Learning from unrealized versus realized prices

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Abstract

Our market experiments investigate the extent to which traders learn from the price, differentiating between situations where orders are submitted before versus after the price has realized. In simultaneous markets with bids that are conditional on the price, traders neglect the information conveyed by the hypothetical value of the price. In sequential markets where the price is known prior to the bid submission, traders react to price to an extent that is roughly consistent with the benchmark theory. The difference is robust to a number of variations. (JEL D82, D81, C91)

1 Introduction

Market prices reflect much information about fundamental values. The extent to which traders are able to utilize this information has important welfare consequences but is difficult to measure as one often lacks control of the traders’ restrictions, beliefs and preferences. One possibility to detect a bias in price inference is to modify the informational environment in a way that is irrelevant for rational traders. If trading reacts to a framing variation that is uninformative under rational expectations, the latter assumption is questionable. We focus on an important dimension of variability between markets, the conditionality of price. In simultaneous markets, the price realization is unknown to the traders at the time when they make their decisions—examples are financial markets with limit orders or other supply/demand function regimes. Theoretically, traders would incorporate the information of each possible price into their bids, as in the Rational Expectations Equilibrium prediction by Grossman (1976), inter alia. But the price information is hypothetical and traders may find it hard to make the correct inference in hypothetical conditions. A host of evidence on Winner’s Curse and other economic decision biases is consistent with this conjecture, as is the psychological evidence on accessibility (Kahneman 2003) and contingent thinking (Evans 2007).

Simultaneous asset markets are a relevant point in case for such failures of contingent thinking; one that has not previously been researched, to our knowledge. In contrast, sequential markets—e.g.

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1Experiments analyzing the Winner’s Curse include, for example, Bazerman and Samuelson (1983), Kagel and Levin (1986), Kagel, Levin, Battalio, and Meyer (1989). For a thorough review on the Winner’s Curse literature see Kagel and Levin (2009).
many quote-based markets and sequential auctions—have the traders know the price at which they can complete their trades. Here, it may still be nontrivial to learn from the price; but both the psychological research on contingent reasoning and the related economic experiments that include treatment variations where simultaneity is switched on and off (Carrillo and Palfrey (2011), Esponda and Vespa (2014) and Li (2016)) suggest that the task is more accessible in a sequential trading mechanism than in a simultaneous one. Our new series of experiments confirms this hypothesis, in a simple and non-strategic market environment where agents act as price takers.

Our market participants trade a single, risky, common-value asset. To trade optimally, a participant considers two pieces of information: her private signal and the information conveyed by the asset price. The latter is informative because it is influenced by the trading activity of another market participant who has additional information about the asset value. To manipulate the accessibility of the price information, we perform the experiment in two main treatments, simultaneous (SIM) versus sequential (SEQ). In treatment SIM, participants receive a private signal and submit a limit order. If the realized market price lies above the limit, the trader buys one unit of the asset, otherwise she sells one unit. Despite the fact that the price has not yet realized, SIM traders would optimally infer the extent to which a high price indicates a high value and, thus, soften the demand’s downward reaction to a higher price, relative to the case that the price is uninformative. The possibility that traders may fail to learn from hypothetical prices is examined by comparing to the treatment with sequential markets, SEQ, where the price is known when traders choose to buy or sell. Conditional thinking is not necessary here but treatments SIM and SEQ are nevertheless equivalent: they have isomorphic strategy sets and isomorphic mappings from strategies to payoffs.

Section 2 presents the experimental design in detail and Section 3 discusses our behavioral hypotheses. We present three benchmark predictions for comparison with the data: first, full naiveté, where the trader learns nothing from the price; second, the Bayes-Nash prediction, where a trader assumes that previous trades are fully rational and accounts for it; and third, the empirical best response that takes into account the actual distribution of previous trades, which may deviate from optimality. We use the latter as our main benchmark for optimality as it maximizes the traders’ expected payments.

The data analysis of Section 4 shows that the participants’ inference of information from the price varies substantially between simultaneous versus sequential markets. In SIM, participants often follow the prediction of the naive model, thus showing ignorance of the information contained in the price. Price appears to matter mainly in its direct influence on the utility from trade—a buyer pays the price, a seller receives it—as is indicated by a comparison between the groups of traders who have uninformative versus informative prices. In contrast, in SEQ, where transaction prices are known beforehand, asset demand is much more affected by the information contained in the price and the large majority of trades are as predicted by empirical best response. Averaging over all situations where the fully naive benchmark differs from the empirical best response, the frequency of naive trading decisions is twice as high in SIM.

Traders also have the option to reverse their limit order, selling at low prices and buying at high prices. This ensures the equivalence between the treatments, see Section 2. In each treatment, we restrict the trades to a single unit of supply or demand per trader.

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relative to SEQ, at 38% versus 19%.

Section 5 identifies various possible sources underlying the difficulty of hypothetical thinking in our markets. One possibility is that the participants feel rather well-informed by their own signals, relative to what they can learn from the price. We thus repeat the experiment with two treatments where early traders are much better informed than later traders, rendering learning from the price more important and more salient. We find that the replication only exacerbates the differences between simultaneous and sequential markets, both in terms of behavior and payoff consequences. This evidence makes it implausible that the bias is driven by negligence or the lack of salience of the price’s informativeness. A further hypothesis is that the effect arises due the difficulty in correctly interpreting human choices. As in the literature examining inference in games versus in single-person tasks (Charness and Levin [2009] [Ivanov et al. 2010]), we therefore ask whether the bias also occurs if the price is generated by an automated mechanism. The corresponding treatment comparison replicates the main results. We can therefore rule out that the effect is driven by the necessity of responding to the behavior of others. Finally, we ask whether the difficulty in contingent reason lies in the amount of required inference, or rather in the hypothetical nature of price. To this end, we run another treatment where only one of the possible prices is considered, but trades are hypothetical. The rate of optimal choices in this treatment lies nearly mid-way between that of the two main treatments, suggesting that the difficulty on contingent thinking is fuelled by both the amount and the hypothetical nature of our hypothetical bids in simultaneous markets.

We then combine the different treatments into an aggregate estimation of information use (Section 5.4). The analysis of the combined simultaneous treatments shows that relative to empirical best response, the participants under-weight the information contained in the price to a degree that is statistically significant (at $p = 0.09$ in a two-tailed test) and that they strongly significantly over-weight their own signals’ importance. In the sequential treatments, they over-weight both price and their own signal. Overall, the estimates indicate that traders far under-weight the prior distribution of the asset’s value but that they nevertheless learn too little from the price in simultaneous markets.

Taken together, the experiments provide evidence of an interaction between market microstructure and the efficiency of information usage. In the language introduced by Eyster and Rabin [2005], we find that the degree of ‘cursedness of beliefs’ is higher when the information contained in the price is less accessible: with price not yet realized, traders behave as if they tend to ignore the connection between other traders’ information and the price. Aggregate demand therefore decreases too fast with the price. The economic bearing of the effect is further discussed in Section 6. We examine the predictions of Hong and Stein [1999] and Eyster et al. [2015] that markets with naive traders, who cannot learn from the price, generate an inefficient and slow price discovery. Naive traders tend to speculate against the price, pushing it back towards its ex-ante expectation also in cases where their own signals are consistent with the direction of price movement. This erroneous speculation reduces the extent to which the price reveals the underlying value. Confirming the prediction, we simulate a standard price setting rule with our data and find that price discovery is slower in simultaneous treatments than in sequential treatments. This implies that in the hypothetical case that further traders would observe the prices that our
participants generate, their expectations of value would be harmed. But naiveté is detrimental not only later players’ payoffs: also the observed payoffs of our market participants themselves is significantly lower in SIM than in SEQ.

While we focus on financial markets, we again emphasize that our finding are also consistent with evidence in very different domains. The experimental literatures in economics and psychology provide several sets of related evidence that conditional inference is suboptimal. Psychologists have confirmed quite generally that decision processes depend on task complexity [Olshavsky, 1979] and that participants prefer decision processes with less cognitive strain. They focus on one model, one alternative or one relevant category when reflecting about possible outcomes and their consequences [Evans, 2007; Murphy and Ross, 1994; Ross and Murphy, 1996]. They also process salient and concrete information more easily than abstract information (see e.g. Odean, 1998 and the literature discussed there). Several authors before us have pointed out that a possibility to reduce the complexity of learning is to proceed in a sequential mechanism, like in quote-driven markets[3] Our experiment suggests a specific manifestation of this effect, namely that drawing the attention to the realized price may enable the decision maker to interpret more easily the information underlying the price. In the related bilateral bargaining experiment by Carrillo and Palfrey (2011), buyers also trade more rationally in a sequential trading mechanism than in a simultaneous one. They processed information more easily and exhibited less non-Nash behavior when facing a take-it-or-leave-it price instead of bidding in a double auction. Similarly, auction experiments find that overbidding is substantially reduced in dynamic English auctions compared to sealed-bid auctions (Levin et al., 1996). Other contributions suggest that traders may systematically disregard relevant information that is conveyed by future, not yet realized events: overbidding decreases substantially as soon as finding the optimal solution does not necessitate updating on future events (Charness and Levin, 2009; Koch and Penczynski, 2014). Another related study is the voting experiment of Esponda and Vespa (2014) who find that when the voting rules follow a simultaneous game that requires hypothetical thinking, the majority of participants behave nonstrategically, whereas in the sequential design they are able to extract the relevant information from others’ actions and behave strategically.

We complement the described evidence on contingent thinking in strategic situations (bilateral bargaining games, auctions and strategic voting games) by addressing financial markets that clear exogenously and where traders are price takers. Our sole focus is on the information contained in the price, which the traders may or may not use rationally. The simple structure of the traders’ decision problems also helps us to straightforwardly assess whether the typical trader makes too much or too little inference from the price.

[3] Shafir and Tversky (1992) note that participants see their preferences more clearly if they focus on one specific outcome. As they observe, “[t]he presence of uncertainty […] makes it difficult to focus sharply on any single branch [of a decision tree]; broadening the focus of attention results in a loss of acuity” (p.457).

2 Experimental Design

The basic framework is identical across treatments, involving a single risky asset and money. A market consists of two agents, agent 1 and agent 2, who each either buy or sell one unit of the risky asset. The asset is worth $\theta \in \{\underline{\theta}, \overline{\theta}\}$, with equal probabilities. Agents do not observe the fundamental value $\theta$ but they each receive a private signal $s_i \in [0, 1]$. The true value $\theta$ determines which of two triangular densities the signal is drawn from, such that in the low-value state the participants receive low signals with a higher probability, and vice versa:

$$f(s_i|\theta) = \begin{cases} 
2(1 - s_i) & \text{if } \theta = \underline{\theta} \\
2s_i & \text{if } \theta = \overline{\theta} 
\end{cases} \quad i \in \{1, 2\} \quad (1)$$

Conditional on $\theta$, the signals of the two agents are independent.

Each agent $i$ faces a separate transaction price $p_i$. The price $p_1$ for agent 1 is uniformly distributed in $[\underline{\theta}, \overline{\theta}]$ and is uninformative about the fundamental value $\theta$. Agent 1 observes his private signal $s_1$ and states his maximum willingness to pay by placing a limit order $b_1$. If $p_1$ lies weakly below $b_1$, he buys one unit of the asset. If $p_1$ strictly exceeds $b_1$, he sells one unit. By checking an additional box, agent 1 may convert his limit order into a “reversed” limit order. A reversed limit order entails the opposite actions: a buy occurs if $p_1$ weakly exceeds $b_1$, otherwise a sell takes place. (Only few participants make use of it; we defer the motivation for allowing reversed limit orders to Section 2.2.)

Let $Z_1$ represent the indicator function that takes on value 1 if a limit order is reversed. Then, agent 1’s demand is the function $X_1$:

$$X_1 = Y_1(1 - Z_1) - Y_1Z_1 \quad (2)$$

$$Y_1 = \begin{cases} 
1 & \text{if } p_1 \leq b_1 \\
-1 & \text{if } p_1 > b_1 
\end{cases} \quad \text{where } p_1 \sim U(\underline{\theta}, \overline{\theta})$$

The task of agent 2 varies across the two main treatments, a simultaneous and a sequential mechanism.

2.1 Simultaneous treatment (SIM)

Agent 2 observes agent 1’s price $p_1$ and her own private signal $s_2$. Like agent 1, she chooses a limit order or, optionally, a reversed limit order. When submitting her decision, she does not know her own price $p_2$.

Participants are informed that the price $p_2$ reflects the expectation of an external market maker, who observes agent 1’s buying or selling decision and who assumes that agent 1 bids rationally upon receipt of his signal $s_1$. They also

$^5$Because of a possible reluctance to sell short, we avoid any notion of short sales in the experimental instructions. Participants are told that they already possess a portfolio that needs to be adjusted by selling or buying one unit of a given asset.
learn the corresponding pricing rule that maps \( p_1 \) and the realized demand of agent 1, \( x_1 \), into \( p_2 \):

\[
p_2 = E[\theta|x_1] = \begin{cases} 
\frac{\theta + p_1}{2}, & \text{if } x_1 = 1 \\
\frac{\theta - p_1}{2}, & \text{if } x_1 = -1 
\end{cases}
\]  

Participants also receive a verbal explanation that for given \( p_1 \), their own price \( p_2 \) can take on only one of the two listed possible realizations, depending on whether agent 1 buys or sells. Through \( X_1 \), \( p_2 \) is influenced by agent 1’s private signal \( s_1 \) and is therefore informative about the asset’s value \( \theta \). Ideally, agent 2 conditions her investment decision on two different sources of information, \( s_2 \) and \( p_2 \).

2.2 Sequential treatment (SEQ)

In treatment SEQ, agent 2 observes the price \( p_2 \) as specified in (3) before making her decision. The game proceeds sequentially, with agent 1 first choosing his (possibly reversed) limit order \( b_1 \). As in treatment SIM, his demand \( X_1 \) determines the price for agent 2, \( p_2 \). Agent 2 observes the realized value of \( \{p_1, p_2, s_2\} \) and chooses between buying and selling at \( p_2 \).

It is straightforward to check that treatments SIM and SEQ are strategically equivalent. Treatment SEQ allows for four possible strategies contingent on \( p_2 \in \{\frac{\theta + p_1}{2}, \frac{\theta - p_1}{2}\} \): \{buy, buy\}, \{buy, sell\}, \{sell, buy\} and \{sell, sell\}. In treatment SIM, enabling agent 2 to observe \( p_1 \) and to reverse her limit order makes the strategy space isomorphic to that of treatment SEQ: the same four combinations of buying and selling contingent on \( p_2 \) are possible in both treatments.

2.3 Payoffs

In each of the treatments, the experimenter takes the other side of the market, which therefore always clears. In case of a buy, the profit \( \Pi_i \) of agent \( i \in \{1, 2\} \) is the difference between the fundamental value and the market price, and vice versa if the asset is sold:

\[
\Pi_i = (\theta - p_i)X_i
\]  

Not only strategy spaces are isomorphic between treatments SIM and SEQ, but also payoffs arising from each combination of strategies and signals are identical. Any rational response to a fixed belief about agent 1 leads to the same purchases and sales in the two treatments.

3 Predictions

We mainly focus on agent 2 and compare the participants’ behavior to three theoretical predictions. The first two are variants of the case that agent 2 has rational expectations and properly updates on her complete information set. As the third benchmark, we consider the case that agent 2 fully neglects the price’s informativeness. In all cases, we assume agents to be risk neutral.
3.1 Rational best response

Agent 1 has only his private signal $s_1$ to condition his bid upon. His optimal limit order $b^*_1$ is not reversed and maximizes the expected profit conditional on $s_1$. It is easy to show (using the demand function (2)) that $b^*_1$ increases linearly in the signal:

$$b^*_1(s_1) = \arg \max_{b_1} E[(\theta - p_1)X_1|s_1] = E[\theta|s_1] = \theta + (\bar{\theta} - \theta)s_1$$

(5)

Under rational expectations about agent 1’s strategy, agent 2 maximizes her expected payoff conditioning on both her private signal $s_2$ and the informative price $p_2$. If her maximization problem has an interior solution, it is solved by the following fixed point:

$$b^*_2(s_2) = E[\theta|s_2, p_2 = b^*_2(s_2)]$$

(6)

The optimal bidding of agent 2 never uses reversed limit orders but follows a cutoff strategy that switches from buying to selling as the price increases. At a price equal to the (interior) cutoff $b^*_2$, the agent is indifferent between a buy and a sell. In particular, with pricing rule (3) the Bayes Nash (BN) strategy of agent 2 simplifies to a step function: $p_2$ reflects the market maker’s expectation, implying that $p_2$ would make agent 2 indifferent in the absence of her own signal $s_2$. The additional information contained in $s_2$ breaks the tie, such that agent 2 buys for $s_2 \geq \frac{1}{2}$, and sells otherwise.

However, the BN best response is not the only relevant ‘rational’ benchmark. In the experiment, participants in the role of agent 1 deviate from their best response $b^*_1$ and participants acting as agent 2 would optimally adjust to it. Their price $p_2$ is still informative about $\theta$ because it reflects $s_1$, but $p_2$ does not generally equal $E[\theta|X_1]$ if $X_1$ is subject to deviations from $b^*_1$. We therefore consider the empirical best response (EBR) to the participants acting as agents 1. The computation of the empirical best response is analogous to the fixed point computation of the BN response response, except that it is based on the observed behavior of agent 1 and computed via a numerical approximation to the fixed point.

The two benchmarks BN and EBR are depicted in Figure 1 (for the parameters of the actual experiment that are reported in Section 4, and using the empirical behavior described in Section 5 for the calculation of EBR), together with the naive prediction that we describe next.

3.2 Best response to naive beliefs

Contrasting the optimal behavior, an agent 2 with naive beliefs does not infer any information from the price. She fails to account for the connection between agent 1’s signal $s_1$ and his action $b_1$ and, instead, conditions on her own signal

$\text{For a simple proof of this statement, verify that if } b^*_2 \text{ were to violate }$ \( [6] \) then there would exist realizations of $(p_2, s_2)$ such that $p_2$ lies in the vicinity of $E[\theta|s_2, p_2 = b^*_2]$ and profits are forgone.

$\text{The kinks in the EBR function arise because of the numerical approximation to the fixed point, which is done for signals that are rounded to lie on a grid with step size 0.1 for close approximation.}$

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s2 only. The maximization problem with naive beliefs is then analogous to that of agent 1 and leads to the same bidding behavior:

\[ b^N_2 = \arg \max_{b_2} E[(\theta - p_2)X_2|s_2] = E[\theta|s_2] = \theta + (\theta - \theta)s_2 \quad (7) \]

The naive strategy is depicted as the straight line in Figure 1. Its underlying naive belief can be viewed as stemming from level-k reasoning or from fully cursed beliefs (Eyster and Rabin 2005). In the level-k framework (for a formulation with private information, see e.g. Crawford and Iriberri 2007) level-0 players ignore their information and randomize uniformly. An agent 2 with naive beliefs, as defined above, is therefore equivalent to a level-1 agent. In our setting, this also coincides with a ‘fully cursed’ strategy of Eyster and Rabin (2005) and Eyster et al. (2015) that best responds to the belief that agent 1’s equilibrium mixture over bids arises regardless of their information.

![Figure 1: Naive, Bayes Nash and empirical best responses.](image)

### 3.3 Hypotheses

As outlined in the Introduction, we conjecture that the updating on additional market information is more difficult in the simultaneous than in the sequential treatment. Using the benchmarks from the previous subsection, we translate this into a behavioral hypothesis:

\[ \text{In fully cursed equilibrium, agent 2 believes that agent 1 with signal } s_1 \text{ randomizes uniformly over his possible bids; agent 2 expects that agent 1 with signal } s_1 \text{ has a bid distribution equal to that resulting from the optimal bids given in (5), independent of } s_1. \]

The perceived mixture of bids by each type of agent 1 therefore follows the distribution \( F(\frac{b_1 - \theta}{\theta - \theta}) = F(s_1) \), with density \( \frac{1}{2} f(s_1|\theta) + \frac{1}{2} f(s_1|\theta') = 1 \). The analysis of Eyster and Rabin (2005) and Eyster et al (2015) also allows for intermediary levels of cursedness, where agents may only partially ignore the information revealed by other agents’ actions. Our estimations in Subsection 5.4 also allow for milder versions of information neglect.
**Hypothesis 1** *Naive bidding is more prevalent in treatment SIM than in treatment SEQ.*

The hypothesis is tested in the next section by considering those decisions of agent 2 where EBR and Naive bidding differ, separately for each of the two treatments.

Our second hypothesis considers the possibility that all participants acting as agent 2 have naive beliefs. In this case, the symmetry of the two agents’ decision problems would preclude any systematic differences between the agents’ bids. We can therefore use agent 1’s bid distribution as an empirical benchmark for naive agents 2. We restrict the comparison to treatment SIM, where the two agents have identical action sets.

**Hypothesis 2** *In treatment SIM, bids of agent 2 do not significantly differ from bids of agent 1.*

4 Experimental Procedures and Results

4.1 Procedures

The computerized experiment is conducted at Technical University Berlin, using the software z-Tree ([Fischbacher, 2007](#)). A total of 144 students are recruited with the laboratory’s ORSEE database ([Greiner, 2004](#)). 72 participants are in each of the treatments SIM and SEQ, each with three sessions of 24 participants. Within each session, the participants are divided into two equally sized groups of agents 1 and agents 2. Participants remain in the same role throughout the session and repeat the market interaction for 20 periods. At the beginning of each period, participants of both player roles are uniform-randomly matched into pairs and the interaction commences with Nature’s draw of \( \theta \), followed by the market rules as described in Section 2. At the end of each period, subjects learn the value \( \theta \), their own transaction price (if not already known) and their own profit. Upon conclusion of the 20 periods, a uniform random draw determines for every participant one of the 20 periods to be paid out for real.

Participants read the instructions for both roles, agents 1 and 2, before learning which role they are assigned to. The instructions include an elaborate computer-based simulation of the signal structure as well as an understanding test. The support of the asset is \( \{ \theta, \tilde{\theta} \} = \{40, 220\} \). Each session lasted approximately 90 minutes and participants earned on average EUR 22.02. Total earnings consist of a show-up fee of EUR 5.00, an endowment of EUR 15.00 and profits from the randomly drawn period (which could be negative but could not deplete the entire endowment). Units of experimental currency are converted to money by a factor of EUR 0.08 per unit.

4.2 Results

4.2.1 Agent 1

Figure 2 shows the implemented buys and sells of participants acting as agent 1, with the corresponding market price on the vertical axis and their private

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9See the Appendix for a set of instructions for treatments SIM and SEQ.
signal on the horizontal axis. The figure also includes the theoretical prediction (thick black line) and the results of a probit estimate of the mean bid. The mean bid increases in the signal, even slightly stronger than is predicted by the benchmark theory. This overreaction is not significant, though.

4.2.2 Agent 2: Testing hypotheses

Hypothesis 1. To evaluate the degree of cursedness, we focus on the area of Figure 1 where naive and optimal strategies make different predictions. Within this area, we calculate the proportion $\eta$ of naive decisions:

$$\eta = \frac{d_N}{d_N + d_B}$$

where $d_N$ and $d_B$ denote the number of orders consistent with naive and EBR predictions, respectively.

Figures 3 and 4 show the relevant observations in treatments SIM and SEQ, respectively. For these observations, naive expectations induce buys for signals below 0.5 and sells for signals above 0.5, while rational expectations induce opposite actions. The empirical measures $d_N$ and $d_B$ correspond to the number of triangle markers and cross markers, respectively. Hypothesis 1 is confirmed if the proportion of naive choices is larger in treatment SIM than in treatment SEQ: $\eta^{SIM} > \eta^{SEQ}$. Neglect of information contained in the price is stronger in a simultaneous market. Appendix Table A4 shows that the share of naive decisions in treatment SIM ($\eta = 0.38$) is twice as large as in treatment SEQ ($\eta = 0.19$). The difference is statistically significant ($p = 0.0091$, Wald test).

An especially strong difference between the two treatments appears in situations where agent 2 has a relatively uninformative signal, $s_2 \in [0.4, 0.6]$, i.e.
Figure 3: Sells and buys within the relevant area in treatment SIM.

Figure 4: Sells and buys within the relevant area in treatment SEQ.
when traders have the strongest incentive to make trading contingent on the price. Despite the isomorphy of the two treatments, the dependence of trade on price differs between treatments in these cases: the frequency of buying at a price below the ex-ante mean of \( p_2 = 130 \) is at 0.68 in SIM and at 0.37 in SEQ. Similarly, the frequency of buying at a high price, above \( p_2 = 130 \), is at 0.28 in SIM and at 0.48 in SEQ. This illustrates that treatment SEQ’s participants were less encouraged by low prices and less deterred by high prices, respectively, than treatment SIM’s participants, which is consistent with a relatively more rational inference in the sequential market.

In Appendix A, we also consider the evolution of decisions in the course of the experiment. We cannot detect any learning success over 20 repetitions.

**Hypothesis 2.** Hypothesis 2 compares the buy and sell decisions of agents 1 and 2 in treatment SIM. Figure 5 reveals that average bid functions do not significantly, or even perceivably, differ from each other. Just like agent 1, agent 2 shows no significant deviations from a linear bidding function, an observation that is consistent with full naiveté of agent 2.

### 5 Possible drivers of information neglect

#### 5.1 Signal strength

One possible driver of the observed information neglect is that the participants’ strong private signals might distract them from the information contained in the price. In a challenging and new environment, participants may perceive the benefit from interpreting the price as relatively low. In real markets, in-

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10 Carrillo and Palfrey (2011) report similar evidence of constantly naive play in their experiment.
vestors may be more attentive to the price’s informativeness, especially when they themselves have little private information.\footnote{We thank an anonymous referee for raising this hypothesis.}

We examine the hypothesis by introducing an asymmetric signal strength between agent 1 and agent 2, keeping the rest of the design unchanged. In two additional treatments with “Low Signal Quality”, LSQ-SIM and LSQ-SEQ (with $N = 70$ and $N = 68$, respectively), agent 2’s signal is less informative. The densities in the new treatments are depicted in Figure 6 and take the following form.

$$f(s_i | \theta = \theta) = 1 - \tau_i (2s_i - 1)$$

$$f(s_i | \theta = \bar{\theta}) = 1 + \tau_i (2s_i - 1)$$

with $\tau_1 = 1$ and $\tau_2 = 0.2$.

We observe that in both treatments LSQ-SIM and LSQ-SEQ the bids of participants in the role of agent 2 deviate significantly from the naive prediction in that they react to the signal more strongly than predicted by naive bidding (see Figure 11). A comparison with the bids in the main treatments SIM and SEQ supports the conjecture that subjects pay more attention to market information when they have less private disadvantage.

However, the discrepancy between the two market mechanisms increases with information asymmetry. The share of naive decisions in treatment LSQ-SEQ (22\%, black triangles in Figure 7(b)) is much smaller than in LSQ-SIM (44\%, black triangles in Figure 7(a)). This significant difference ($p = 0.0003$, Wald test) corresponds to a steeper estimate of the average bidding curve in LSQ-SEQ, see Figure 11. The tables in the appendix also show that differences in frequencies of buys and sells between the two mechanisms are highly significant for various signal ranges, and that they tend to be larger than in the comparison of SIM and SEQ. For example, participants in the role of agent 2 of LSQ-SEQ act very frequently against their own signal. In sum, the importance of trading mechanisms for rational decision making prevails under the new informational conditions.

5.2 Strategic uncertainty

Strategic uncertainty adds to the complexity of the trading game. For an accurate interpretation of price, participants in the role of agent 2 need to consider
the trading behavior of agent 1 and their ability to do so may vary between simultaneous and sequential mechanisms. In other words, the mere necessity of assessing the human-agent-driven EBR (not just the simpler BN response) may lead to more suboptimal behavior by agent 2 in treatment SIM relative to SEQ. We therefore examine whether the treatment effect appears also in two additional treatments with “No Player 1” (NP1), containing 40 participants in NP1-SIM and 46 in NP1-SEQ, all of whom act in the role of agent 2. In these treatments we delete agent 1’s presence. Participants acting as agent 2 are informed that the price is set by a computerized market maker who receives an additional signal. This additional signal follows a distribution that mimics the information that the market maker receives in the two main treatments when observing the demand $X_1$ of an agent 1 who behaves rationally.

For better comparison with the main treatments, the instructions of the NP1 treatments retain not only much of the wording but also the chronological structure of the main treatments. Participants in NP1 treatments thus learn about the existence of $p_1$, which is presented to them as the “initial value” of the asset’s price, and they learn that the market maker observes an additional signal that is correlated with the asset’s value. Like in the main treatments, the instructions display the updating rule (3) and explain that it results in the price $p_2$ at which the participants can trade and which reflects the expected value (phrased as the “assessment” by the market maker) of the asset’s value, conditional on the additional signal but not conditional on the participants’ own signal.

The data show no strong differences between the NP1 treatments and the main treatments. Figure A.1 shows that the estimated bidding curve in NP1-SIM exhibits the same slope as the curve in SIM, with a mild downward shift, whereas behavior in NP1-SEQ is very close to that of SEQ.\footnote{In the new treatment, the relevant distributions of signals (one for each asset value) is shown in a graphical display. The instructions do not explain how the distributions are determined.} The downward shift in NP1-SIM is more pronounced for low signals and leads to a significant deviation from the naive benchmark (Multiple binomial testing with Bonferroni correction rejects 1 out of 9 hypotheses at .0055 significance level, see Appendix). Despite this deviation, the average bid does not increase disproportionally in the private signal as the rational benchmark predicts. Another mild difference is that the use of reversed limit orders is smaller.
Most notably, the effect of simultaneous versus sequential trading persist. The share of naive decisions is two and a half times higher in NP1-SIM than in NP1-SEQ (45.27% vs. 17.67%). We also observe significantly more buys at high prices and more sells at low prices in NP1-SEQ (see Table in Appendix). Figure 8 shows the individual decisions for cases where naive and rational predictions differ, in treatments NP1-SIM (Figure 8(a)) and NP1-SEQ (Figure 8(b)), respectively.

5.3 Number of decisions per treatment

Our last treatment addresses the question whether the higher frequency of naive decisions in SIM may be driven by the additional cognitive strain that a larger amount of inference requires. Perhaps, it is not conditional thinking per se that is difficult for the participants, but rather the fact that they have to make two decisions in treatment SIM (one for each possible price realization) but only one in treatment SEQ. We therefore introduce a “hypothetical” sequential treatment (Hyp-SEQ) with 62 participants, which rules out higher dimensionality of strategies as a source of difficulty. Treatment Hyp-SEQ is analogous to SEQ in that after learning agent 1’s price $p_1$, participants in the role of agent 2 specify their buying or selling preferences for only a single price $\hat{p}_2$. However, $\hat{p}_2$ is only a candidate price $\hat{p}_2$ is equiprobably drawn from the two price values that are possible after updating via rule (3). Participants decide whether they would buy or sell at $\hat{p}_2$ and the decision is implemented if and only if agent 1’s demand induces the realization $p_2 = \hat{p}_2$. Otherwise, agent 2 does not trade and makes zero profit.

Participants in treatment Hyp-SEQ thus face only one price and make only one decision, so the dimensionality of the task is identical to that in SEQ. (The instructions are almost word-for-word identical.) But the nature of the decision in Hyp-SEQ is conditional, like in treatment SIM. We can therefore assess the importance of task dimensionality by comparing SIM versus Hyp-SEQ, and the role of conditionality by comparing SEQ versus Hyp-SEQ.

The average bidding curves show no large difference between the treatments SIM and Hyp-SEQ, or between those of agents 1 and 2 of treatment Hyp-SEQ: The curves in Appendix Figures 13(a) and 13(b) exhibit approximately the same ascending slope. Moreover, the Appendix also shows that naive in NP1-SIM (9%) than in SIM (15%).
bidding conditional on the signal cannot be rejected for treatment Hyp-SEQ, in multiple binomial testing.

However, Figure 9 and Table A.4 in the Appendix show that the frequency of making suboptimal decisions (η) in Hyp-SEQ lies well in between those of SEQ and SIM. The difference between treatments SIM and Hyp-SEQ, 0.38 versus 0.25, is statistically significant, whereas the one between Hyp-SEQ and SEQ, 0.25 versus 0.19 is not.

Altogether, we conclude from the above tests that reducing the number of hypothetical trading decision reduces the degree of naiveté significantly, but does not eliminate it. The possible conjecture that the frequent naive decisions that we observe in simultaneous mechanisms can be attributed to a single determinant is therefore implausible.

### 5.4 Random Utility Model

This subsection pools the data, for a statistical comparison of the information usage in sequential versus simultaneous mechanisms. We combine the data from all simultaneous treatments into a data set “SIM+” and those from sequential treatments into a data set “SEQ+”. (Data from the hybrid treatment Hyp-SEQ are not used here.) We assume the probability with which agent 2 buys the risky asset in decision \( i \) follows a logistic distribution, allowing for an over-weighted or under-weighted relevance of the available pieces of information:

\[
P(X_2 = 1 | u_i, s_2, p_2) = \frac{e^{\lambda(\hat{E}[\theta | p_1, p_2, s_2] - p_2 + u_i)}}{1 + e^{\lambda(\hat{E}[\theta | p_1, p_2, s_2] - p_2 + u_i)}},
\]

\[\text{(9)}\]

\[\text{14}\]

Our working paper version, Ngangoue and Weizsäcker (2015) shows a first version of the experiment where the simultaneous treatment elicits buy and sell preferences for a list of 26 hypothetical prices (treatment “Price List”), instead of 2 as in the present paper’s treatment SIM. There, we find the neglect of the price informativeness to be even more pronounced, which is also consistent with an effect of task dimensionality. The previous experiment, however, also has other differences to the present one.
\[
\hat{E}[\theta|p_1, p_2, s_2] = 40 + 180 \cdot \hat{P}(\theta = 220|p_1, p_2, s_2) 
\]

\[
\hat{P}(\theta = 220|p_1, p_2, s_2) = [1 + LR(s_2)^{-\beta} \cdot LR(p_2)^{-\alpha}]^{-1} 
\]

The choice probability depends on subjective expected payoff, given by \(\hat{E}[\theta|p_1, p_2, s_2] = p_2\). The parameter \(\lambda\) reflects the precision of the logistic response and \(u_i\) is the random utility shifter, which we assume as i.i.d. normally distributed with mean 0 and variance \(\sigma_u^2\). To allow for irrational weighting of information, we introduce the subjective posterior probability of the event that \(\theta = 220\), given by \(\hat{P}(\theta = 220|p_1, p_2, s_2)\). Analogous to the method of updating assessment that was introduced by Grether (1992), we let the posterior probability depend on the likelihood ratios of the signal and the price, \(LR(s_2) \equiv \frac{P(\theta=220|s_2)}{P(\theta=40|s_2)}\) and \(LR(p_2) \equiv \frac{P(\theta=220|p_2)}{P(\theta=40|p_2)}\), respectively, which are exponentiated by the potentially irrational weights \(\beta\) and \(\alpha\) that the participant assigns to the signal’s and the price’s informational content. A participant with naive beliefs (a ‘fully cursed’ participant) would correctly weight the signal, \(\beta = 1\), but would ignore the information in the price, \(\alpha = 0\). An intermediary level of cursedness translates into \(\alpha\) between 0 and 1. A rational trader would correctly weight the signal and the price, \(\beta = \alpha = 1\). The model also allows for an over-weighting of the signal or the price, by letting \(\beta\) or \(\alpha\) exceed 1.

We estimate the model via Maximum Simulated Likelihood (MSL). To arrive at \(LR(p_2)\), we estimate the distributions \(P(p_2|\theta = 220)\) and \(P(p_2|\theta = 40)\) via kernel density estimation and infer \(\frac{P(\theta=220|p_2)}{P(\theta=40|p_2)}\) for each \(p_2\) in the data set.

Table 1: Results of MSL estimation

<table>
<thead>
<tr>
<th></th>
<th>Treatments SIM+</th>
<th>Treatments SEQ+</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta)</td>
<td>2.54**</td>
<td>1.36****</td>
</tr>
<tr>
<td>(0.90)</td>
<td>(0.36)</td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.60*</td>
<td>1.85***</td>
</tr>
<tr>
<td>(0.26)</td>
<td>(0.22)</td>
<td></td>
</tr>
<tr>
<td>(\lambda)</td>
<td>0.0230***</td>
<td>0.0373***</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>(\sigma_u)</td>
<td>0.0010</td>
<td>0.0039</td>
</tr>
<tr>
<td>(N)</td>
<td>2220</td>
<td>2260</td>
</tr>
</tbody>
</table>

Note: * \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\). Std. Err. in parentheses. Hypothesis testing for \(\beta\) and \(\alpha\) refers to one-sided tests of deviations from 1.

The estimates are reported in Table 1 and confirm the findings of the previous subsections. In the simultaneous mechanisms, the estimated \(\alpha\) of 0.60 lies well below the optimal value 1, albeit at a somewhat marginal statistical significance of \(p = 0.09\). While this difference from 1 reflects the hypothesis that participants pay too little attention to the price’s informativeness, we can
also reject the extreme formulation of Hypothesis 2, stating that participants are fully naive: $\alpha$ differs significantly from 0.

In the treatments with sequential mechanisms, the perceived levels of informativeness of signal relative to price are reversed. These treatments induce a significant over-weighting of the price’s likelihood ratio ($\alpha = 1.85$)\textsuperscript{15}. The weighting of the private signal decreases from 2.54 to 1.36 between the simultaneous and the sequential treatments. Both $\beta$ estimates significantly differ from 1. Overall, the evidence from sequential treatments shows that the prior distribution of the fundamental values is under-weighted and that, confirming Hypothesis 1, sequential markets reveal a significantly smaller inference from the price than simultaneous markets.

\section{Discussion: Information neglect in markets}

This section discusses the possible impact of naiveté on market efficiency. We begin by stating a classical question of market prices: how do prices that arise after a given trading pattern differ from equilibrium prices? Notice that this question addresses the welfare of subsequent traders in the same market who are, however, outside of the set of traders that we consider in the experiment. We therefore have to resort to auxiliary calculations. We then also consider the actual payoff of our experimental participants.

\textit{Pricing} A natural measure of price efficiency is the speed at which price aggregates the traders’ dispersed pieces of information and converges to fundamental value. With naive traders in the market, this speed may be reduced. Moreover, naive traders may distort the price recovery process by suppressing some subsets of possible signals more than others. Two theoretical contributions that study the implications of naiveté on price are by Hong and Stein (1999) and Eyster et al (2015). They both find, with different models, that the presence of naive traders creates a bias of early prices towards their ex-ante expectation. The reason is that naive traders are likely to engage in excessive speculation based on their own signal—they bet against the market price too often. This pushes price towards its ex-ante expectations\textsuperscript{16}.

In order to test this implication with our data, we have to rely on a specific mechanism with which pricing might occur after agent 2 has completed his trades. For simplicity and for consistency with the rule governing $p_2$, we calculate the price that a market maker would set in Bayes Nash equilibrium: the market maker sets the price $p_3$ equal to $E[\theta|x_1, x_2]$, where $x_1, x_2 \in \{-1, 1\}$ denote the realized demand of agents 1 and 2, assumed to follow the Bayes-Nash prediction. In our main treatments SIM and SEQ, the price that a hypothetical agent 3 would face from this pricing rule

\textsuperscript{15}This relates to Levin et al. (1996)’s finding that participants in the English auction put relatively more weight on the latest drop-out prices compared to their own signal.

\textsuperscript{16}Hong and Stein (1999) analyze a dynamic model where information dispersion is staggered in the market and where naive traders are myopic but can be exploited by sophisticated (but cognitively restricted) traders who start betting against the naive traders eventually. Price can therefore overshoot at a later stage in the cycle. Eyster et al’s (2015) model uses partially cursed equilibrium to show the bias in pricing, using a more standard (and more static) model of financial markets with incomplete information akin to that in Grossman (1976).
reduces to a simple function of $p_2$ and $x_2$.

$$p_3 = \begin{cases} 
\frac{-8800 + 310}{50 + p_2} & \text{if } x_2 = 1 \\
\frac{-8800 + 50 + p_2}{310 - p_2} & \text{if } x_2 = -1 
\end{cases}$$

Under the given pricing rule, price moves towards its extremes fast if both signals $s_1$ and $s_2$ deviate from their expectation in the same direction. In this case either both agents buy or both agents sell, in Bayes Nash Equilibrium. For all cases where $s_1$ and $s_2$ lie on the same side of 0.5, Figure 10 shows in the resulting distribution of equilibrium price $p_3$ as dashed line, with much probability mass located towards the extremes. In contrast, if agent 2 bids naively, then he will tend to sell at high prices and buy at low prices, creating excessive density of $p_3$ near the center of the distribution (dotted line).

Figure 10 also depicts the kernel densities of the price $p_3$ that would arise from the actual trading in treatments SIM and SEQ. The price distribution under SIM is close to that of naive bidding. In SEQ, prices deviate more from the prior expectation of 130 and the distribution lies far closer to that of the rational pricing.

To quantitatively assess price efficiency under the two treatments, we ask about the variance of the fundamental value conditional on the price $\text{Var}[\theta | p_3]$. It captures the error in market expectations given information contained in $p_3$. Conditional variance is significantly lower in treatment SEQ than in SIM, at high level of significance ($p=0.00$, nonparametric median test) and with a somewhat sizable difference: in treatment SIM, the price explains on average 21% of the variance in the fundamental value, versus 27% in treatment SEQ.

Profits. The difference between simultaneous and sequential mechanisms also affects the distribution of profits of agent 2. A corresponding difference occurs in each of the relevant treatment comparisons, but is statistically significant.

17In treatments LSQ, $p_3$ is more complex: $p_3 = \frac{1030(-8.54p_2)}{770 + p_2}$ if $x_2 = 1$, $p_3 = \frac{-770(11.43p_2)}{p_2 - 1030}$ else.

18The kernel densities exhibit the same pattern when taking into account all observations; the bi-modal shapes are less pronounced, though.
only in the comparison LSQ-SIM versus LSQ-SEQ, i.e. with asymmetry in the informativeness of signals. Less informed traders benefit from sequential information processing, where the employed updating is more rational. The results on mean and median profits of each treatment is in Table A5 in the appendix. It is also noteworthy that the distribution of profits conditional on price $p_2$ in LSQ-SEQ is mirror-inverted to the one in LSQ-SIM (see Figure 14(b) in the Appendix). This emphasizes the importance of pre-trade transparency to restrain insider trading: the majority of traders in LSQ-SIM lose significant amounts, whereas the majority of traders in LSQ-SEQ make gains.

7 Conclusion

How well traders are able to extract information in markets may depend on the markets’ designs over and above ‘rational’ reasons. Although different but isomorphic trading mechanisms should entail the same outcomes, decisions may vary. Our experiments provide an example where a specific subset of inferences are weak: traders in simultaneous markets, where optimal trading requires Bayesian updating on hypothetical outcomes, do not account for the price’s informativeness. They therefore neglect information revealed by others’ investments. However, when the reasoning is simplified to updating on a single realized event, such ‘cursedness’ is mitigated. Traders are thus more likely to detect covert information while focusing on a single outcome. In this sense, the degree of inference and consequently the quality of informational efficiency interact with market design. Of course, this is only a single setting and despite the numerous robustness checks in the paper we must not presume generalizability. It’s a stylized experiment, no more and no less. Subsequent work may address, for example, the largely open research question about the extent to which the increased price efficiency in sequential trading is beneficial once the trading game is extended to a more dynamic trading environment with more than two consecutive traders.
References


## A Appendix

### A.1 Descriptive Statistics

Table A1: Share of buys at low prices for varying signal intervals

<table>
<thead>
<tr>
<th>Treatment</th>
<th>All signals</th>
<th>[0 - 0.2]</th>
<th>[0.2 - 0.4]</th>
<th>[0.4 - 0.6]</th>
<th>[0.6 - 0.8]</th>
<th>[0.8 - 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSQ-SEQ</td>
<td>.4106 (.044)</td>
<td>.1667 (.042)</td>
<td>.2432 (.060)</td>
<td>.4231 (.067)</td>
<td>.6 (.081)</td>
<td>.6897 (.067)</td>
</tr>
<tr>
<td>LSQ-SIM</td>
<td>.5714 (.037)</td>
<td>.3171 (.063)</td>
<td>.4783 (.066)</td>
<td>.56 (.072)</td>
<td>.7407 (.056)</td>
<td>.7733 (.066)</td>
</tr>
<tr>
<td>Diff.</td>
<td>-.1606**</td>
<td>-.1504*</td>
<td>-.2351**</td>
<td>-.1369</td>
<td>-.1407</td>
<td>-.0836</td>
</tr>
<tr>
<td>N</td>
<td>736 160 143 153 156 133</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Treatment</th>
<th>All signals</th>
<th>[0 - 0.2]</th>
<th>[0.2 - 0.4]</th>
<th>[0.4 - 0.6]</th>
<th>[0.6 - 0.8]</th>
<th>[0.8 - 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NP1-SEQ</td>
<td>.3403 (.030)</td>
<td>.0392 (.023)</td>
<td>.1048 (.035)</td>
<td>.3333 (.051)</td>
<td>.6538 (.058)</td>
<td>.8462 (.060)</td>
</tr>
<tr>
<td>NP1-SIM</td>
<td>.4495 (.033)</td>
<td>.1214 (.042)</td>
<td>.1939 (.048)</td>
<td>.5789 (.062)</td>
<td>.8088 (.058)</td>
<td>.9245 (.044)</td>
</tr>
<tr>
<td>Diff.</td>
<td>-.1092**</td>
<td>-.0823*</td>
<td>-.0891</td>
<td>-.2456***</td>
<td>-.155*</td>
<td>-.0784</td>
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<tr>
<td>N</td>
<td>825 209 203 163 146 118</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p < 0.1, **p < 0.05, ***p < 0.01. CRSE in parentheses.
Table A2: Share of buys at high prices for varying signal intervals

<table>
<thead>
<tr>
<th>Treatment</th>
<th>All signals</th>
<th>[0 - 0.2]</th>
<th>[0.2 - 0.4]</th>
<th>[0.4 - 0.6]</th>
<th>[0.6 - 0.8]</th>
<th>[0.8 - 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSQ-SEQ</td>
<td>.6151 (.038)</td>
<td>.2537 (.067)</td>
<td>.5294 (.070)</td>
<td>.7 (.066)</td>
<td>.8 (.056)</td>
<td>.7848 (.053)</td>
</tr>
<tr>
<td>LSQ-SIM</td>
<td>.3050 (.038)</td>
<td>.2239 (.059)</td>
<td>.2 (.058)</td>
<td>.1818 (.047)</td>
<td>.4464 (.066)</td>
<td>.5079 (.081)</td>
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<tr>
<td>Diff.</td>
<td>.3101***</td>
<td>.0298</td>
<td>.3294***</td>
<td>.5182***</td>
<td>.3536***</td>
<td>.2769***</td>
</tr>
<tr>
<td>N</td>
<td>635</td>
<td>134</td>
<td>106</td>
<td>147</td>
<td>106</td>
<td>142</td>
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<table>
<thead>
<tr>
<th>Treatment</th>
<th>All signals</th>
<th>[0 - 0.2]</th>
<th>[0.2 - 0.4]</th>
<th>[0.4 - 0.6]</th>
<th>[0.6 - 0.8]</th>
<th>[0.8 - 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>NP1-SEQ</td>
<td>.6738 (.027)</td>
<td>.1475 (.047)</td>
<td>.3889 (.062)</td>
<td>.7 (.063)</td>
<td>.8817 (.042)</td>
<td>.9626 (.018)</td>
</tr>
<tr>
<td>NP1-SIM</td>
<td>.4523 (.030)</td>
<td>.1132 (.042)</td>
<td>.0882 (.053)</td>
<td>.225 (.044)</td>
<td>.6813 (.063)</td>
<td>.8302 (.035)</td>
</tr>
<tr>
<td>Diff.</td>
<td>.2215***</td>
<td>.0343</td>
<td>.3007***</td>
<td>.475***</td>
<td>.2004***</td>
<td>.1324***</td>
</tr>
<tr>
<td>N</td>
<td>821</td>
<td>114</td>
<td>140</td>
<td>170</td>
<td>184</td>
<td>213</td>
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Note: *p < 0.1, **p < 0.05, ***p < 0.01. CRSE in parentheses.

Table A3: Acting against one’s own signal (treatment prices)

<table>
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<tr>
<th></th>
<th>( p_2 \leq 130 )</th>
<th>( s_2 &gt; .5 )</th>
<th>( p_2 &gt; 130 )</th>
<th>( s_2 \leq .5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSQ-SEQ</td>
<td>.5976 (.059)</td>
<td>.4323</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSQ-SIM</td>
<td>.7326 (.049)</td>
<td>.1939</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference</td>
<td>-.135*</td>
<td>.2383***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>351</td>
<td>320</td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>( p_2 \leq 130 )</th>
<th>( s_2 &gt; .5 )</th>
<th>( p_2 &gt; 130 )</th>
<th>( s_2 \leq .5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>NP1-SEQ</td>
<td>.6815 (.049)</td>
<td>.3584</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NP1-SIM</td>
<td>.8446 (.045)</td>
<td>.1198</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Difference</td>
<td>-.1631**</td>
<td>.2386***</td>
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<td></td>
</tr>
<tr>
<td>N</td>
<td>327</td>
<td>340</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p < 0.1, **p < 0.05, ***p < 0.01. CRSE in parentheses.
Figure 11: Estimated average bids in treatments LSQ-SIM and LSQ-SEQ.

Figure 12: Estimated average bids in treatments NP1-SIM and NP1-SEQ.

Figure 13: Buys and sells of agents 1 and 2 of treatment Hyp-SEQ.
Table A4: Shares of naive decisions

<table>
<thead>
<tr>
<th></th>
<th>SIM</th>
<th>SEQ</th>
<th>LSQ-SIM</th>
<th>LSQ-SEQ</th>
<th>Hyp-SEQ</th>
<th>NP1-SIM</th>
<th>NP1-SEQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>η</td>
<td>.3760</td>
<td>.1851</td>
<td>.4449</td>
<td>.2222</td>
<td>.2478</td>
<td>.4527</td>
<td>.1767</td>
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<td></td>
<td>(.0472)</td>
<td>(.0518)</td>
<td>(.0445)</td>
<td>(.0334)</td>
<td>(.042)</td>
<td>(.0506)</td>
<td>(.0326)</td>
</tr>
<tr>
<td>N</td>
<td>117</td>
<td>108</td>
<td>227</td>
<td>261</td>
<td>117</td>
<td>148</td>
<td>181</td>
</tr>
</tbody>
</table>

Note: CRSE in parentheses. Significant difference at 1% level between SIM & SEQ, between LSQ-SIM & LSQ-SEQ and between NP1-SIM & NP1-SEQ.

Figure 14: Kernel density of profits in class 2 of treatments SIM, SEQ, LSQ-SIM, LSQ-SEQ and NP1-SIM,NP1-SEQ.

Table A5: Profits of participants in class 2

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
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</thead>
<tbody>
<tr>
<td>SIM</td>
<td>27.63</td>
<td>44</td>
</tr>
<tr>
<td>SEQ</td>
<td>30.65</td>
<td>43.25</td>
</tr>
<tr>
<td>LSQ-SIM</td>
<td>-1.24</td>
<td>-18.25</td>
</tr>
<tr>
<td>LSQ-SEQ</td>
<td>.85</td>
<td>21</td>
</tr>
<tr>
<td>HYP-SEQ</td>
<td>14.71</td>
<td>0</td>
</tr>
<tr>
<td>NP1-SIM</td>
<td>25.30</td>
<td>50.5</td>
</tr>
<tr>
<td>NP1-SEQ</td>
<td>28.36</td>
<td>52.5</td>
</tr>
</tbody>
</table>
A.2 Multiple Binomial Testing

We test the null hypothesis that the probability to buy conditional on the signal corresponds to the probability under naive expectations, that is \( H_0 : \pi(s^j) = s^j, j = 1, \ldots, 9. \)

For the treatments LSQ+ the null adjusts to \( H_0 : \pi(s^j) = .4 + .2 \cdot s^j, j = 1, \ldots, 11. \)
A.3 Learning

To investigate whether participants learn over time, we divide observations into two time subsections: an early time interval for the rounds one to ten and a late interval for later rounds. In the subset of price-signal realizations where naive and Bayesian predictions differ, the proportion of naive decisions does not change significantly over time in any of the individual treatments (except for treatment LSQ-SEQ), as shown in Table A8. Furthermore, plotting the share of naive decisions across periods does not display any systematic pattern of decay. Even pooling treatments into simultaneous and sequential variants does not reveal any learning effect. In this sense, the sequential variant of the game does not systematically facilitate learning about the other agents’ private information.

Table A8: Proportion of naive decisions

<table>
<thead>
<tr>
<th></th>
<th>SIM</th>
<th>SEQ</th>
<th>LSQ-SIM</th>
<th>LSQ-SEQ</th>
<th>Hyp-SEQ</th>
<th>NP1-SIM</th>
<th>NP1-SEQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>First 10</td>
<td>.3971</td>
<td>.2127</td>
<td>.4741</td>
<td>.2810</td>
<td>.2909</td>
<td>.5128</td>
<td>.1596</td>
</tr>
<tr>
<td></td>
<td>(.060)</td>
<td>(.074)</td>
<td>(.052)</td>
<td>(.046)</td>
<td>(.056)</td>
<td>(.070)</td>
<td>(.044)</td>
</tr>
<tr>
<td>Last 10</td>
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Note: *p < 0.1, **p < 0.05, ***p < 0.01. CRSE in parentheses.