatment relative to the PUB treatment. Panel A in Table 4 gives an estimate of these magnitudes. For the PUB treatment, the Market 3 pricing inefficiency is around 50% whereas in the PVT treatment, it is around 140%. To ensure that these results are not driven by large errors in the closing periods for which the fundamental value approaches zero, we also report the simple average absolute deviation, without scaling by value in the denominator. The results using this second measure of inefficiency (Table 4, Panel B) shows a similar pattern but greatly increased efficiency.

As a basis of comparison, we compute a benchmark by calculating the level of inefficiency had all trades occurred at the price of fifty cents, which is we call the naive pricing. As can be seen, the PUB treatment has lower inefficiency than the naive pricing, more so in Markets 2 and 3. In contrast, the PVT treatment has greater inefficiency even relative to naive pricing, which implies that the cascades are even worse than an equilibrium where there is no information given to participants. The above suggest that not only does correlation efficiency fail, the comparative efficiency of the public and private treatments (Hypothesis 3) is also rejected based on these univariate tests. However, we will further test these two hypotheses, correlation efficiency and comparative efficiency, in a multivariate setting to demonstrate this.

3.2 Regression analysis of price dynamics and information aggregation

The above univariate results suggest that the PVT markets have significantly less information aggregation and greater price inefficiencies that the PUB markets. However, this does not provide credence to prices being unbiased as well as correlated with fundamental value in the PUB treatment. Nor does the lack of correlation indicate that there are information price cascades of the nature that we speculate occur in PVT sessions. To provide further evidence on the first three hypotheses - rational expectations (hypothesis 1), correlation efficiency (hypothesis 2), and comparative efficiency (hypothesis 3), we consider the following simple model for determination of price changes.

$$\Delta P_{smt} = \alpha + \beta \Delta V_{smt} + \epsilon_{smt}, \tag{1}$$

where s denotes the session number (one through eight), m the market repetition (one through three), and t the trading period (two through nine).

Under Hypothesis 1 of Rational Expectations Equilibrium, we should find that α equals zero and β equals one. Under Hypothesis 2, one does not need α to be zero as this would simply imply a lack of matching of the mean changes of the prices and mean changes of value. What would be the implication for β? In particular, if the volatility of the dependent and independent variables were equal, then by the definition of the regression coefficient, a correlation coefficient of one would imply that β should also be one. On the other hand, if this were not true, the correlation could be one, but β can be different from one. For testing hypothesis 2, we use this less restrictive test of correlation efficiency. If we reject correlation efficiency with the weaker hypothesis test of β different from zero, this is a strong rejection. Under comparative efficiency, we should find that β for the public and private treatments should be equal.

Table 5 gives the results of this test for both the PUB and PVT treatments.[4] First, we confirm our first result there is no information aggregation in the PVT sessions as β is not significant in this case. However, in the PUB treatment β is significant but we can reject the null hypothesis that it is one. Also note that the intercept term is different from zero in both treatments, and a joint test that $\alpha = 0$ and $\beta = 1$ is rejected as well. Hence, we have our second result.

Result 2. *We reject the rational expectations equilibrium in both the PUB and PVT treatments.*

Further, the results in Table 5, Panel C shows that the PVT treatment has significantly lower aggregation of information relative to the PUB treatment. This implies that we also

[4]In the public and PVT treatments, there were 216 periods in total of trading across all sessions and all markets (total of 8 sessions for each treatment with 9 periods per market and 3 markets per session) Out of this, in the public market, there were 5 periods with no trading and there were 6 periods with no trading in the PVT treatment.

reject that the comparative efficiency of PUB and PVT treatments (Hypothesis 3).

The specification of Equation 1 and the associated hypothesis on its parameter values impose both informational efficiency - i.e., there exists a one-to-one relationship between the changes in prices and fundamental value that incorporates all information regardless of how disparate - and price efficiency. We now consider an alternative empirical specification that better delineates these two efficiencies. Motivated in part from the results in Figures 1- 3 where it appears that public markets react with a lag, we modify the empirical specifications to model the price process rather than change in prices from one period to the next.

$$P_{smt} = \alpha_s + \beta_0 \Delta V_{smt} + \beta_1 \Delta V_{sm,t-1} + \beta_2 P_{sm,t-1} + \epsilon_{smt} \quad (2)$$

Apart from including the lagged change in value as an explanatory variable, another important change in this specification relative to the previous one is that we include session specific intercepts, α_s. Given that the intercept captures the average pricing error, allowing it to vary across sessions could possibly increase the magnitude of the slope coefficients. A second more important reason for allowing for session specific intercepts is that it will allow us to test for the possibility of informational cascades..

Tables 6 and 7 present the results of estimating Equation 2 separately for the PUB and PVT treatments. For considering the appropriate data for the dependent variable, we report the results of using the mean, median and closing price as different dependent variables. These estimations, and subsequent ones, are estimated by feasible generalized least squares with session specific variances because we generally reject the hypothesis of equal variances in each session for both the PUB and PVT treatments.[5] We also test, but do not report, for autocorrelations using the Breusch-Pagan test and do not find evidence for autocorrelation in the error terms for all our presented specifications.

With respect to the PUB treatment (Table 6), we find a significant effect for change in value for both the current period, ΔV_{smt}, as well as for the previous period, $\Delta V_{sm,t-1}$, suggesting delayed impact of information on prices. Approximately only fifty percent of

[5]The null hypothesis of homoscedasticity is not rejected in all specifications. For example, in the PUB treatment with mean price as the dependent variable, homoscedasticity is not rejected. Likewise, for the PVT treatment with closing price, the hypothesis of equal session specific variances is not rejected. However, to be consistent, we choose the same method of estimation for all specifications.

the change in fundamental value resulting from a urn draw is realized in the current price, while another thirty percent of this change in value is incorporated by the price of the subsequent period. The estimates for the coefficient on lagged price range from 0.91 to 0.96. Each of these estimated coefficients is significantly different from 1 and standard tests reject the presence of a unit root.[6] Next, note that the intercept is insignificantly different from zero for the public market, suggesting that adding the lagged change in value allows a greater explanatory power. Furthermore, using an alternative unreported specification with session-specific intercepts, a Wald test of the session specific intercepts being different from each other is not rejected. Accordingly, for all subsequent estimation, we use only a single intercept term for the PUB sessions.

Next, in Table 7, we examine the estimation results for the PVT treatment. We find a dramatic departure from the PUB treatment results. In particular, the coefficients of change in value in the current period, ΔV_{smt}, and the lagged change in value, $\Delta V_{sm,t-1}$, are statistically insignificant. Thus, neither current information nor lagged information has any effect on prices. The impact of the lagged price is also significantly lower relative to the PUB treatment. The R^2 are also significantly lower relative to the PUB market with values between 61% and 77%. Thus, the results that rational expectations, correlation efficiency and comparative efficiency continue to be rejected with this alternative empirical specification of price determination.

Even more striking, the session specific intercepts are significantly different from zero and from each other. We interpret this result (session specific intercepts different from zero and different from each other) as more formal statistical evidence for the presence of price cascades in the private treatment. Specifically, this result suggests that prices in the PVT treatment are session specific mean reversion processes. The corresponding stationary points are the home grown price norms at which informational price cascades form. Let's consider the stationary price for a PVT session, denoted P_s. Once an informational price cascade forms, i.e. a stationary point reached,

$$P_{smt} = \alpha_s + \beta_2 P_{sm,t-1} + \epsilon_{smt}.$$

[6] Due to the small number of observations in each session, these unit root tests are conducted by taking all the end of period observations of each treatment and stacking them together.

If one takes expectations on both sides, then one has the following

$$E[P_{smt}] = \frac{\alpha_s}{1 - \beta_2}.$$

Thus, a non zero intercept implies the presence of a long run steady state price as long as β_2 is less than one. We report the calculated stationary price for each session in the last column of Table 7, and inspection of the price plots in Figures 4 and 5 confirms the accuracy of how the stationary prices match the level of the price cascades. In our calculation of the stationary price, we use the coefficients from the regression on the median price because it always results in a value that lies between the same calculations based upon the mean and closing price regressions. Note that the difference between these calculated values is never more than five cents. In summary, the fact that every PVT session specific intercept is significantly positive provides strong evidence of informational cascades. In contrast, the PUB session intercepts are jointly not significantly different from zero. Thus, not only do we document lack of information aggregation, we provide a possible mechanism for the presence of lack of aggregation, namely that there are information price cascades. We summarize the regression analysis with the statement of our next two results.

Result 3. *We reject correlation efficiency (hypothesis 2) for the PVT treatment. We reject that the comparative aggregation of the PUB and PVT treatments are equal (hypothesis 3).*

Result 4. *The non-aggregation of information in the PVT treatment manifests itself as informational price cascades. Hypothesis 4 is supported.*

3.3 Robustness checks of regression results

Potentially we have omitted some important confounding factors in our regression analysis of price dynamics. In this subsection, we investigate the robustness of these results to such confounding factors. In particular, we assess the possibility price bubbles - often observed in the early stages of a session - influence information aggregation, and also evaluate whether the experience subjects gain over their participation in the three market leads to increased information aggregation.

Figures 2-5 show that bubbles frequently occur at least in initial trading periods and initial markets. Bubbles are often observed and well studied in market experiments for long lived assets, see Porter and Smith (2008) for a recent survey. The presence of bubbles in this experiment may have consequences for our results regarding information aggregation and price efficiency. First, if prices do in fact adjust appropriately to information outside of a bubble, then experiencing a bubble within a session would result in errors at least in the estimates of the constant coefficient. Second, structurally, rational participants observing a bubble may switch from evaluating the asset according to its fundamental value to its speculative potential, as documented in Hirota and Sunder (2007). This could impact the marginal effect of change in value on price (or change in price). Consequently, it is possible the lack of aggregation in the PVT treatment and the partial price efficiency in the PUB treatment are partly driven by such bubble effects.

To test these notions, we need a clear definition of what constitutes a bubble. In the popular press, as well as academic literature, bubbles are usually defined as large positive deviations of traded prices from fundamental value, where fundamental value is usually estimated. In the current context, since value can be precisely known, and this deviation can also be estimated precisely, we are still left with a choice as to what constitutes a 'large' deviation. Further, for the private treatment, the lack of aggregation may imply in some cases that this deviation is large without participants necessarily acting in an irrational manner in terms of switching from fundamental to speculative valuation.

Therefore, the bubble definition that we use is one in which all participants can definitely identify price has exceeded fundamental value regardless of the belief about the signals observed by other participants or how new information is used to update the expected value of the dividend. Namely, we define a trade strictly above one dollar as a bubble trade. Given the common knowledge of the dividends by all participants, no belief structure would support this valuation. Using this definition, we present some summary statistics for the presence of bubble trades by market and by treatment in Table 8.

For both treatments, bubbles are present to a greater degree in the first market relative to the third market. This is consistent with prior literature that suggests that bubbles generally reduce with participant experience (Smith, Suchanek, and Williams, 1988; Dufwenberg, Lindqvist, and Moore, 2005; Smith, van Boening, and Wellford, 2000). However, the prevalence of bubble trades is lower in the private treatment relative to the public treatment. This provides preliminary evidence against the notion that bubbles may be causing the results on the lack of aggregation in the PVT treatment versus the PUB treatment.

To further investigate this, we create a period specific bubble dummy B_{smt} that takes a value of one if 50% or more of the trades in a given period take place at a price above one, and zero otherwise.[7] We modify the empirical specification in Equation 2 to add a bubble dummy, as well as interactions of the bubble dummy with the change in value, and the lagged bubble dummy with the lagged change in values - allowing for lagged impact of bubbles on information aggregation. Specifically, the equation estimated is of the following form,

$$P_{smt} = \alpha_s + \beta_0 \Delta V_{smt} + \beta_1 \Delta V_{sm,t-1} + \beta_2 P_{sm,t-1} + \beta_3 B_{smt} + \beta_4 B_{smt} * \Delta V_{smt} + \beta_5 B_{sm,t-1} * \Delta V_{sm,t_1} + \epsilon_{smt}.$$

In contrast to Table 7, we use only the closing price as the dependent variable as the contemporaneous bubble indicator can be used as an independent variable only in this case. By adding the bubble dummy, we can capture the average impact of bubbles on the intercept, and by interacting with the change in value and lagged changed in value, we can examine the impact of bubbles on information aggregation. If bubbles were an important factor in the lack of aggregation results, we should expect to find that β_4 and β_5 should be negative and significant, and β_0 should become positive and significant with an estimate closer to 1 relative to table 7. We also estimate a similar model by interacting bubbles with price changes in the difference specification as in Equation 1.

The results in Table 9 show otherwise. β_0, the coefficient on ΔV, continues to be insignificant for the PVT treatment. Interaction terms of the bubble dummy with change in value or lags of these are not significant, indicating that the presence of bubbles does not impact information aggregation. Further, the session specific intercepts continue to be significant (results not shown in the table), and different from each other, showing that the cascading effect documented earlier is robust to the impact of bubbles. The insignificance of bubbles

[7] This indicator is computed excluding the last trade of the given period as we will be using the closing price as the dependent variable in the empirical specification.

continues to be true in the difference specification. The results for the PUB treatment is similar. In other unreported regressions, we also investigate an alternative definition of bubble using a positive deviation of price from value by 50% or more to define a bubble trade. The results are very similar to that found using the above definition of bubble trades.

Table 9 on the incidence of bubbles suggests that bubbles decrease in the second and third markets relative to the first market. The above suggests that market participants may be learning to aggregate information better as well with trading experience. To investigate this, we have a similar empirical specification to equation 2 where we interact the market number with the change in value. The results presented in Table 10, show some evidence for learning in the PUB treatment. The point estimates for the impact of change in value are greater for Markets 2 and 3 relative to Market 1, even though the differences are not statistically significant. In contrast, the results for the PVT market shows absolutely no pattern. Thus, learning across markets does not explain the finding of a lack of aggregation in the PVT treatment.

3.4 Portfolio adjustments

We now shift from the analysis of prices to addressing some natural questions regarding the subjects' portfolio adjustments and how they utilize their private information. For example, given the presence of informational price cascades, do traders simply disregard their private information and select asset holdings unconditional upon their private information, in other words do they herd? Do traders with correct information outperform those who don't? Do traders act upon their information when they receive it, or are they strategic and delay trading in order to not reveal and better exploit it? If traders successfully adjust their portfolios to take advantage of their information, how do they do so without leaking information into the market and breaking a price cascade?

If subjects exploit informational advantages, we should expect to see the final number asset units held to differ conditional on whether a subject observed a Red or Black draw. On the other hand, if subjects simply herd we should see no such differences. In Table 11 we report the average number of asset units held at the conclusion of a market conditional upon market number and signal type observed, as well as the standard deviation for each of these statistics. Using the endowment of five units of the assets as a benchmark, those with who receive a Black signal reduce their holdings by approximately one unit and those who receive a Red signal add about one unit. This would suggest subjects are not herding, except the standard deviation are quite large and we can't reject the hypothesis that average final asset holdings are not the same for both Black and Red signal receivers.

Of course, examining the final asset holdings is not a complete picture, traders could increase their portfolio value (assets and currency) through effective trading which could manifest itself through effective currency accumulation as well as adjustment in asset holdings. So we compare the subjects' market earnings, currency plus terminal dividends of held assets, according to the true dividend and the observed signal. We report this market-by-market in Table 12. In this table, we segregate the individuals by the type of signal that they received - red or black. There is some evidence that subjects do use there information to earn more. When the dividend is zero, those who receive a Black signal earn about forty-nine cents more than the autarky outcome (simply holding the endowment), and those who receive a Red signal lose eighty-nine cents on average. When the dividend is one dollar, the result is almost symmetric, with those who observe a Black draw on average lose eighty-seven cents, and the those who observe a Red draw gain fifty cents on average. Once again, the standard deviation on these statistics is quite high and none of the differences are statistically significant.

It turns out the high standard deviations in asset holdings and market earnings arise from an important heterogeneity in how subjects choose portfolios. In Figure 7, we plot the empirical CDF's of asset holdings conditional on receiving a Red or Black signal. There are several features worth noting. First, the support for both distributions is quite large; zero to thirteen for those who observe a Black signal, and zero to fifteen for those whose observe a Red signal. There many people choosing corner solutions, such as the twenty percent of the Black signal receivers and ten percent of the Red signal receivers who hold no units of the asset. Finally, casual inspection suggest the empirical CDF of Red first order stochastically dominates that of Black. We quantify this conclusion with a nonparametric hypothesis test suggested by Barrett and Donald (2003) which rejects the absence of first order stochastic dominance for any plausible level of significance.[8] Evidently some traders adjust their portfolios based upon their signals and benefit, while at the same time there is overall tremendous variation in portfolio adjustments. It turns out that this variation is what allows traders to utilize information without transferring it to the market.

3.5 Timing and informational content of market actions

How are some subjects able to use their private information to make profitable portfolio adjustments without transmitting this information to the market? One conjecture is that a subject may wait to act on such information so as to not transmit the signal by his actions, and thus erodes its value (Foster and Viswanathan, 1994, 1996). As we will demonstrate, this conjecture is partially wrong as many informed subjects quickly trade upon receipt of their information. However, it turns out they are able to do so with impunity, because many of the other subjects, who are not informed, are also engaging in trades. This creates a large amount of noise trades that dilutes the informational content of the insider's market actions.

Let's consider how fast a subject makes a trade after observing a draw from the urn. Figure 8 plots the empirical cumulative probability of the contract at which the period's informed trader makes her first transaction within the period. Surprisingly, many subjects act quickly, about twenty-four percent are a party to the first contract, and almost twenty percent more make their first trade as a party to the second contract of the period. One the other hand, slightly over thirty percent of the subjects do not make any trade in the period that are the informed trader. Clearly, subjects utilize the endogenous timing of when to take market action in a diverse ways. The other side of this coin is that clearly many subjects makes trades when they are non-informed, which is in contradiction to what many rational theories dictate (Milgrom and Stokey, 1982; Tirole, 1982).

Given there is uncertainty that the informed trader is one of the parties to a trade, we examine how likely it is that a given trade reveals information about the last observed draw. First, we define noise trades as any trade between two non-informed traders. Trades that

[8]The test-statistic is $z * (\frac{mn}{m+n})^{0.5}$ where m and n are the number of observed Black and Red draws respective, and z is the absolute of maximum difference between the two empirical CDF's. The p-value of this statistic is $\exp(-2 * z^2)$.

involve the informed trader will be classified as either informative or non-informative. We argue an informative trade occurs when the informed trader takes an action that allows others (conditional upon knowing the trader's action) to infer the period's signal.

We start be assuming that any impact a signal has on price is realized by the end of the trading period and is reflected in the closing price. So, when assessing the informational content of a trade, we consider whether the price is an increase or decrease from closing price of the previous period. We ask under what types of actions and circumstances does a informed trader reveal the value of her signal? Consider the following scenario - suppose the informed trader buys a unit at a price higher than the previous closing price. Is this purchase is rational given the observed signal? Clearly, the informed trader would not agree to purchase if the signal was Black, because that signal would cause her expectation of the dividend to fall below the previous closing price. However, if the signal was Red, then her expected value of the dividend will increase, and purchasing the asset at a higher price is now rationalizable. Thus, we can see buying at a higher price separates the two possible signals and provides information to the market. Now, let's suppose the informed trader was the seller, rather than the buyer. Selling at a higher price is rational irrespective of whether the signal was Red or Black, hence this trade provides no new information to the market. We call such a trade as non-informative. Note that there is a possibility that an informed trader who saw a Black signal still buys at a higher price - thus violating the rationality described before. We classify this type of contrarian trade also as non-informative. From similar arguments, a price decrease from the previous closing price is informative only if the informed trader was a seller, which would only be rational if the signal was Black. Table 13 shows how we sort different trades into different categories.

With these classification of signals, we calculate the proportion of informative signals. Figure 9 plots the results of trades classified as above with the order of the trade within a given period - the idea being to examine how long it takes for the informed trader's information to be incorporated into the price.

The figure is striking for two reasons. First, a large proportion of trades (conditional on the order of trading within the period) are noise traders, i.e., trades where both participants do not have any information in the given period. For example, for the first trade in any given period, about seventy-five percent involve noise traders. This pattern continues for most trades. A second even more striking fact is that only around fifty percent of the informed subjects' trades are actually informative for the first trade.

Consider the following thought experiment. If an outsider wanted to infer the likelihood that the insider obtained a positive signal in a given period, then observing the opening trade of the next period being transacted at a higher price relative to the previous period, the chance of the trade reflecting positive information is only around 10%-15%. This provides a strong reason for the lack of aggregation. The proportion of informative trades is too low relative to the total number of trades. The large presence of noise traders transacting at a home grown price norm also compounds the lack of information aggregation as informed traders can make portfolio adjustments without affecting a change in price. At the same time, the fact that traders adjust their portfolios in response to signal, suggest that cascades do not manifest due to herding in terms of behavior, but rather only due to low informativeness of trades.

The result that noise traders can reduce information aggregation is also empirically observed in Bloomfield, O'Hara, and Saar (2009), where they have a treatment where traders are explicitly paid for creating noise trades. They find that this reduces efficiency of the market in terms of pricing. However, they do not document cascades of the type we document here. While noise trading is not a treatment variable in our experiment, as can be seen from above, it does emerge as a large fraction of trades and an important economic determinant of price cascades.

4 Experimental tests on the fragility of price cascades

The informational price cascades in our PVT sessions are quite prominent and unexpected. Hence, there is likely some skepticism about whether such phenomenon are general or restricted to the specific circumstances of the experimental design. In an attempt to address this issue, we earlier identified two possible limitations in our experimental design section: information monopoly of the signal for each trader, and the fraction of traders who observe the signal. With respect to the number of traders observing the signal; one conjecture is that price cascades rely upon there being a monopoly for each signal, and creating any competition for informational rents and induces full information aggregation (Holden and Subrahmanyam, 1992, 1994). A second conjecture is that increasing ratio of informed traders to non-informed traders will reduces the amount of noise trade, suggesting a continuous increase in the rate of information aggregation. Our 2SIG and 4SIG design allows us to evaluate these two conjectures. The 2SIG treatment allows us to measure the effect of breaking the monopoly of the informed trader (Hypothesis 6), and the 4SIG treatment permits identification of increasing the fraction of informed traders (Hypothesis 5).

Note that in both these cases, apart from breaking the monopoly and increasing the fraction of insiders, we also increase the precision of the signals of each insider. Other theoretical literature suggests that increasing the precision of insiders may induce better aggregation (Diamond and Verrecchia (1981),Vives (1995)). We will test for possible confounding effects of increased precision in a later section.

4.1 Impacts on informational price cascades

Again, we start by considering time series plots of all trade prices and fundamental value for both the 2SIG and 4SIG sessions, Figures 10 and 11. Casual inspection of the 2SIG plots clearly reveals price cascades that span across multiple markets in three out of four of the sessions, and a possible price cascade in Market 2 of the remaining session. This suggests that removing the monopoly of the informed trader is not sufficient to preclude the formation of price cascades. In contrast, we don't observe any multi-period price cascades in the 4SIG sessions. Although there is some suggested price inertia in the early periods of some markets, and often - but not always - the movement of price is towards fundamental value in later periods of the market. This movement from a price norm early in the market towards fundamental value later in the market suggests that having one-half the subjects observe each signal and subsequently subjects information reaching a precision level, the cascade phenomenon breaks.

Next, we quantitatively evaluate the presence of information aggregation by examining the correlation between all contract prices and fundamental value, which Table 14 presents. The evidence is quite negative for information aggregation in the 2SIG treatment. Overall, the correlation is virtually zero, and when conditioning upon the market number we have no increasing trend, and two out of three markets exhibit negative correlation. This brings of our next result.

Result 5. *Monopoly over each signal is not necessary for the formation of informational price cascades. We reject Hypothesis 6 that lack of informational monopoly would result in aggregation of information.*

On the other hand, there is significant and positive correlation for all three markets and overall for the 4SIG treatment; and we see higher correlations in Markets 2 and 3 versus Market 1. However, these levels are lower than those for the PUB treatment. Thus, the 2SIG treatment appears to exhibit zero information aggregation like the PVT treatment, and the 4SIG treatment seems to generate partial information aggregation relative to the PUB treatment.

To further corroborate this, we ran the same empirical specifications in terms of price difference (Equation 1) and price levels[9] (Equation 2) in Table 16.[10] First, we find that 2SIG results are similar to those of the PVT treatment. In the price difference and price level regressions, the coefficients for change in fundamental value are never significant. Further, price level regressions in Table 16 show that 2SIG prices are a session specific mean reversion processes, with stationary prices at which cascades form. The results for 4SIG reveal that information is starts to aggregate and price responds to new information and the corresponding change in value, albeit not as strongly as the PUB treatment. The coefficient for ΔV_{smt} is significant in both price difference and level regressions, but we note an interesting variation in its value depending upon the price measure used. For mean and median price, the coefficient is roughly half the of the value estimated in the PUB treatments; however, when closing price is used the coefficient is almost the same as the PUB treatments. The suggests, with half of the subjects informed, there is movement of prices towards fundamental value *within* a market period.

[9] In this case we report regressions without the $\Delta V_{sm,t-1}$ variable. With only four sessions in each treatment we wished to utilize as much data as possible, and the coefficient was not significant in unreported regressions.

[10] In unreported results, we perform all the alternative tests including examining the impact of bubbles and learning on information aggregation, and find no effects.

4.2 Portfolio effects in 2SIG and 4SIG treatments

The lack of difference in the 2SIG treatment and the PVT treatment, and the increasing aggregation in the 4SIG treatment naturally lead us to the question whether subjects portfolio decisions and earnings reflect herding behavior. First, we examine if the number of asset units held at the market conclusion is similar to the PVT treatment. The results presented in table 17, report final asset holdings conditional on information and market. We divide traders based on the composition of the signals they received over the course of the market. For the 4SIG session, those who received more Red signals than Black as classified as Favor Red, those that received more Black than Red signals are classified as Favor Black, and those that received an equal number of Red and Black signals are classified as Neutral. The results show a similar pattern of reaction to information as with the PVT treatment in Table 11. In particular, participants who get net positive information increase their holdings of the risky asset and those with net negative information decrease their holdings of the risky asset.

Next we provide, in Figure 12, histograms of trades classified into informative, non-informative and noise trades. While the 2SIG treatment is quite similar to the PVT treatment, the 4SIG treatment strikingly differs with a visibly higher ratio of informed to noise trades. To see this more clearly, we compute for a given period the ratio of the number of informative trades to the total number of trades. We report the average ratio all three treatments (PVT, 2SIG, and 4SIG) by market and overall in Table 18. The results highlight that increasing the fraction of informed traders increases the likelihood of informed trading significantly and this is possibly one mechanism of the greater aggregation of the 4SIG treatment relative to the 2SIG and PVT treatments.

4.3 Exploration into the sources of aggregation

As mentioned earlier, the 2SIG and 4SIG treatments differ from the PVT treatment among several dimensions: (1) competition among insiders, (2) greater precision of inside information, and (3) larger fraction of informed traders relative to total traders. We have already rejected the role of competition among insiders as being the an important factor in the lack of aggregation. Here we focus on the role of the fraction of insiders, while also investigating the confounding effect of increased precision.

The empirical specification is similar to that of Equations 1 and 2, except that we interact the changes in ΔV_{smt} with percentage informed defined as follows.In the PUB market, one hundred percent of the traders get information in each period and thus the proportion is one. In the PVT treatment, this proportion is $\frac{1}{8}$, in the 2SIG treatment, the proportion is $\frac{2}{8}$, and in the 4SIG treatment, the proportion is likewise $\frac{4}{8}$. We use this variable 'proportion of informed traders' as the proxy for fraction of informed traders. The results are presented in Table 19. In an alternate specification, we also formally test Hypothesis 5 by interacting a dummy variable for the treatment with ΔV_{smt}. We find that percentage informed has a positive impact of aggregation thereby implying that finding support for Hypothesis 5. As a separate test of the same hypothesis, we find that interaction of ΔV_{smt} with the dummies for the different treatment are supported, although not completely. The difference between the PVT and 2SIG is not significant, although the differences between PVT and 4SIG, and 2SIG and 4SIG are significant. These results are robust to excluding the public treatment from the regression analysis. Further, we can now state our final result.

Result 6. *We find partial support for Hypothesis 5.: The ranking of information aggregation is 4SIG, 2SIG and PVT, however, there is no difference between aggregation in the 2SIG and PVT treatments.*

One confounding effect in these regressions is that traders also have increased precision of signals as we go from PVT to 4SIG. To measure individual precision, we define the following variable. At the end of each period, we compute the maximum of the absolute value of the signal of all the traders in the market. Thus,

$$\text{Maximum Precision}_{smt} = \underset{i}{\text{Max}} |\#\mathcal{R}(i)_{smt} - \#\mathcal{B}(i)_{smt}|, \tag{3}$$

where $\#\mathcal{R}(i)$ and $\#\mathcal{B}(i)$ are the number of Red and Black chips respectively that trader i has already observed in session s, market m, and by period t. For the PUB treatment, this would just be the equal to the absolute value of the total number of red signals and the total number of black signals. For the PVT treatment, since each trader always has only one signal, this would just be equal to 1. For the two and four signal treatments, this would vary from period to period depending on the precision of the trader with the most precise signal. When this measure of precision is interacted with change in value, it has a positive and significant effect on aggregation, but the percentage informed continues to be significant (results not reported). However, in a sub-sample analysis, that excludes the public treatment, the interaction of precision with change in value is not significant. Thus, while precision may be increasing aggregation, the current experimental set up is not powerful enough to detect this. On the other hand, increasing precision does not impact the result on the percentage of informed traders resulting in greater aggregation for the sub-sample.

5 Conclusion

We conclude by discussing how our study and findings relate to the existing experimental literature, and suggesting future directions of inquiry. The initial premise of our study was to ask if the long lived asset and accompanying long sequence of informative private information of Bikhchandani, Hirshleifer, and Welch, leads to full aggregation or leads to cascades, when placed in a market with decentralized private information and effectively replacing social with market learning. They were strong precedents that such information aggregations failures would not occur. In particular, the continuous double auction is heralded in the experimental economics community for the large domain of economic environments in which it successfully implements competitive equilibrium outcomes (Smith, 2010).

In terms of experimental setup, we choose aggregate uncertainty, a long lived asset and homogeneous valuations for the asset. We are motivated in these aspects to a large extent by examining making the experimental set up as close as possible to real life markets where most of these conditions are satisfied. A critical distinction from the prior literature is that we allow completely endogenous timing of trades, both for insiders as well as outsiders. This allows substantial freedom for insider to time their trades as well as non informed traders to trade.

In experimental tests of fully revealing rational equilibrium, information robustly aggregates and efficient pricing occurs with homogeneous preferences, one-period lived assets, and aggregate certainty (Plott and Sunder (1982, 1988)). In studies that follow the same

Plott and Sunder design except adopt environments with aggregate uncertainty, such as Forsythe and Lundholm (1990) and Bruguier, Quartz, and Bossaerts (2010), information aggregation and the rational equilibrium solutions do not perform as well, although still better than competing theories. Likewise, Copeland and Friedman (1987, 1991) examine information aggregation in a four period asset market and find weaker support for the rational expectations equilibrium. Further, in the social learning literature, it's been robustly shown theoretically and experimentally that allowing for rational market makers who endogenously set price information fully aggregates (Avery and Zemsky (1998), Drehmann, Oechssler, and Rider (2005), Cipriani and Guarino (2005)). Therefore, a priori, it should be reasonable to anticipate that information should aggregate in our experimental set up.

It is hard to imagine our results could be more different. We observed essentially zero aggregation when there was a monopoly or duopoly on the signals. Moreover, price was the opposite of noisy; in almost every case market prices locked in on a home grown expectation which would span across multiple markets in a session.

What are the potential reasons for the informational cascades that we observe? Hints can be found in prior literature. For example, one of the modeling choices we make is to have aggregate uncertainty. A particularly interesting form of aggregate uncertainty is not the identification of the true state by pooling informed traders information, but rather if there are insiders at all. Camerer and Weigelt (1991) conducted experiments in which informed traders were given the realized state of the world before trading, however, there was uncertainty as to whether there would be any insiders. In this setting, sometimes when there was no informed trader, prices would move to an equilibrium that corresponded to a state for when there were informed traders and a particular realized signal. These false equilibrium outcomes are called information mirages. Likewise, using a similar experimental set up with signals that can be purchased for a cost, Hey and Morone (2004) document that there is significant price volatility that increase with level of signal cost for the signal, the are a number of bubbles in low dividend states, and occasionally there were mirages (or herds in this case) with price converging to the wrong dividend value.

Another study to our experimental set up is Barner, Feri, and Plott (2006), with which we share many elements except aggregate certainty is achieved in the last period of the market. Subjects have homogeneous values for the four possible dividend levels. However, there are always multiple informed traders each period - so there is no treatment like our PVT one. With this structure, they find much more support for the rational expectation equilibrium and information aggregation hypothesis than we do, although they do find some bubbles (price moving the opposite direction of the signal) and mirages (price moves in the direction suggested by the signal but to the wrong price). The above suggest that aggregate uncertainty plays an important role in the formation of information cascades.

Another potential reason is the endogenous timing of trades that informed traders have. The only effort we are aware of that incorporate flexible competitive prices with endogenous timing is the experimental study by Park and Sgroi (2009) in which subjects are provided signals of heterogeneous strength prior to trading. Their focus however is on the effects of differentially precise signals and its impact on the actions of insiders. However, it should be noted that a subject can make at most two transactions and therefore is still different from the experiment in this paper.

This complete freedom for timing of trades creates a large amount of trading, both for insiders as well as for noise trades. Theoretically, we know that this timing option should create partial aggregation (Kyle (1989)) but not cascades. Empirically, Bloomfield, O'Hara, and Saar (2009) observe that when the number of non-informed traders increases price efficiency is reduced when the realized value is far from the prior expected value, but price efficiency increases when that difference is small. Further, informed traders tend to wait until the latter part of the period to trade. While we do not observe a temporal pattern of insider trading within a round, and the noise trading is not a treatment variable in our experimental set up, we document similar results except that in our set up, this actually leads to cascades. Thus, the endogenous timing option for insider trading appears also be an important ingredient for informational cascades.

One potential concern of our results is their robustness to biases on account of subject's inconsistency with Bayesian updating. There are a number of studies that investigate this aspect in the context of market pricing experiments - for example, Camerer (1987), using a single period asset with found that Bayesian pricing did reasonably well, although there were large variances, and some evidence of the representativeness heuristic. Gillete et al. (1999)

is one of the earliest studies with long lived assets. Their experimental set up allows them to distinguish between judgment biases and pricing biases. They find evidence for both. This point is also made by Caginalp et al. (2008) who study markets for a two-period lived asset and avoid the Bayesian updating issue altogether by simply giving subjects new probabilities for the two possible dividend values after the first period. In this case, they find that prices under-react significantly and correlate highly with the period one prices. However, there are no strong a-priori reasons to believe that lack of Bayesian updating would impact the private treatment much more than the public treatment.

Clearly, we have answered the question that market learning and social learning are not equivalent and one should be careful in using social learning models to gain insights in asset markets. However, our results also suggest new questions. Is there an equilibrium foundation for the price cascade phenomenon or is does this have a behavioral foundation? In terms of further experimental inquiry there are several avenue of interesting inquiry including sequences of shorter lived assets, settings with aggregate certainty, and introducing public signals along side private ones to see if that triggers price responses that cause information to flow back into the market. Finally, one would like to know if price cascades can be observed in equity markets. Clearly such mis-pricing would be important and valuable to find, but also difficult to identify.

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A Sample instructions: 2SIG treatment

Experimental instructions (Please read along quietly while the experimenter reads aloud.)

You are now participating in an experiment which studies decision making in Asset markets. Contingent on your decisions in this experiment, you can earn money in excess of your participation fee of S$10. Hence, it is important that you read these instructions very carefully.

Also, we request you do not use hand phones, laptop computers, or use the lab's desktop computer except for the experimental software application. You may read quietly if there is a lull. Please refrain from talking for the duration of the experiment, or looking at other' computer monitors. If at some point you have a question, please raise your hand and we will address it as soon as possible. If you do not observe these rules, we will have to exclude you from this experiment and all associated payments, and ask you to leave.

The experiment consists of four consecutive markets. The first market will last for three periods and is solely for practice. You will not receive any earnings. The last three markets will last nine periods each; and you will receive any associated earnings in Singapore dollars. All payments to you will be privately made at the conclusion of the experiment.

We next will answer the following two questions?

1) What is the asset that we will trade?

2) How does the trading system work?

A.1 What is the asset we will trade?

In each market, there is a single type of asset you can buy or sell. This asset only pays a dividend after the last round, and this dividend will either be $0 or $1. The asset holds no value other than this dividend. Prior to each of the four markets, we will determine the value of this by tossing a fair coin. If the coin lands Flower face up then the dividend will be $0, and if the coin lands Crest face-up, the dividend will be $1. Thus, there is a fifty percent chance the dividend is $0 and a fifty percent chance the dividend is $1. Note, we will not reveal the value of the dividend until AFTER the last round of trading.

However, we will provide information relevant to the true value of the dividend over the course of the market. After each trading period, except for the last one, we will randomly select a chip from an urn that contains Red and Black chips and then RETURN that chip to the urn. Knowledge of the chip color is important because the number of Red chips and the number of Black chips placed in the urn is determined by the true value of the dividend. If the dividend is \$0, we will place four (4) Red and eight (8) Black chips in the bowl. On other hand, if the dividend is \$1, we will place eight (8) Red chips and four (4) Black chips in the urn. Only after the last trading period, will we permit a trader to examine and confirm the contents of the bowl if they request.

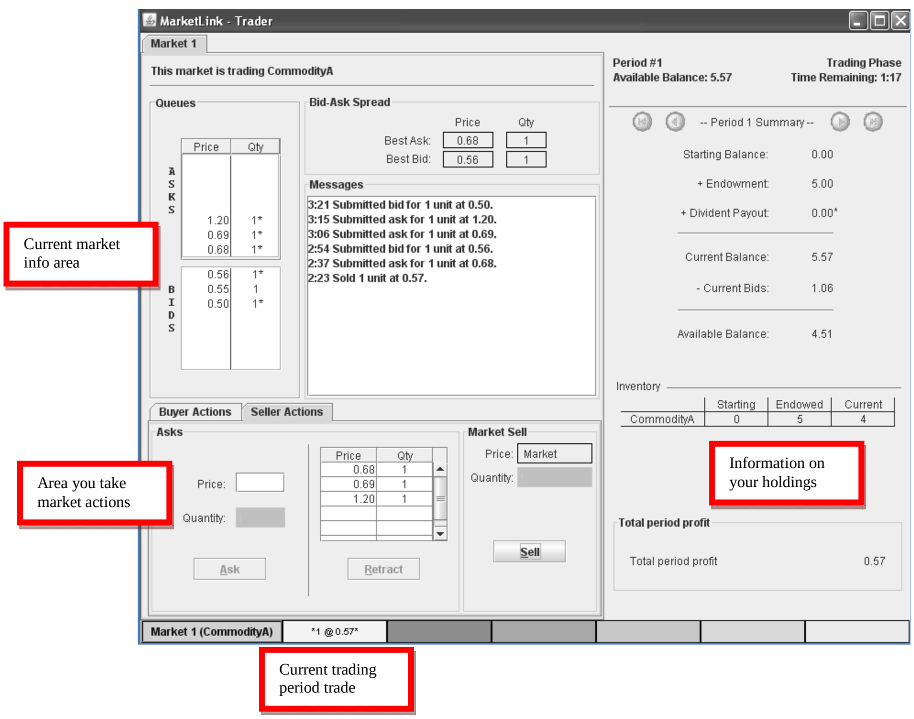
Each time we draw a chip, we will reveal the color only to a pair of participants, who are randomly matched with each other. The order in which the pairs are given the information is randomly determined as well. Specifically, the eight participants will be randomly matched to form four pairs. These pairs will then be randomly ordered to be informed of the chip color in periods 1 to 4. Then, for periods 5 to 8, the eight participants will once again be randomly matched into new pairs - which are placed in random order. Thus, each participant will get exactly two signals through the course of the trading experiment, once between periods 1 to 4, and then once again between periods 5 to 8.

We adopt the following protocol to keep the recipients of the information anonymous. We first draw the chip in this room but out of view, note the color, and replace it to the urn. Then we place a slip of paper in each of the envelopes numbered one through eight (corresponding to the number posted in each participant's computer carrel.) If you are one of the two participants that we inform of the chip color this period, your slip of paper will say 'BLACK' or 'RED' (according to the color of the chip.) All other envelopes will contain a slip of paper with the word 'NONE' on it. When you receive your envelope each period, you must view the contents carefully, and you must not communicate or show others the content. After inspecting the contents put this slip of paper back in the envelope, but do not seal the envelope. Early in the trading period, someone will come and collect the envelope.

Lastly, we address the issue of what assets and currency one has available to make trades in the market. Prior to the first round of trading in each market, every participant in the market will be given five (5) units of the asset and \$5. There will be no other disbursement of currency or units of the asset in that market. You currency balance and inventory of assets will carry over in each round of trading. You may sell a unit of the asset as long as your inventory has at least one unit, and you may buy a unit of the asset as long as you have sufficient currency on hand. After the last round of trading, the dividend will be paid on each asset. You earnings will be the sum of your dividends and your final currency balance, and the participation fee of $10.

A.2 How does the trading system work?

The trading system is a so called continuous double auction, i.e., at any point during a trading period, you can act as buyer or seller.



The market view has four areas.

1. The right-hand side of the screen provides "Information on your holdings." Here, you will find your Starting Balance (currency carried over from the previous period,) Endowment (currency you receive from the experimenter - for this experiment $5 and only in period 1), Dividend payouts from previous period (will always be zero in this experiment except for the last period), Current Balance, Current Bid balance (currency you have committed to bids in the current trading period), and Available Balance (amount

of currency on hand with which you can generate new bids or purchases at current asks). This is also where you can view your inventory of the Asset.

2. The bottom row displays the sequence of prices for unit of the asset for the current trading period.

3. The lower left corner is the area in which you take market actions. Here you can click on the ‘Buyer Actions’ tab to submit a bid price to the market at which you are willing to purchase a unit, or you can click on the ‘Buy’ button to purchase a unit at the current lowest ask price in the market. Here, you can also click on the ‘Seller Actions’ tab to submit an ask price to the market at which you are willing to sell a unit, or you can click on the ‘Sell’ button to sell a unit at the current highest bid in the market.

4. The upper left corner contains information on current market conditions (all participants see this information except which bid/ask belong to specific other participants.) ‘Queues’ are the lists of the current bids and asks that have been submitted to the market but have not yet been selected. Your outstanding bids and asks will be marked with an asterisk to the right of them. The ‘Bid-Ask’ Spread gives the current (lowest available) ask price to sell and the current (highest available) bid to purchase.

A.3 How to make trades?

As suggested, there are four types of actions you can take in a trading period; submit a bid price to purchase, and ask price to sell, purchase by accepting the lowest outstanding ask, and sell by accepting the highest outstanding bid. You can also do these in any sequence you want. For example, you can simultaneously have an outstanding bid, an outstanding ask, and then purchase at the lowest ask in the market (as long as it isn’t your outstanding ask.) You may also have multiple outstanding bids and/or asks at a given time.

There are some basic rules governing what bids and asks you may submit. 1) When you submit a new bid, it must be at least as large as the current bid and you must have at least the bid amount of currency available. 2) When you submit a new ask, it must be at least as small as the current ask and you must have at least one unit of the Asset in inventory (Note, when you successfully submit an ask, your inventory of available assets is reduced by one.) 3) If you attempt to buy a unit at the current ask, then you must have enough available currency and you can't attempt to purchase from yourself. 4) If you attempt to sell at the current bid, you must have a unit available and you can't sell to yourself. 5) All bids and asks will be stored in the queues, you may withdraw any bid or ask you submit as long as it is neither the current bid or ask. To withdrawal a bid or ask, highlight in the list found in the lower left corner and click the retract button.

When a contract occurs, the associated bid or ask is removed from the bid-ask queues. If you are involved in the contract, your currency holdings and asset inventory will be automatically adjusted. Finally, when the trading period ends, all bids and asks are removed from the queue (and the associated asset units and currency are credited back to the participants)

To summarize, you may purchase a unit of the asset in two ways; you may submit a bid price to buy that becomes the current bid and another participant 'sells' to you, or you may choose to 'buy' at the current lowest ask. Likewise, you may sell an asset in two ways; you may submit an ask price to sell that becomes the current ask and another participant 'buys' from you, or you may choose to 'sell' at the current highest bid.

Remember, each market has nine trading periods. Each of the trading periods will last 1.5 minutes. The practice market is an exception; it will have only three 2.5 minute trading periods. We will privately flip a coin to determine the final dividend value of the asset prior to the market. After each trading period, we will draw a chip from an urn whose composition is determined by the true dividend value. After the last trading period of the market, the value of the dividend will be revealed and your market earnings calculated.

At this time please locate the small window on your monitor titled login. Locate the box host, it should have a number that is the same as the one written on the whiteboard. If not click on the down arrow tab and that number should be on the list. Select it. Next, enter your student matric number into the username field (all CAPITAL LETTERS). Then click connect. You will receive a message asking you to wait for the experiment to start. If you can't reach this step raise your hand and someone will come and assist you.

Figure 1: Trades prices and value in a PUB and a PVT session

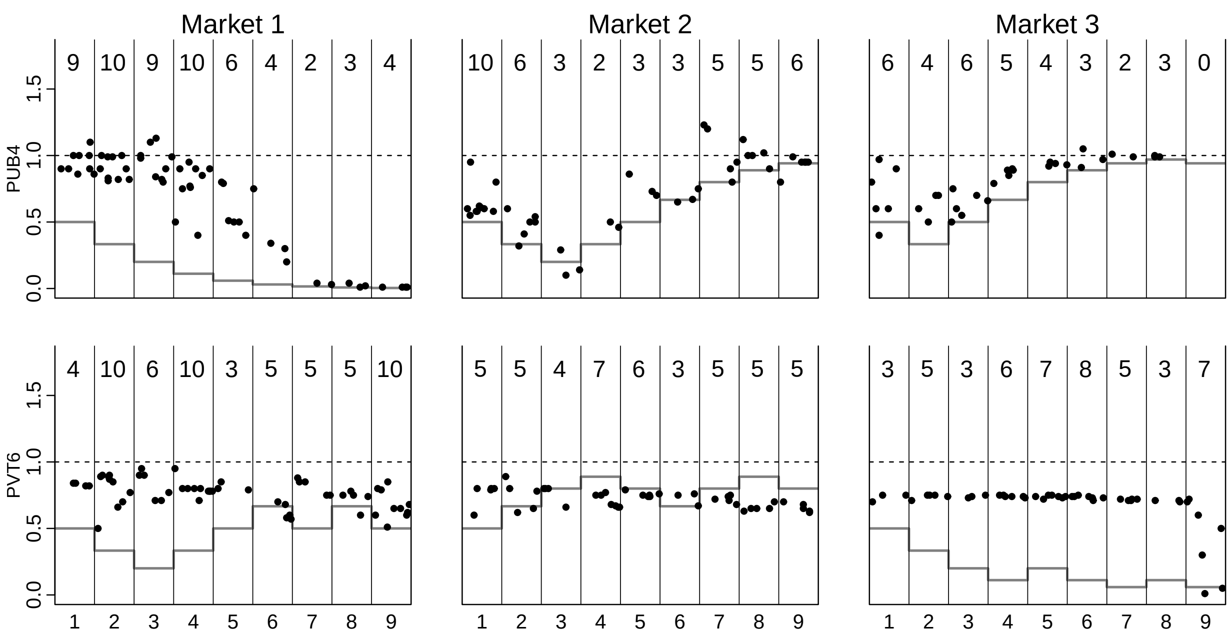


Figure 2: PUB treatment sessions individual contract prices and fundamental value.

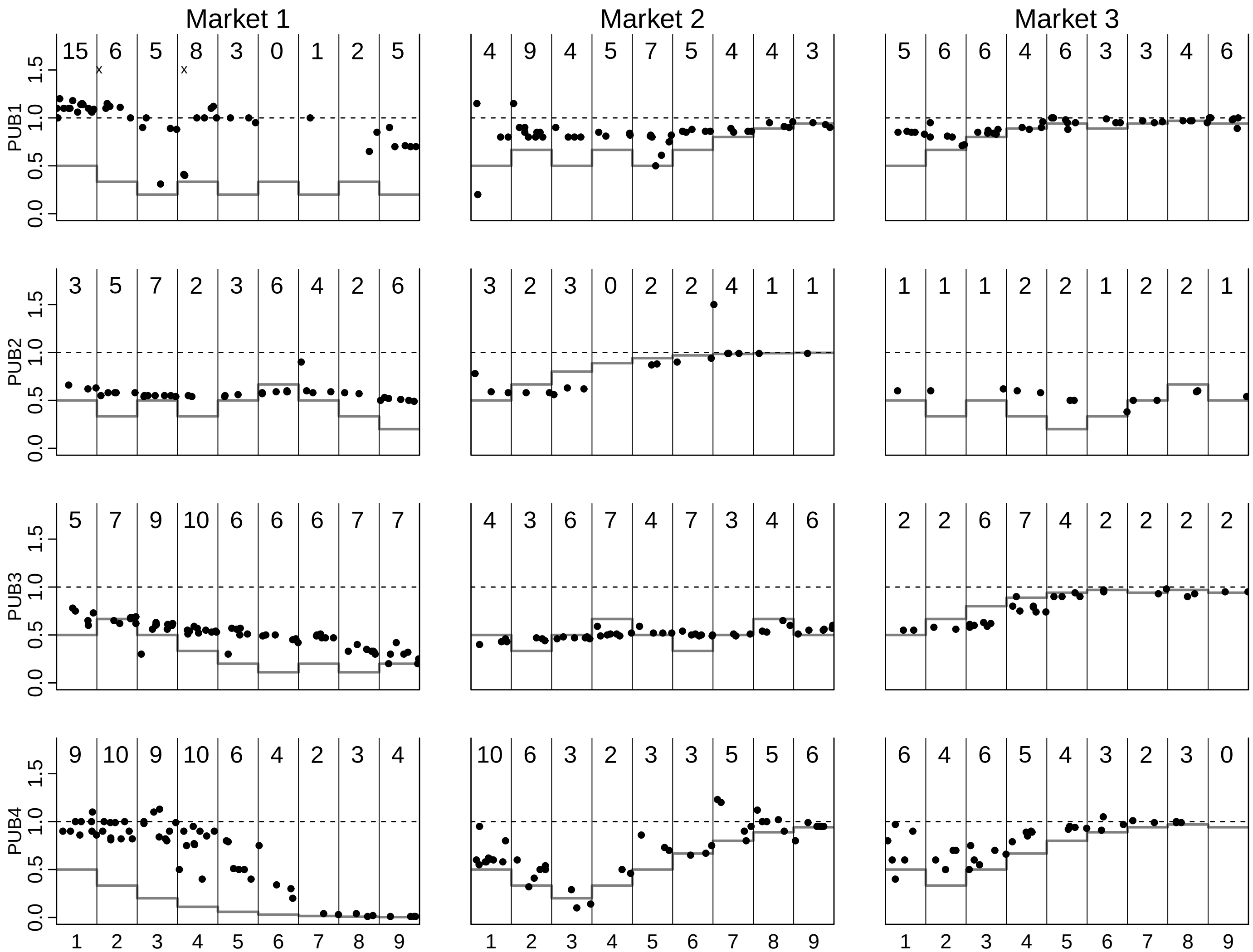


Figure 3: Continued PUB treatment sessions individual contract prices and fundamental value.

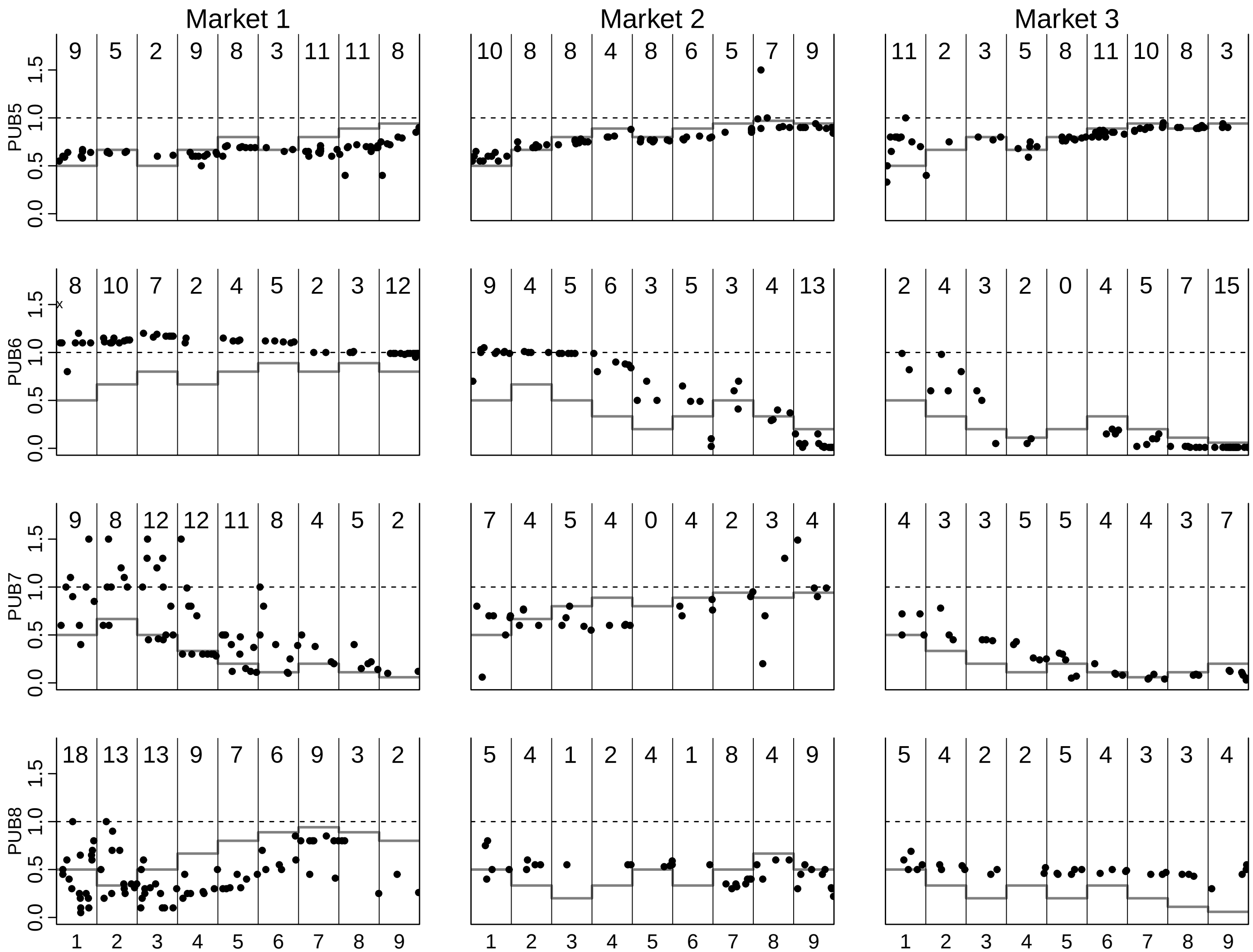


Figure 4: PVT treatment sessions individual contract prices and fundamental value.

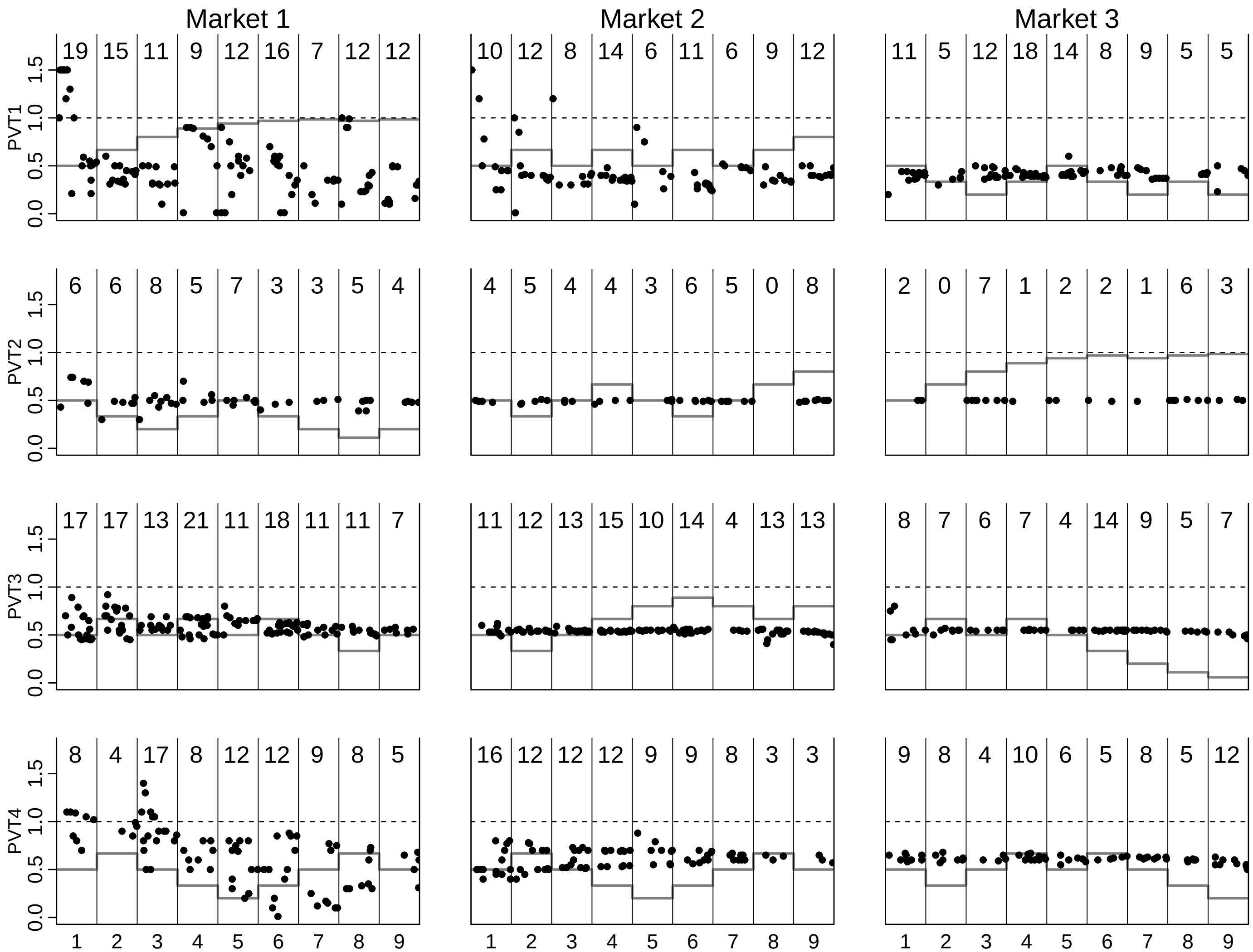


Figure 5: Continued PVT treatment sessions individual contract prices and fundamental value.

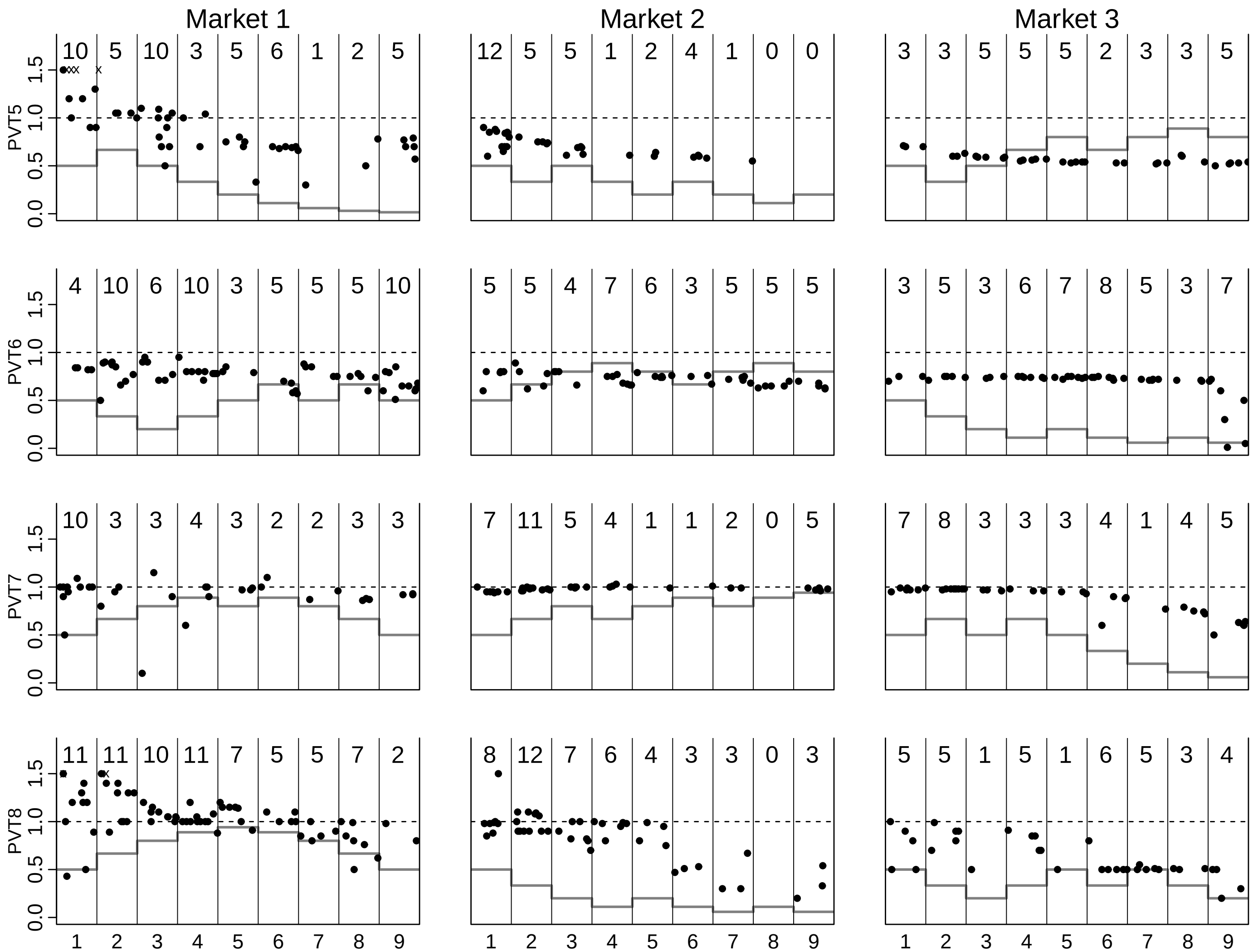


Figure 6: Times series of correlation of fundamental value with the mean, median and closing prices in each period and market.

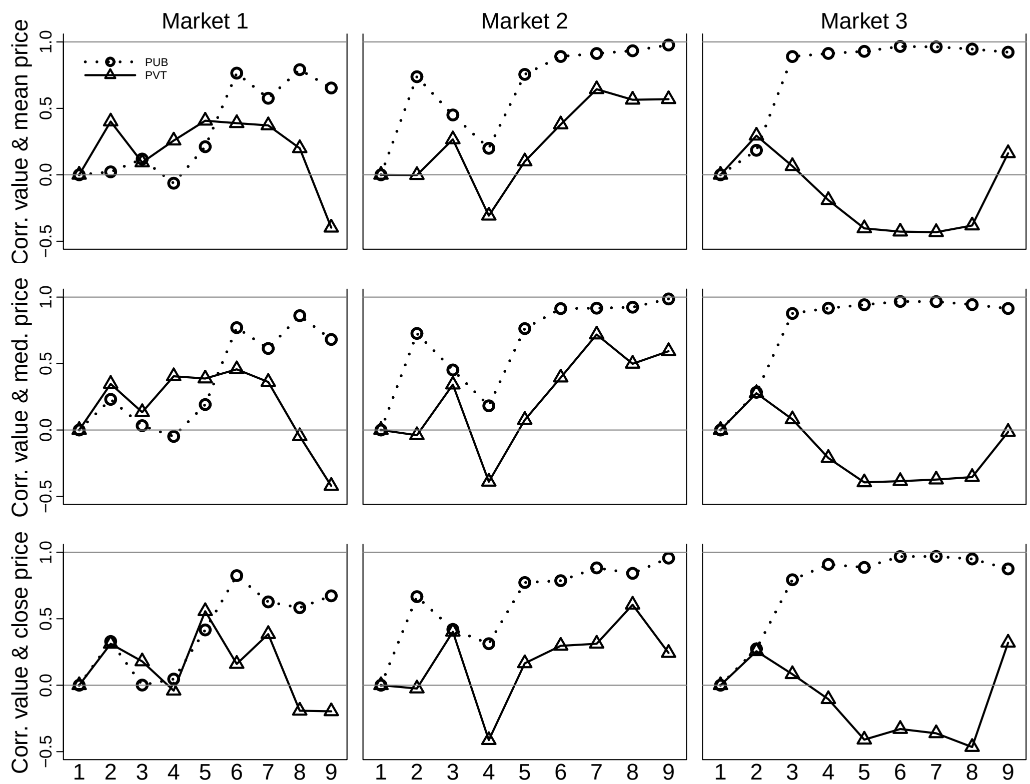


Figure 7: Empirical CDF of Final Asset Holdings for Red and Black Signal Receivers

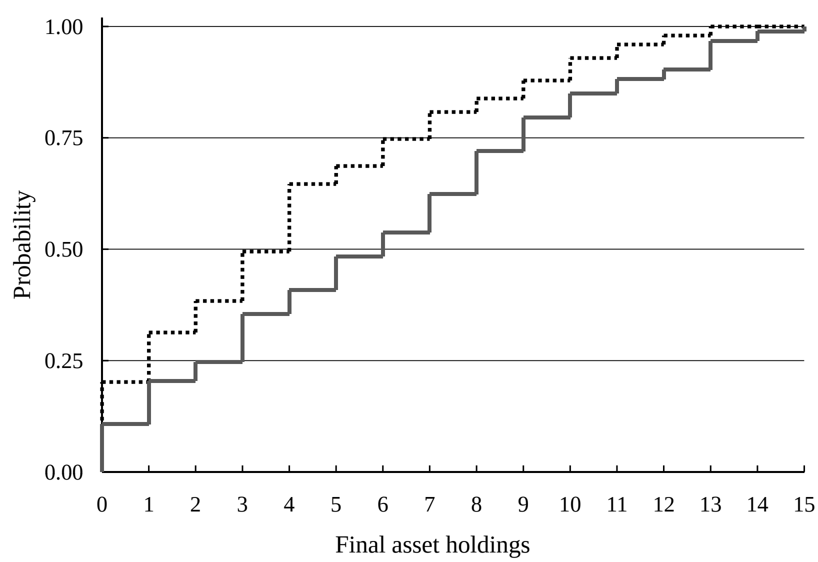


Figure 8: Empirical CDF of Insiders First Contract: PVT

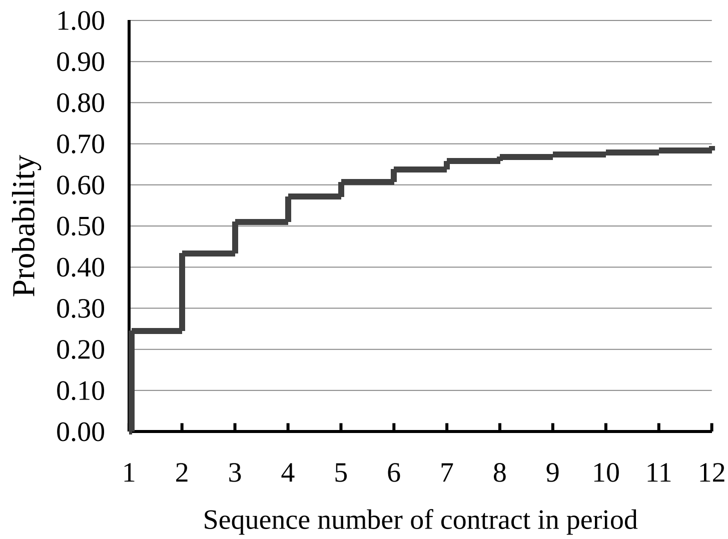


Figure 9: Count of informative, noninformative, and noise contracts according to trade number in period

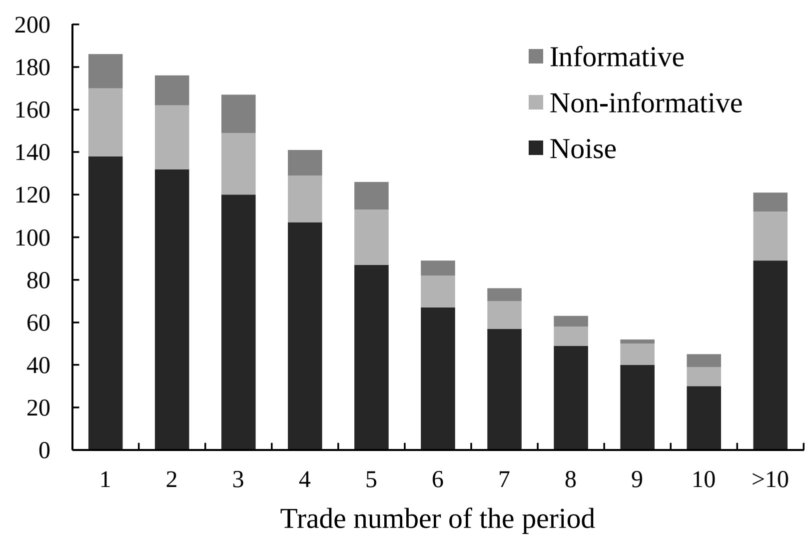


Figure 10: 2SIG treatment sessions individual contract prices and fundamental value.

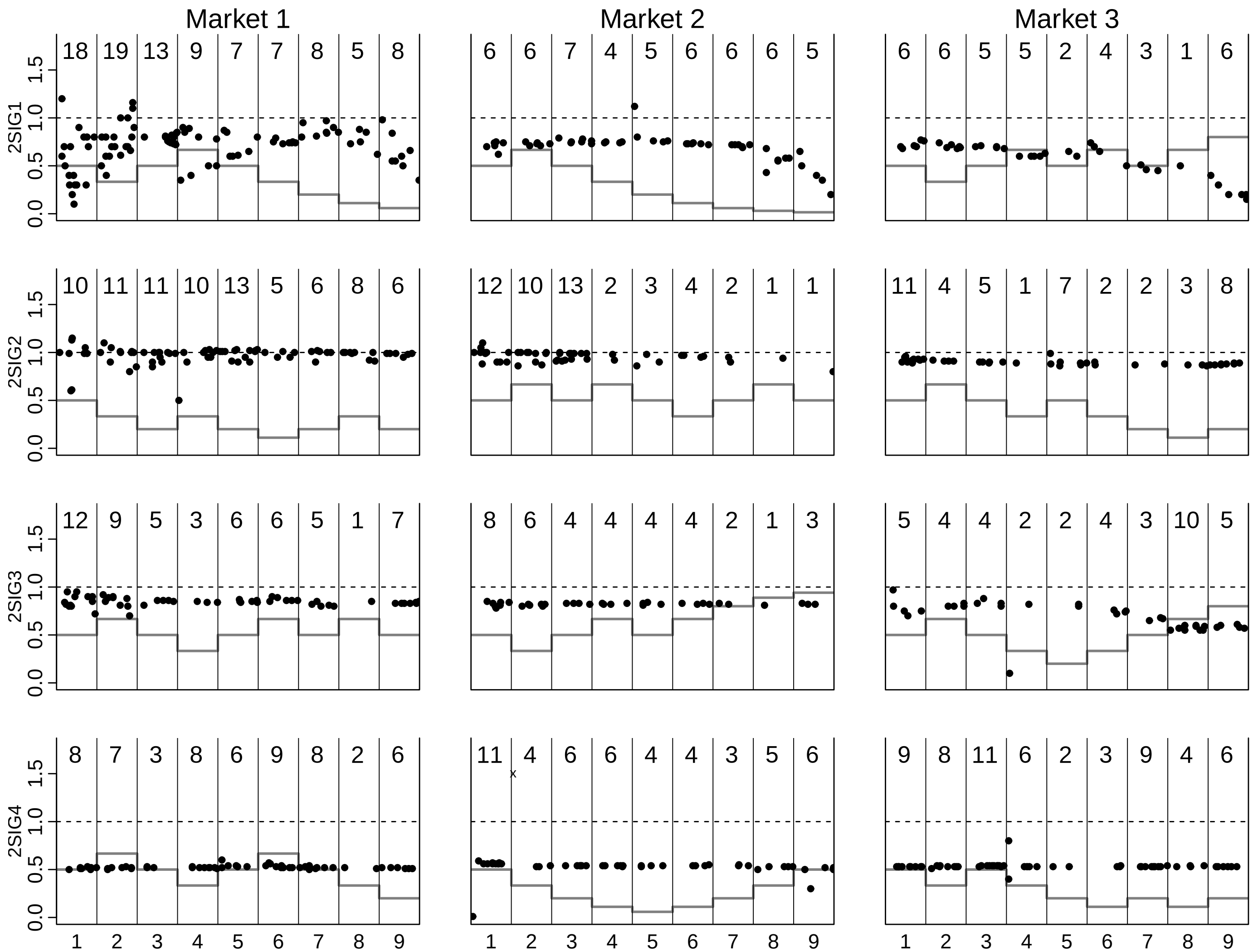


Figure 11: 4SIG treatment sessions individual contract prices and fundamental value.

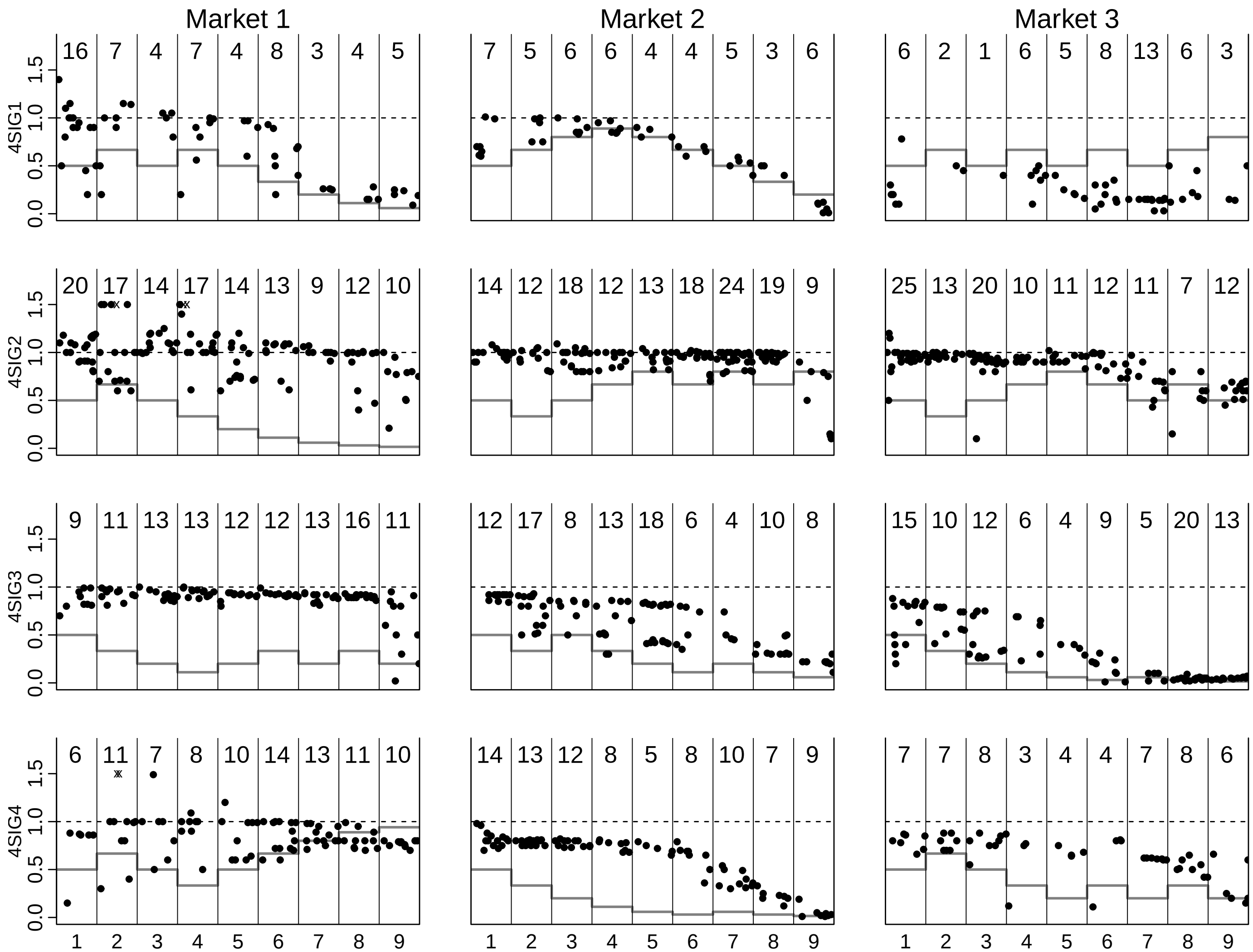


Figure 12: The number of informative, non-informative, and noise contracts by trade number in period: 2SIG and 4SIG

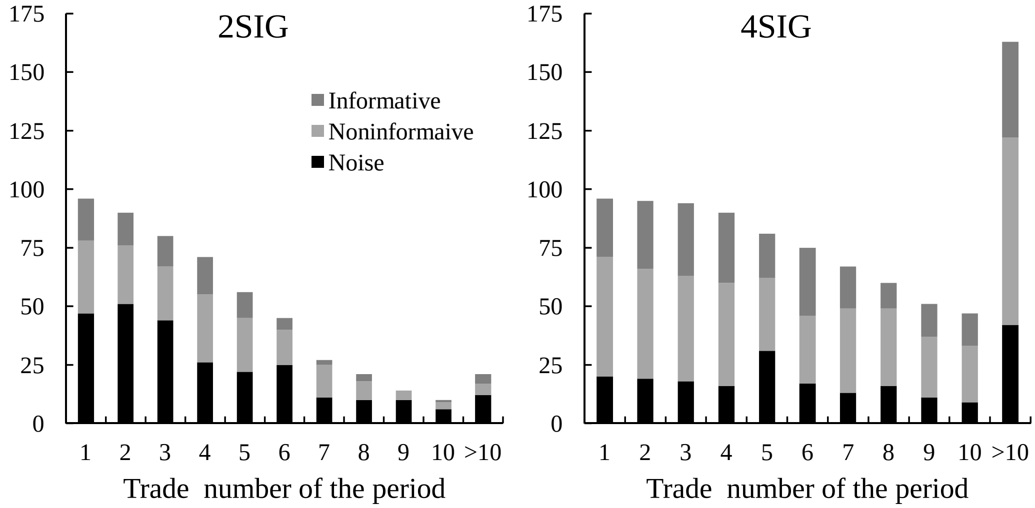


Table 1: Expected dividend conditional on $\#\mathcal{R} - \#\mathcal{B}$

$\#\mathcal{R} - \#\mathcal{B}$	0	1	2	3	4	5	6	7	8
$E[d(a)]$	0.50	0.67	0.80	0.89	0.94	0.97	0.98	0.99	1.00
$\#\mathcal{R} - \#\mathcal{B}$	0	-1	-2	-3	-4	-5	-6	-7	-8
$E[d(a)]$	0.50	0.33	0.20	0.11	0.06	0.03	0.02	0.01	0.00

Expected values are rounded to the nearest one hundredth.

Table 2: Experimental Design

Treatment	Acronym	Markets	Show-Up Fee	Sessions
Public Information	PUB	3	S$10	8
Private Information	PVT	3	S$10	8
Private Information with Two Informed Traders	2SIG	3	S$10	4
Private Information with Four Informed Traders	4SIG	3	S$10	4

Table 3: Correlation between all trade prices and value: PUB and PVT

		Market 1	Market 2	Market 3	Overall
Private signal	Correlation	0.29	0.66	0.88	0.54
	Observations	473	338	291	1102
	P-value	0.00	0.00	0.00	0.00
Public signal	Correlation	-0.03	-0.11	0.05	0.01
	Observations	576	473	399	1448
	P-value	0.53	0.02	0.37	0.61

Table 4: Inefficiency Measures

Panel A: Pricing inefficiency measure = $\frac{|\text{Price-Value}|}{\text{Value}}$

		Overall	Market 1	Market 2	Market 3
PUB	Mean Price	70%	129%	29%	50%
	Median Price	68%	121%	29%	51%
	Close Price	65%	109%	32%	53%
PVT	Mean Price	131%	165%	84%	141%
	Median Price	132%	168%	81%	145%
	Close Price	128%	157%	96%	130%
p-value	Mean Price	0.02	0.62	0.00	0.00
	Median Price	0.02	0.51	0.00	0.00
	Close Price	0.01	0.44	0.01	0.01
Naive Pricing		98%	119%	66%	107%

Panel B: Pricing inefficiency measure = |Price-Value|

		Overall	Market 1	Market 2	Market 3
PUB	Mean Price	18%	29%	14%	12%
	Median Price	18%	28%	13%	12%
	Close Price	18%	26%	15%	12%
PVT	Mean Price	27%	29%	23%	29%
	Median Price	28%	31%	23%	29%
	Close Price	27%	29%	25%	27%
p-value	Mean Price	0.00	0.83	0.00	0.00
	Median Price	0.00	0.41	0.00	0.00
	Close Price	0.00	0.42	0.00	0.00
Naive Pricing		20%	20%	19%	21%

Table 5: Regressions for Equation 1 using mean, median, and closing price

Panel A: PUB treatment

Independent Variables	Δ(Mean Price)	Δ(Median Price)	Δ(Closing Price)
ΔV_{smt}	0.460	0.393	0.397
	*0.081******	*0.066******	*0.068******
Intercept	-0.020	-0.016	-0.017
	*0.010**	*0.008**	*0.008**
Observations	183	183	183
R^2	0.15	0.18	0.17
Wald test of equality of α=0 and $\beta = 1$	33.93	37.25	36.13
Probability $> \chi^2$	<.0001	<.0001	<.0001

Panel B: PVT treatment

Independent Variables	Δ(Mean Price)	Δ(Median Price)	Δ(Closing Price)
ΔV_{smt}	-0.011	-0.051	-0.047
	0.082	*0.064*	*0.057*
Intercept	-0.022	-0.024	-0.025
	*0.011**	*0.009******	*0.008******
Observations	182	182	182
R^2	0.00	0.00	0.00
Wald test of equality of α=0 and $\beta = 1$	3.77	7.54	10.13
Probability $> \chi^2$	0.151	0.023	0.006

Panel C: Test for difference in treatments

Independent Variables	Δ(Mean Price)	Δ(Median Price)	Δ(Closing Price)
$\Delta V_{smt}*$ PVT	-0.445	-0.446	-0.495
	*0.089******	*0.092******	*0.114******
ΔV_{smt}	0.400	0.396	0.461
	*0.066******	*0.068******	*0.084******
Intercept	-0.021	-0.020	-0.020
	*0.006******	*0.006******	*0.008******
Observations	365	365	365.00
R^2	0.10	0.10	0.08

*, **, and *** indicate 10%, 5%, and 1% levels of significance respectively.
This convention holds throughout the paper.

Table 6: Regressions for Equation 2 in PUB treatment

Independent Variable	Mean Price	Median Price	Closing Price
ΔV_{smt}	0.491	0.466	0.468
	*0.091******	*0.072******	*0.072******
$\Delta V_{sm,t-1}$	0.308	0.321	0.347
	*0.085******	*0.066******	*0.067******
$P_{sm,t-1}$	0.907	0.955	0.946
	*0.042******	*0.035******	*0.035******
Intercept	0.038	0.007	0.010
	0.029	*0.024*	*0.024*
Observations	159	159	159
R^2	0.78	0.86	0.85

Table 7: Regressions for Equation 2 in PVT treatment

Independent Variable	Mean Price	Median Price	Closing Price	Stationary Price
ΔV_{smt}	-0.066	-0.054	-0.040	
	0.075	*0.061*	*0.054*	
$\Delta V_{sm,t-1}$	0.046	0.059	0.061	
	0.072	*0.058*	*0.051*	
$P_{sm,t-1}$	0.328	0.566	0.564	
	*0.084******	*0.068******	*0.065******	
α_1	0.259	0.175	0.177	0.40
	*0.041******	*0.035******	*0.033******	
α_2	0.330	0.215	0.216	0.49
	*0.056******	*0.045******	*0.042******	
α_3	0.358	0.234	0.235	0.54
	*0.051******	*0.043******	*0.040******	
α_4	0.397	0.247	0.250	0.57
	*0.058******	*0.046******	*0.044******	
α_5	0.396	0.255	0.244	0.58
	*0.064******	*0.052******	*0.049******	
α_6	0.441	0.297	0.297	0.68
	*0.066******	*0.055******	*0.051******	
α_7	0.609	0.385	0.380	0.89
	*0.085******	*0.069******	*0.065******	
α_8	0.446	0.272	0.282	0.60
	*0.073******	*0.062******	*0.059******	
Observations	159	159	159	
R^2	0.61	0.73	0.77	
Wald stat. all α_i equal	32.660	19.720	22.810	
Probability $> \chi^2$	<.0001	0.006	0.002	

Table 8: Percentage of bubble trading periods according to alternative criteria

Panel A

Treatment	Market	Max. Price > 1	Med. Price > 1	Mean Price > 1	Min. Price > 1
PUB	I	33.8	19.72	18.31	14.08
PUB	II	14.29	4.29	8.57	1.43
PUB	III	8.57	1.43	1.43	0.00
PVT	I	29.17	18.06	12.5	5.56
PVT	II	17.91	4.48	4.48	2.99
PVT	III	1.41	0.00	0.00	0.00

Panel B

Treatment	Market	(1) No. of trade	(2) No. of trade price>1	(3)=(2)/(1)	No. of periods
PUB	I	473	71	15.0%	71
PUB	II	338	15	4.4%	70
PUB	III	291	2	0.7%	70
PVT	I	576	69	12.0%	72
PVT	II	473	12	2.5%	67
PVT	III	399	0	0.0%	71

Table 9: Impact of bubbles on information aggregation and price efficiency.

	Price Level		Δ Price	
Independent Variable	PUB	PVT	PUB	PVT
ΔV_{smt}	0.493	-0.077	0.500	-0.050
	(0.093)***	(0.075)	(0.094)***	(0.089)
$\Delta V_{sm,t-1}$	0.313	-0.002	0.281	0.099
	(0.087)***	(0.072)	(0.086)***	(0.085)
$P_{sm,t-1}$	0.904	0.232		
	(0.044)***	(0.089)**		
B_{smt}	0.049	0.171	0.011	-0.007
	(0.092)	(0.085)**	(0.092)	(0.094)
$B_{smt} * \Delta V_{smt}$	-0.238	0.214	-0.183	-0.680
	(0.749)	(0.783)	(0.763)	(0.906)
$B_{sm,t-1} * \Delta V_{sm,t-1}$	0.039	0.833	-0.260	-0.352
	(0.030)	(0.563)	(0.490)	(0.649)
Observations	159	159	159	159
R^2	0.79	0.64	0.22	0.02
Wald stat. all α_i equal		39.38		
Probability > χ^2		<.0001		

Note: Estimates of intercept terms are suppressed.

Table 10: Impact of learning on information aggregation and price efficiency

	PUB			PVT		
Independent Variable	Closing Price	Median Price	Mean Price	Closing Price	Median Price	Mean Price
$P_{sm,t-1}$	0.923	0.965	0.965	0.371	0.552	0.582
	(0.041)***	(0.035)***	(0.036)***	(0.073)***	(0.057)***	(0.055)***
ΔV_{smt}	0.420	0.324	0.265	-0.084	-0.118	-0.050
	(0.138)***	(0.113)***	(0.116)**	(0.118)	(0.096)	(0.087)
$\text{Market}_2 * \Delta V_{smt}$	0.085	0.096	0.205	-0.034	0.029	-0.056
	(0.191)	(0.156)	(0.161)	(0.167)	(0.137)	(0.124)
$\text{Market}_3 * \Delta V_{smt}$	0.032	0.117	0.193	0.204	0.209	0.132
	(0.209)	(0.171)	(0.176)	(0.169)	(0.138)	(0.125)
Num. Obs.	183	183	183	182	182	182
R^2	0.76	0.83	0.82	0.63	0.74	0.77

Note: Estimates of intercept terms are suppressed.

Table 11: Average final asset units holdings conditional upon signal

Signal	Market 1	Market 2	Market 3	Total
Black	4.64	3.72	4	4.13
Stand. dev.	*3.58*	*3.52*	*3.84*	*3.65*
Red	5.39	6.06	6.37	5.92
Stand. dev.	*3.88*	*4.27*	*4.46*	*4.17*
Total	5.00	5.00	5.00	5.00
Stand. Dev.	*3.55*	*3.97*	*4.52*	*4.01*

Table 12: Average market profit conditional on signal and true dividend

	$d(a) = 0$		$d(a) = 1$	
Signal	Black	Red	Black	Red
Market 1	5.51	3.98	9.35	10.48
Stand. dev.	*3.59*	*3.71*	*2.34*	*3.32*
Market 2	5.38	4.37	8.98	10.55
Stand. dev.	*3.39*	*2.57*	*2.21*	*1.93*
Market 3	5.53	4.05	7.49	10.36
Stand. dev.	*2.52*	*2.72*	*2.28*	*2.17*
Total	5.49	4.11	9.13	10.5
Stand. dev.	*2.96*	*2.84*	*2.24*	*2.58*

Table 13: Sorting rules of trades into Noise, Informative, and Non-informative Classifications

Price Change	Signal	Informed Trader Role	Classification
-	-	None	Noise
Positive	Red	Buyer	Informative
Positive	Red	Seller	Non-informative
Positive	Black	Either	Non-informative
Negative	Black	Seller	Informative
Negative	Black	Buyer	Non-informative
Negative	Red	Either	Non-informative
None	Either	Either	Non-informative

Table 14: Correlation between all trade prices and value: 2SIG and 4SIG

		Market 1	Market 2	Market 3	Overall
2SIG	Correlation	-0.30	0.29	-0.10	-0.02
	Observations	285	184	178	647
	P-value	0.00	0.00	0.18	0.59
4SIG	Correlation	0.10	0.62	0.51	0.36
	Observations	384	367	319	1070
	P-value	0.05	0.00	0.00	0.00

Table 15: 2SIG and 4SIG price difference regressions

	2SIG			4SIG		
Variable	Clos. P.	Med. P.	Mean P.	Clos. P.	Med. P.	Mean P.
ΔV_{smt}	-0.087	0.011	-0.053	0.507	0.212	0.178
	0.065	*0.008*	*0.015*	*0.176******	*0.015******	*0.013******
Intercept	-0.022	-0.013	-0.013	-0.039	-0.053	-0.051
	*0.009****	*0.008*	*0.015*	*0.023**	*0.015******	*0.013******
Numb. of obs.	96	96	96	96	96	96
R^2	0.02	0.00	0.00	0.08	0.04	0.04

Table 16: 2SIG and 4SIG price level regressions

Variable	2SIG Closing Price	2SIG Median Price	2SIG Mean Price	2SIG Stationary Price	4SIG Closing Price	4SIG Median Price	4SIG Mean Price
$P_{sm,t-1}$	0.811	0.730	0.255		0.741	0.963	0.997
	*.127****	*.117****	*.117***		*.089****	*.065****	*.058****
ΔV_{smt}	-0.103	-0.003	-0.108		0.415	0.205	0.175
	.053	*.066*	*.088*		*.174***	*.116**	*.099**
α_1	0.067	0.151	0.483	0.56	0.118	-0.032	-0.051
	.090	*.082**	*.085****		*.065**	*.048*	*.042*
α_2	0.163	0.245	0.687	0.91	0.179	-0.011	-0.045
	.119	*.113***	*.113****		*.095**	*.069*	*.061*
α_3	0.141	0.205	0.585	0.76	0.093	-0.035	-0.055
	.104	*.094***	*.096****		*.072*	*.053*	*.045*
α_4	0.097	0.140	0.417	0.52	0.163	-0.029	-0.045
	.071	*.064***	*.072****		*.076***	*.057*	*.049*
Numb. of obs.	96	96	96		96	96	96
R^2	0.76	0.81	0.57		0.56	0.78	0.82
Wald statistic for all α_i equal	8.22	6.23	25.47		1.91	0.27	0.09
Probability $> \chi^2$	0.042	0.101	<.001		0.591	0.966	0.992

Table 17: Portfolio adjustments in 2SIG and 4SIG treatments

2SIG	Market 1	Market 2	Market 3	Total
2 Black	4.85	5.22	1.78	4.06
Stand. dev.	*4.28*	*4.41*	*2.54*	*4.06*
1 Red 1 Black	4.50	3.69	5.29	4.45
Stand. dev.	*4.09*	*4.08*	*4.45*	*4.16*
2 Red	6.80	7.71	7.78	7.52
Stand. dev.	*2.59*	*1.98*	*4.44*	*3.25*
Total	5.00	5.00	5.00	5.00
Stand. dev.	*3.95*	*4.05*	*4.51*	*4.13*
4SIG	**Market 1**	**Market 2**	**Market 3**	**Total**
Favor Black	4.72	3.95	3.57	4.12
Stand. dev.	*3.80*	*3.54*	*8.09*	*5.16*
Neutral	3.57	6.88	5.92	5.59
Stand. dev.	*3.15*	*4.49*	*7.17*	*5.58*
Favor Red	7.14	6.00	6.50	6.61
Stand. dev.	*4.38*	*4.90*	*4.85*	*4.42*
Total	5.00	5.00	5.00	5.00
Stand. dev.	*3.89*	*4.08*	*7.15*	*5.20*

Table 18: Ratio of informative trades to total trades

	Mean Values		
	PVT	2SIG	4SIG
Market 1	6.7%	15.2%	27.3%
Market 2	9.0%	16.3%	30.6%
Market 3	11.1%	18.4%	27.4%
Overall	8.4%	16.4%	28.5%

Table 19: Impact of fraction of informed traders

	Panel A		
Independent variables	Δ Mean price	Δmedian price	Δ Close price
Intercept	-0.026	-0.025	-0.029
	*0.005******	*0.005******	*0.006******
ΔV_{smt}	-0.131	-0.104	-0.095
	*0.062****	*0.06**	*0.077*
$\Delta V_{smt}*$ Percent Informed	0.062	0.060	0.077
	*0.108******	*0.105******	*0.133******
R^2	0.07	0.07	0.07
Observations	557	557	557

	Panel B		
Independent variables	Δ Mean price	Δmedian price	Δ Close price
$\Delta V_{smt}*$ PVT	-0.450	-0.451	-0.491
	*0.099******	*0.097******	*0.123******
$\Delta V_{smt}*$ 2SIG	-0.461	-0.395	-0.511
	*0.109******	*0.104******	*0.134******
$\Delta V_{smt}*$ 4SIG	-0.190	-0.150	-0.093
	*0.114**	*0.112*	*0.146*
ΔV_{smt}	0.403	0.4	0.475
	*0.074******	*0.072******	*0.09******
Intercept	0.07	0.07	0.09
	*0.005******	*0.005******	*0.006******
P value for Wald Statistic			
$\Delta V_{smt}*$ PVT = $\Delta V_{smt}*$ 2SIG	0.912	0.571	0.879
$\Delta V_{smt}*$ 2SIG = $\Delta V_{smt}*$ 4SIG	0.021	0.031	0.006
$\Delta V_{smt}*$ PVT = $\Delta V_{smt}*$ 4SIG	0.007	0.005	0.005
R^2	0.07	0.07	0.07
Observations	557	557	557