Received: 16 March 2021 | Accepted: 11 May 2021

DOI: 10.1111/ecin.13010

ORIGINAL ARTICLE

Economic Inquiry

Benchmarking information aggregation in experimental markets

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Abstract

Theoretical and experimental literature have provided mixed insights on the ability of financial markets to perfectly aggregate private information into asset prices. We conduct an experiment designed to benchmark information aggregation in markets. In our lab experiment, we randomly assign subjects to different institutional environments, either a market or a Becker–DeGroot–Marschak mechanism. We find evidence that market interaction is worse for information aggregation. The difference between the two environments is driven by price-insensitive traders who seem unable to learn from market prices. Price-sensitive traders, by contrast, learn equally well in both environments.

KEYWORDS

experiment, information aggregation, markets

JEL CLASSIFICATION

D02, D03, C92

1 | INTRODUCTION

One of the properties of efficient markets that economists have been most fascinated by is their ability to aggregate private information held by market participants which is revealed in prices. Sometimes markets are even created with the sole purpose of aggregating information. Such prediction markets have been shown to outperform opinion polls in predicting the outcome of elections (Berg et al., 2008; Forsythe et al., 1992), expert forecasts in sports (Spann & Skiera, 2009), or sales forecasts in business (Plott & Chen, 2002). In other contexts, however, like in financial markets, the evidence on successful information aggregation is more mixed. While early empirical literature found support for the efficient market hypothesis (Fama, 1965, 1970; Scholes, 1972), subsequent research produced opposite evidence (De Bondt & Thaler, 1985; Ito et al., 1998; Jegadeesh & Titman, 1993). These mixed results extend to lab experimental studies where some have found evidence of "good" information aggregation (Camerer & Weigelt, 1991; Forsythe & Lundholm, 1990; Forsythe et al., 1992; Plott & Sunder, 1988) and some evidence of substantial divergence between market prices and underlying fundamentals (Corgnet et al., 2018, 2019; O'Brien & Srivastava, 1991; Page & Siemroth, 2018). One difficulty in understanding how well markets aggregate

Abbreviations: BDM, Becker–DeGroot–Marschak; RE, rational expectations.

information is that there is no natural alternative institution to which we can compare the market's performance. Our paper attempts to provide one such benchmark.

To this purpose, we design a lab experiment where we randomly assign subjects to different artificial institutional environments.[1] In treatments with market interaction (the market treatments), two assets are in parallel traded via a call auction mechanism (Plott & Smith, 2008a). In the non-market treatments, we remove the strategic interaction among traders. Here, prices of assets are determined via a Becker–DeGroot–Marschak (hereafter BDM) mechanism (Becker et al., 1964). Both institutional environments are tested under two information conditions. Treatments with public information present no information aggregation problem, while in their counterparts information about asset returns is private. All treatments are designed in such a way that the information available to participants across the market and non-market variations is exactly identical. The only difference is how prices are determined.

We assess information aggregation using two measures. First, we ask whether first-order stochastic dominance of assets is reflected in the way assets are ranked by their prices. This is a minimal measure of correct aggregation. Second, we compare prices in the treatments with private information to prices in treatments that have public information about asset returns, but are otherwise identical. If information aggregation is perfect, then prices under the private and public information treatments should be the same. Further, any difference between the two institutions (market and non-market) that is *not* related to information aggregation should appear in the public information treatments as well. This differences-in-differences design hence allows us to cleanly identify differences in information aggregation across the two institutions.

The market and the BDM mechanism rank assets correctly with 95% and 93% probability, respectively, under public information and with 65% and 73% probability, respectively, under private information. Neither of these differences between institutions are statistically different. However, with respect to our second measure we find that markets do significantly worse compared to the non-market institution.[2] Prices are further away from the public information benchmark in the market compared to the BDM mechanism. Hence, across the two measures, we find that information aggregation is worse in the market than in our non-market benchmark.

We then explore several factors that could explain these results and find that the difference is driven by price-insensitive traders who seem unable to learn from market prices. Because of this we assume they perceive a wedge between their subjective beliefs and the market price, which they cannot rationalize by their priors.[3] As the fictitious market price (labeled "group value") is purely informational and not directly payoff relevant under the BDM mechanism, it seems intuitive that such traders would ignore it and simply follow their subjective beliefs. In the market by contrast, the price is harder to ignore (as it has to be paid) and the wedge between the price and the subjective prior would then lead participants to perceive ambiguity and to act accordingly. This is what worsens the market's performance in terms of information aggregation. We also show that, in contrast to price-insensitive traders, price-sensitive traders learn equally well in the market as they do under the BDM mechanism.

Our research contributes to a long tradition of experimental research on information aggregation in markets dating back to the 1980s. Plott and Sunder (1982) studied five experimental markets and found that in all but one prices promptly adjusted to near their rational-expectation values. Similar results are found in Friedman et al. (1984). Plott and Sunder (1988) studied the information aggregation properties of an oral double-auction where, in contrast to the previous literature, the state of nature is unknown to every trader. They found that in markets where only one asset is traded the rational expectations (RE) model performs poorly. In contrast, in markets with uniform dividends among traders or with a complete set of state-contingent assets, the RE model outperforms other competing models in predicting market prices. Recently, though, Corgnet et al. (2019) failed to replicate the results by Plott and Sunder (1988).

Forsythe and Lundholm (1990) investigated the role of trading experience and common knowledge of the set of payoffs. They found that both conditions are jointly, but not separately, sufficient for prices to converge to the RE equilibrium. Similar results are found in Copeland and Friedman (1991) where traders receive information either sequentially or simultaneously in a computerized double-auction. While a model of partial revelation of information better predicts the allocation of assets in their study, market prices are consistent with the RE predictions. O'Brien and Srivastava (1991) analyze more complex markets with experienced traders and without common knowledge about the distribution of private information. In contrast to the results from simpler environments, it is found that markets are on average inefficient in aggregating all the available information.[4] In a meta-study on experimental double auctions, Page and Siemroth (2018) find that while publicly announced information tends to be well reflected in prices, this is not the case for private information.

There are also some experimental studies on prediction markets. Healy et al. (2010) test the performance of double-auction prediction markets for different information structures. Although the double-auction market, when compared with other mechanisms, performs relatively well with a simple information structure, it performs the worst when the information structure becomes more complex. Ledyard et al. (2009) report that double-auction markets do not always generate more accurate predictions than other mechanisms (see also Hanson et al. [2006]). Page and Siemroth (2017) conduct a prediction market experiment with the possibility of information acquisition and conclude that bidders tendency to over-acquire information might be part of the explanation why prediction markets tend to aggregate information well.

The main difference between our work and existing literature is how market performance is assessed. Previous literature studied markets in isolation and contrasted outcomes to theoretical predictions. This approach has the downside that when theoretical predictions and market outcomes differ, it is not clear whether this difference is due to the market failing to aggregate information or to the model using the "wrong" assumptions on (e.g., risk) preferences. Even if the difference between theory and empirical outcomes can be unambiguously attributed to an information aggregation failure, it is usually not possible to assess the extent of failure, as there are no natural benchmarks to assess whether a mispricing is "small" or "large." In our paper, by contrast, we benchmark information aggregation in markets against a comparable non-market institution. This approach allows us to net out the effect of market interaction and to obtain a benchmark against which to assess the quantitative importance of deviations from perfect aggregation.

To our knowledge, there is only one previous paper comparing the BDM mechanism with a market institution, albeit in a different context. Bohm et al. (1997) examine the sensitivity of the BDM mechanism to the choice of the upper bound of the randomly generated price and thus, its ability of eliciting reservation prices. They report that when the upper bound is close to an expected real maximum buying price, the BDM mechanism generates individual evaluations comparable to a double-auction market. The experimental market they use is, however, designed such that traders are unable to influence transaction prices. Unlike us and the literature cited above Bohm et al. (1997) are not interested in aggregation of private information in the market.

Our paper is organized as follows: In Section 2, we describe the experimental design; Section 3 contains our main results; Section 4 provides a discussion of mechanisms; and Section 5 concludes. Experimental instructions, information about the sample as well as additional tables and figures can be found in an Online Appendix.

2 | METHOD

2.1 | Experimental design

In all treatments of our experiment, groups of five participants trade two separate assets for three *repetitions* of ten *trading periods* each. Starting out with one unit of each asset at the beginning of every trading period, participants independently and simultaneously submit buying and selling prices—that is, participants indicate for each asset the prices at which they are willing to sell their unit and they are willing to buy an additional unit. Both assets have a return of either 50, 100, or 150 and the probability distributions over these three outcomes are three-fifths, one-fifth, and one-fifth for one asset (asset L) and one-fifth, one-fifth, and three-fifths for the other one (asset H) respectively. Thus, asset H first-order stochastically dominates asset L. Having two assets allows us to focus on differences in how these two assets are valued on market level and to test whether they are correctly ranked according to the market price (i.e., whether the stochastic dominance relation is reflected in the ranking).

Our experiment consists of a $2 \times 2 \times 2$ between-subjects design, and each participant is exposed to only one of the eight different treatments as summarized in Table 1. Treatments differ according to (a) whether assets are traded in a market or not, (b) whether there is public or private information, and (c) whether feedback on individual bids and asks is provided via order books. We continue with a detailed description of these treatment dimensions and variations.

2.1.1 | Institution (market vs. BDM)

In order to isolate the effect of market incentives and analyze their implication on information aggregation, we implement two different institutional environments. Both have equal decision frameworks and information conditions. They only differ whether participants interact via a market mechanism.

In treatments with market interaction (*Market*), participants trade via a call auction mechanism (Plott & Smith, 2008b). Assets are traded every time some participant's buying price is above another participant's selling price. The market price of each asset is determined to allow all possible simultaneous trades of this asset and is made public

TABLE 1 Overview of treatments

Information condition		Public information		Private information	
Institution		BDM	Market	BDM	Market
Bid-Ask feedback	Without	Pub–BDM–NoBAF	Pub–Mkt–NoBAF	Priv–BDM–NoBAF	Priv–Mkt–NoBAF
	With	Pub–BDM–BAF	Pub–Mkt–BAF	Priv–BDM–BAF	Priv–Mkt–BAF

Abbreviation: BDM, Becker–DeGroot–Marschak.

after every trading period. If market clearing can be achieved with a range of prices, then the midpoint of this range is adopted as the market price (see Appendix A for further details). In case trade is not feasible—that is, when the lowest selling price is above the highest buying price – every participant keeps her initial stocks endowment and no market price is determined.

In treatments without market interaction, participants buy and sell assets via a *BDM* mechanism. Every trading period, transactions are determined according to a price that is a randomly drawn number from a uniform distribution between 50 and 150. Participants with a buying price above this number purchase a stock unit while those with a selling price below the random number sell their asset. Hence, in the *BDM* treatments individual trades do not depend on market prices that result from aggregated buying and selling prices. In order to make the two institutional environments comparable in the information made available to the participants, a simulated hypothetical market price (determined from bids and asks in the same way as the market price in the *Market* treatment), labeled *group value*, is communicated after each trading period. This treatment variation allows us to compare the behavior induced by the double-auction market with an institution where strategic interactions are absent but which is informationally equivalent to the market setting.

2.1.2 | Information condition (public vs. private information)

We further vary the information available to participants. In the *Public information* treatments, all participants are publicly informed about both assets' probability distributions over return values. Hence, there is no information aggregation problem. By contrast, in the *Private information* treatments, participants receive for each asset a *private signal* that provides a hint about the assets' probability distributions over return values. Signals are chosen in such a manner that perfect information (on which asset leads to higher expected returns) is available at the group level.

At the beginning of each repetition participants received two signals: one for each asset. In some repetitions, the distribution of signals over participants was according to

$$\rho_1 = \{\,(150, 50), (50, 150), (100, 50), (150, 50), (150, 100)\,\},$$

in other repetitions according to

$$\rho_2 = \{\,(150, 50), (50, 100), (100, 150), (150, 50), (150, 50)\,\}.$$

For instance, if the set of signals was ρ_2, there would be three participants who would receive the signal (150, 50) (i.e., signal 150 for asset H and signal 50 for asset L); one participant would receive the signal (50, 100) and one participant the signal (100, 150).

These two signal distributions were carefully designed in order to have some, but not all, participants start out with signals that are in agreement with the true ranking. They ensure that private information needs to be aggregated in order for the market to price correctly, but also that all information relevant to a correct pricing was available on market level. For instance, for the first asset (in this case asset H), three participants see the value 150, one the value 100 and one the value 50, which perfectly reflects the (3/5, 1/5, 1/5) probability distribution.

Participants did not know the signal distributions, so that the information on their signals would not reveal any information on the signals that others received. Use of the two signal distributions was varied across repetitions and groups (see the Online Appendix for details).

Comparing prices between the *Public information* and *Private information* variations allows us to cleanly identify differences in information aggregation across the institutions, as any difference between the two institutions that is *not* related to information aggregation should appear in the *Public information* treatments as well.[5]

2.1.3 | Bid-Ask feedback (with or without)

Our last treatment variation concerns the feedback given to participants after each trading period. In the first variation (*without Bid-Ask feedback*), participants can only exploit their private information about asset prices in order to unveil the state of nature. This setting mirrors markets in which little information about other traders' choices and outcomes are provided and the only available information are the market prices. Under the second feedback variation (*with Bid-Ask feedback*), participants further observe other traders' bids and asks (after the trading period). This type of markets resembles more transparent markets where other traders' outcomes and information can be inferred from their behavior. These two variations allow for comparisons of market and non-market settings in more and less information-rich environments. They also manipulate the salience of social comparisons, which is one potential channel through which markets could differentially affect bidding behavior.

2.1.4 | Procedures

The experiments were conducted in the experimental laboratory at Maastricht University between March 2014 and February 2017.[6] In total, we recruited 320 undergraduate students to participate in the experiment using ORSEE (Greiner, 2015). Students were evenly allocated over treatments, such that we have 40 students participating in each of the eight treatments. Table D1 provides basic randomization checks and shows that treatments were balanced with respect to key variables.

For each treatment, we collected buying and asking prices over three repetitions of 10 trading periods using z-Tree (Fischbacher, 2007). Since the participants were operating in fixed groups of five, this gives us eight independent observations per treatment. In order to avoid income effects and eliminating hedging opportunities between the two markets, final payments in the experiment were based on the earnings in one randomly chosen market in one randomly chosen trading period. Since participants were not given a cash budget during the trading phase, in the event that a trader made a loss on trade (resulting from buying an asset for a price that exceeded the drawn return value), this loss was covered by the show-up fee.[7]

In a post experimental questionnaire, we elicited information on participants' characteristics and personalities (see Appendix B). A typical session lasted about 2 hours and average earnings were about 16.06 Euros, including a 5 Euros show-up fee.

2.2 | Theoretical predictions

Before we discuss the results, we briefly describe the theoretical predictions concerning information aggregation properties of our setting. While the purpose of the experiment is *not* to test these predictions, it can be useful to have them in mind as a benchmark for how information aggregation might work in theory in this setting. It is well known that double auctions with sufficiently many buyers and sellers, who can bid using a sufficiently fine discrete set of prices, do have an equilibrium that is arbitrarily close to the fully revealing RE equilibrium (Reny & Perry, 2006). Our setting does not quite fit this well studied case, but it is easy to show that also in our environment the state of nature is eventually revealed by the equilibrium price.

For the sake of exposition, let us denote the state space by $\Omega = \Omega_H \times \Omega_L$ with[8]

$$\Omega_i = \left\{ \left(\frac{1}{5}, \frac{1}{5}, \frac{3}{5}\right), \left(\frac{1}{5}, \frac{3}{5}, \frac{1}{5}\right), \left(\frac{3}{5}, \frac{1}{5}, \frac{1}{5}\right), \left(\frac{2}{5}, \frac{2}{5}, \frac{1}{5}\right), \left(\frac{2}{5}, \frac{1}{5}, \frac{2}{5}\right), \left(\frac{1}{5}, \frac{2}{5}, \frac{2}{5}\right) \right\}, \; i = H, L.$$

Hence, consistent with the assets in our experiment, states are probability distributions over the three return values 50, 100, and 150.

We focus on the *Market* treatment with *Private information* and without bid-ask feedback for signal distribution ρ_1. Assume agents are risk-neutral and have prior beliefs uniformly distributed on all the states contained in Ω.[9] It is straightforward to show (Appendix C) that the agent with signal (50, 150) will have posterior beliefs that imply an expected value of 95 for asset *H* and 105 for asset *L*, with these values reversed for the two agents with signal (150, 50). The agent with signal (100, 50) will have an expected value for asset *H* of 100 and an expected value for asset *L* of 95 and the agents with signal (150, 100) will have an expected value of 105 and 100 for asset *H* and *L* respectively. In the first trading period, the ordered bids for asset *H* will be (105, 105, 105, 100, 95) and the ordered asks will be (95, 100, 105, 105, 105), which means that asset *H* will trade at a price of 105 (below its expected value of 120). Analogously, asset *L* will trade at a price of 95, above its expected value of 80. From these prices agents recognize that at least three agents have received a signal of 150 for asset *H* and a signal of 50 for asset *L*. Thus all private information will be revealed already in the first period. Under these theoretical assumptions, hence, information aggregation is relatively straightforward in our setting and prices should reflect all private information early on in the experiment.[10] We consider a more general setting in Appendix C1 and a case where traders are strategic in Appendix C2.

3 | MAIN RESULTS

The main results presented in this section are focused on comparing how well markets aggregate information compared to an institution which shares all the same features in terms of outcomes and information flows, except for the fact that trade is not bilateral (our *BDM* treatments).

Figure 1 shows the average market prices over time for both assets and both institutional environments under the two information treatments. Both assets are on average priced below their expected values (120 and 80 for asset *H* and *L*, respectively) in the *Public information* treatment where there is no information aggregation problem, and there does not seem to be a substantial difference between *BDM* and *Market* in this information condition. Under *Private information* prices differ from their *Public information* counterparts in both treatments. Note first that in both the *BDM* and

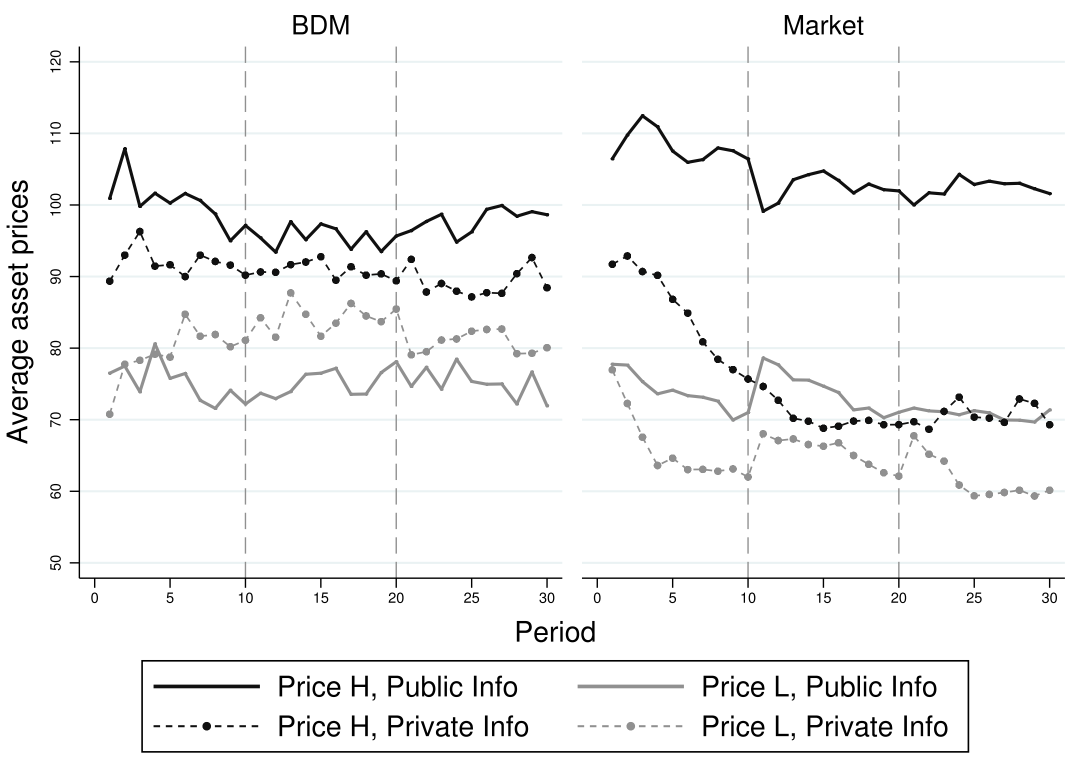

FIGURE 1 Average prices of both assets by institution. Treatments are pooled with respect to the bid-ask feedback dimension. All observations from all markets and groups are included as long as trade was feasible and a market price (group value) determined. The solid and dashed lines represent stock prices in *Public information* and *Private information* treatments respectively. The left panel shows fictitious prices under the *BDM* mechanism (*group value*) and the right panel *Market* prices

the *Market* treatment, the prices of the two assets move closer together than when returns are public information. This is intuitive, since under *Private information* there is ambiguity regarding the identity of the high and low value assets.

More specifically, in the *BDM* treatments asset H is underpriced compared to the public information case, while the opposite holds for asset L. In the *Market* treatments both assets are substantially undervalued and the difference to the public information case seems bigger than it is in the *BDM* treatments. Note also that prices don't start lower in the *Market* treatments compared to the *BDM*. Hence these lower prices are learned. This suggests that market interaction is detrimental for information aggregation. We will now investigate this possibility more formally.

In our statistical analysis, we will use two measures of information aggregation. The first measure (*Correct Ranking*) examines whether assets H and L are ranked correctly by market prices. This is a weak measure of information aggregation simply asking whether the stochastic dominance relation between assets is correctly reflected by how their market prices are ranked. Our second measure (*Perfect Aggregation*) is more ambitious and compares, for each institution, asset prices in the *Private information* treatments with their counterparts in the *Public information* treatments where there is no information aggregation problem. If stock prices under private information are the same as under public information, then all private information is revealed in the price. If markets successfully aggregate information, we should find no differences between the public information and private information conditions using either of these measures. As in Figure 1, we pool data from the variations with and without bid/ask feedback. Appendices D and E contain tables and figures where we split them out.

3.1 | Correct ranking

We start with the less demanding measure of information aggregation (Correct Ranking), which asks how frequently the price for asset H exceeds the price for asset L. Table 2 shows results from LPM and Probit estimates of the probability that assets are correctly ranked depending on our treatment dimensions:

$$Pr(p_H > p_L)_{it} = \alpha + \beta \; Private\ info_i + \gamma \; Market_i + \delta \; Private\ info_i \times Market_i + X_{it} + \epsilon_{it}, \tag{1}$$

where $Pr(p_H > p_L)_{it}$ is the probability that the market price of asset H exceeds that of asset L in group i in period t, *Private info* is a dummy for the treatments with private information and *Market* is a dummy variable for the *Market* treatments. X_{it} represents other covariates such as the signal distribution (ρ_1) or the repetition.

The *Market* and the *BDM* mechanism rank assets correctly with 95% and 93% probability, respectively, under public information and with 65% and 73% probability, respectively, under private information. We find no significant difference between the two institutions in the likelihood of ranking assets correctly under *Public information*: the coefficient γ is small and not statistically significant in any of the specifications. This result persists also under *Private information*. While in both the *BDM* and the *Market* private information decreases the probability to rank correctly—the coefficients β and $\beta + \delta$ are significantly negative ($p < 0.01$)—we find no difference between the two institutions according to this criterion: the coefficient $\gamma + \delta$, although negative, is never significantly different from zero ($p > 0.219$). This result is robust when we control for additional covariates (columns (2), (3), (5), and (6)) and is true under both bid-ask feedback variations (see Appendix D).

3.2 | Result 1 (correct ranking)

There is no significant difference between the *Market* and the *BDM* mechanism in terms of the likelihood that assets are ranked correctly.

3.3 | Perfect aggregation

Next, we turn to the more ambitious measure to examine information aggregation. We estimate for each asset the following model:

TABLE 2 Correct ranking

Prob (price H > price L)	LPM			Probit (dy/dx)		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.933*** (0.025)	0.933*** (0.025)	0.910*** (0.034)			
Private info (β)	−0.204*** (0.048)	−0.237*** (0.067)	−0.236*** (0.066)	−0.236*** (0.063)	−0.256*** (0.067)	−0.258*** (0.066)
Market (γ)	0.018 (0.046)	0.017 (0.046)	0.023 (0.045)	0.086 (0.086)	0.086 (0.086)	0.093 (0.085)
Private info × market (δ)	−0.101 (0.082)	−0.099 (0.117)	−0.101 (0.117)	−0.136 (0.100)	−0.133 (0.113)	−0.135 (0.112)
ρ_1		0.069 (0.106)	0.073 (0.101)		0.048 (0.074)	0.061 (0.066)
ρ_1 × market		−0.007 (0.162)	−0.015 (0.159)		−0.008 (0.110)	−0.021 (0.105)
Repetition 1			0.101** (0.045)			0.103** (0.047)
Repetition 2			−0.035 (0.049)			−0.032 (0.044)
$\beta + \delta$	−0.305	−0.336	−0.337	−0.372	−0.389	−0.393
p-value test $\beta + \delta = 0$	0.000	0.001	0.000	0.000	0.000	0.000
p-value test $\lvert\beta + \delta\rvert \leq \lvert\beta\rvert$	0.109	0.200	0.194	0.088	0.119	0.113
$\gamma + \delta$	−0.084	−0.081	−0.078	−0.050	−0.047	−0.042
p-value test $\gamma + \delta = 0$	0.219	0.451	0.468	0.322	0.512	0.554
Observations	1572	1572	1572	1572	1572	1572

Note: LPM (columns (1)–(3)) and probit (columns (4)–(6)) estimates of Equation (1). Robust standard errors (clustered at the group level) in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The smaller number of observations is due to the fact that in some rounds at most one asset is traded, such that a price is not properly specified for at least one of the assets.

$$MP_{it} = \alpha + \beta \; Private\ info_i + \gamma \; Market_i + \delta \; Private\ info_i \times Market_i + X_{it} + \epsilon_{it}, \tag{2}$$

where MP_{it} is the market price in group i in period t, and other variables as introduced earlier. Table 3 reports the results.

In the absence of an aggregation problem (*Public information* treatments), prices of both assets are below their expected values. The intercept, representing *BDM* treatments under *Public information*, in columns (1) and (4) is around 98 and 76 for assets H and L, respectively. The coefficient γ, which measures the impact of market interactions under public information, is never statistically different from zero at any conventional significance level. This implies that we find no statistical difference, in terms of asset prices, between the two institutions when there is no aggregation problem.

Turning the analysis to the *Private information* treatments, neither the *BDM* nor the *Market* aggregate information perfectly. The coefficients β and $\beta + \delta$, representing the effect of private information in the *BDM* and *Market* institutions, respectively, are both significantly different from zero in all specifications. Prices under private information are, hence, different from prices under public information. As illustrated in Figure 1, while private information induces a decrease in prices for asset H and an increase for asset L in *BDM* (β), in the *Market* treatments both assets are undervalued: the coefficient $\beta + \delta$ is significantly negative in all specifications ($p < 0.05$).

When we compare the effect of *Private information* between the two institutions, we find that in *Market* treatments the price for asset H presents larger negative departures from its *Public information* counterpart – that is, we do reject the null hypothesis of $|\beta + \delta| \leq |\beta|$. For asset L we cannot reject this hypothesis ($p > 0.2$). All these results are robust when controlling for additional covariates (columns (2), (3), (5), and (6)) and are true for both bid-ask feedback conditions (see Appendix D).

3.4 | Result 2 (perfect aggregation)

Under private information prices for asset H are further away from the public information benchmark in the *Market* compared to the *BDM* mechanism.

Does the worse performance in terms of perfect aggregation in the market decrease or increase prices compared to the *BDM*? The coefficient $\gamma + \delta$ measures the impact of market incentives under *Private information*. We find that market interaction significantly decreases prices of both assets when compared to the *BDM* ($p < 0.01$) but this effect is not there when there is no information aggregation problem (γ). Hence, there is no difference between the prices in the *Market* and *BDM* treatments in the absence of an information aggregation problem.[11] With private information, however, we find different results. Markets as an institution do *not* perform better than the *BDM* in aggregating information. While there is no significant difference on the likelihood of ranking assets correctly, prices in the market differ more strongly from the public information counterparts compared to the *BDM*. In some cases markets lead to considerable mis-pricing.

4 | DISCUSSION AND ADDITIONAL RESULTS

In this section, we discuss possible mechanisms leading to Results 1 and 2. The first thing to notice is that in the absence of an information aggregation problem, that is in the *Public information* treatments, there is no difference between the *Market* and *BDM* institutions neither in terms of correct ranking nor in terms of average prices (Tables 2 and 3). This suggests that mechanisms where markets affect preferences or beliefs per se are not likely to be the main driver of our results. In other words any explanation of the differences identified above must be directly or indirectly linked to the informational structure. In the following we discuss several such potential mechanisms.

4.1 | Learning: Price-sensitive and -insensitive traders

In this section, we outline our main explanation for why prices for asset H are further away from the public information benchmark in the *Market* compared to the *BDM* with private information (Result 2). We should first emphasize that our

TABLE 3 Perfect aggregation

	Price asset *H*			Price asset *L*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	98.328*** (2.676)	98.328*** (2.677)	96.472*** (2.824)	75.834*** (1.514)	75.833*** (1.515)	74.419*** (1.580)
Private info (β)	−8.130** (3.346)	−9.558*** (3.684)	−9.556*** (3.550)	5.634** (2.809)	5.641* (3.108)	5.638* (2.976)
Market (γ)	6.369 (4.292)	6.369 (4.295)	6.407 (4.268)	−2.355 (2.450)	−2.356 (2.451)	−2.389 (2.434)
Private info × market (δ)	−21.359*** (5.576)	−20.683*** (5.878)	−20.727*** (5.720)	−14.738*** (4.227)	−14.615*** (4.782)	−14.605*** (4.730)
ρ_1		2.783 (2.641)	3.013 (2.457)		−0.010 (2.050)	−0.052 (1.853)
$\rho_1 \times$ market		−1.293 (4.274)	−1.581 (3.986)		−0.246 (2.941)	−0.158 (2.746)
Repetition 1			5.999*** (1.771)			1.549 (1.162)
Repetition 2			−0.246 (1.225)			2.719** (1.061)
$\beta + \delta$	−29.489	−30.241	−30.283	−9.104	−8.974	−8.967
p-value test $\beta + \delta = 0$	0.000	0.000	0.000	0.004	0.014	0.015
p-value test $\lvert\beta + \delta\rvert \leq \lvert\beta\rvert$	0.000	0.000	0.000	0.206	0.243	0.241
$\gamma + \delta$	−14.990	−14.314	−14.319	−17.093	−16.971	−16.993
p-value test $\gamma + \delta = 0$	0.000	0.000	0.000	0.000	0.000	0.000
Observations	1761	1761	1761	1653	1653	1653

Note: GLS regression of Equation (2). Robust standard errors (clustered at the group level) in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

explanation does not rely on fundamentally different preferences, nor on different strategies. Such explanations are inconsistent with our experimental evidence as we will demonstrate in Sections 4.2.1 and 4.2.2. Instead we start from the observation, demonstrated in this section, that the difference between the two institutions is driven by price-insensitive traders, who are apparently not able to learn from the market price.[12] We then argue that participants who are not able to learn from the price are more likely to ignore it and follow their subjective prior in the *BDM* where the price is purely informational, but does not actually have to be paid. By contrast, in the *Market* they are more likely to perceive ambiguity, which—in the presence of ambiguity aversion—will lead to lower bids as we formally demonstrate in Appendix C.

We now outline this explanation in more detail. To empirically classify traders into price-sensitive and -insensitive we follow the methodology by Asparouhova et al. (2015) who classify participants based on the slope in an OLS regression where period-by-period changes in asset holdings are regressed on the difference between the actual asset price in the experiment and the expected value of the asset using correct (updated) probabilities. A negative slope means participants decrease their asset holdings when the asset is overpriced, that is they are price-sensitive. A zero slope indicates price-insensitivity and a positive slope indicates what Asparouhova et al. (2015) call "perverse" price-sensitivity, that is participants increasing their holdings of overpriced assets. Following Asparouhova et al. (2015) we use cutoffs for the t-statistic of -1.6 and 1.9 to indicate price sensitivity in either direction and classify participants as price-insensitive whose t-statistic falls in between these cutoff values.[13]

This procedure classifies a total of 85 participants (53%) in *Market* treatments as price-insensitive to both assets (39 in *Public information* and 46 in *Private information*); the remaining 75 participants (47%) are price-sensitive to at least one asset (41 in *Public information* and 34 in *Private information*). This is in line with Asparouhova et al. (2015) who find that 69 participants (58%) are price-sensitive and 51 (42%) are price-insensitive.[14] In the *BDM* treatments there are 59 price-sensitive and 101 price-insensitive traders (respectively, 35 and 24 in *Public information* and 45 and 56 in *Private information*). Given the large fraction of price-insensitive traders it is important to understand their role in the information aggregation process.

Table 4 shows the results of regressions comparing bids and asks of price-sensitive and price-insensitive traders across the different settings.[15] The table shows that for asset H information aggregation is not perfect for either type of trader and either type of institution with both coefficients β and $\beta + \delta$ significantly different from zero.[16] When it comes to our differences-in-differences analysis comparing public and private information in BDM and the market, we find that there is no statistically significant difference in the public-private information gap in bids and asks for price-sensitive traders, while there is a substantial gap for price-insensitive traders, which is highly statistically significant. For asset H, in particular, the coefficient δ is sizable and the hypothesis $|\beta + \delta| \leq |\beta|$ summarily rejected for price-insensitive traders. All these results are robust when controlling for additional covariates. The treatment difference we observed in Section 3, and in particular the massive drop in prices for this asset seen in Figure 1, seems driven by price-insensitive traders. For asset L price-sensitive traders' bids do not differ significantly between the public and private information cases with particularly the value of $\beta + \delta$ being very close to zero. For price-insensitive traders there are statistically significant differences between public and private information also for asset L and also here we reject the hypothesis $|\beta + \delta| \leq |\beta|$.[17]

Why do price-insensitive traders behave differently across the two institutions? As the price (*group value*) is not directly payoff relevant for participants in the *BDM* condition (it affects payoffs only via beliefs), it seems intuitive that traders in the *BDM* who do not learn from the price decide to ignore it, that is, use their subjective priors to determine their bids and asks. This is also in line with the pattern of roughly constant prices over time seen in Figure 1. In the market, by contrast, it is harder for participants to ignore the price they have to pay for an asset. Hence, here, when confronted with the dissonance between subjective priors and the price, it seems intuitive that traders who do not learn correctly from the price do not ignore it, but instead perceive ambiguity. In Appendix C, we show that under weak assumptions agents who perceive ambiguity will place lower bids for an asset than those who do not.[18] This would explain the downward trend in prices in the *Market* treatment particularly for asset H (see Figure 1).

There is a considerable and diverse body of literature broadly showing that ambiguity (typically generated exogenously) might affect market outcomes, though the design as well as the direction and the size of the effects differs across studies with some finding negative effects on prices and some finding no effects (Bossaerts et al., 2010; Corgnet et al., 2013; Huber et al., 2014; Ngangoué, 2017; Sarin & Weber, 1993).[19] In our data, we find that asks/bids for both assets are shifted upwards/downwards for price-insensitive traders (see Table 4) in line with ambiguity aversion. In the next section, we consider other possible mechanisms.

TABLE 4 Bids and asks of price-sensitive and price-insensitive traders for both assets

	Asset *H*				Asset *L*			
	Sensitive to *H*		Not sensitive		Sensitive to *L*		Not sensitive	
	Ask	Bid	Ask	Bid	Ask	Bid	Ask	Bid
Constant	111.895*** (5.261)	86.141*** (5.048)	113.250*** (3.011)	83.974*** (2.481)	85.981*** (5.060)	69.879*** (3.662)	88.243*** (1.742)	64.348*** (1.292)
Private info (β)	−14.722** (6.618)	−14.839*** (5.180)	−6.168* (3.714)	−6.423** (3.244)	15.477** (6.472)	4.169 (6.081)	4.206 (2.723)	4.070** (1.919)
Market (γ)	−9.070 (7.068)	0.353 (7.050)	5.501 (3.976)	13.467*** (3.927)	−5.263 (6.245)	−7.933* (4.196)	−8.087*** (2.346)	2.357 (1.936)
Private info × market (δ)	5.833 (9.292)	−7.797 (7.958)	−25.357*** (5.787)	−25.134*** (4.899)	−12.635 (8.865)	−6.051 (6.769)	−9.671** (4.387)	−11.952*** (2.738)
ρ_1	4.085 (3.783)	3.999* (2.337)	2.745 (2.229)	1.755 (1.430)	3.598 (3.855)	1.905 (2.496)	−2.843 (2.116)	−1.988* (1.121)
Repetition 1	13.354*** (2.898)	7.196*** (2.420)	5.691*** (1.618)	0.270 (1.459)	2.720 (3.345)	−1.557 (2.122)	5.558*** (1.207)	0.153 (0.652)
Repetition 2	0.487 (2.586)	1.421 (1.927)	−1.219 (1.056)	−1.336* (0.798)	1.114 (2.990)	−0.679 (2.115)	3.408*** (1.219)	1.565** (0.744)
$\beta + \delta$	−8.889	−22.635	−31.525	−31.557	2.842	−1.882	−5.464	−7.881
p-value test $\beta + \delta = 0$	0.229	0.000	0.000	0.000	0.680	0.632	0.195	0.001
p-value test $\lvert\beta + \delta\rvert \leq \lvert\beta\rvert$	0.735	0.164	0.000	0.000	0.923	0.617	0.411	0.118
$\gamma + \delta$	−3.237	−7.443	−19.856	−11.667	−17.897	−13.985	−17.758	−9.594
p-value test $\gamma + \delta = 0$	0.591	0.044	0.000	0.000	0.004	0.008	0.000	0.000
Observations	2310	2310	7080	7080	2130	2130	7290	7290

Notes: For asset *H* the table uses only participants who are price sensitive for asset *H*. Those are 42 participants for asset *H*. Hence the "insensitive" category here includes (i) the 75 participants who are price-insensitive to both assets, but also (ii) 43 participants who are price-insensitive to *H*, but price-sensitive to *L*. Analogously for asset *L*. Data of 7 (6) participants are missing for asset *H* (*L*), since it was not possible to classify their sensitivity for the respective asset due to either lack of variability in their behavior/holdings or market prices were missing. Clustered standard errors at the group level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 | Other potential mechanisms

In this subsection, we discuss other potential mechanisms and provide evidence why we believe that they are unlikely to be a key driver of our results. We first study differences in preferences (Section 4.2.1), then differences in strategic behavior (Section 4.2.2), and last differences in cognitive strain (Section 4.2.3) between the two environments. It is important to note that we are not denying that differences in preferences or strategic behavior may exist. We argue, however, that they are not the main underlying reason behind the results discussed in Section 3.

4.2.1 | Differences in preferences

If the differences observed across institutions would be driven by different preferences over outcomes across the two institutions, then these differences should also be observed within the *Public information* treatments. Table 3 shows that —if such differences exist—they are not translated into market prices. We can hence rule out explanations based on simple differences between preferences over outcomes.

Still, preferences (even if the same across environments) might play a role in other ways. One notable difference between the *Market* treatments and the *BDM* treatments is that, because in the *Market* treatment assets are traded, risks between traders are negatively correlated in the sense that a favorable realization for a traded asset is benefiting the agent who bought the asset while it is an implicit loss for the agent who sold the asset. If agents care about social comparisons this negative correlation could affect their behavior. More formally, sensitivity to such implicit losses can be captured by a model of reference dependent preferences (Kőszegi & Rabin, 2006) incorporating a social comparison reference point (Schmidt et al., 2015).

Consider an agent i facing a lottery with K outcomes x_k and associated probabilities p_k ($k = 1, ..., K$), and a lottery with L (social comparison) reference points r_ℓ ($\ell = 1, ..., L$) with $q_{k\ell}$ being the probability distribution over pairs (x_k, r_ℓ). In the state (x_k, r_ℓ), agent i receives outcome x_k while his reference point is r_ℓ. We define the agent's utility V on the domain of outcomes x and reference points r,

$$V(x,r) = \eta \sum_k p_k u(x_k) + \psi \sum_{k,\ell} q_{k\ell} v(u(x_k) - u(r_\ell)).$$

The first term is the expected (consumption) utility of the gamble (asset) held, weighted by factor η. The parameter ψ in the second term controls the sensitivity to social comparison. We assume that $v(0) = 0$ and $v' > 0$. In order to understand how social comparison affects trading prices, it suffices to consider a simple swap between assets H and L between agent i and j, taking the other's payoff as "reference point." We show in Appendix C that the more sensitive agent i is to social comparison (everything else equal), the more reluctant is she to swap assets when she is owning the H asset. That is, the more sensitive she is to social comparison, the more valuable asset H is relative to asset L. Hence with social comparison sensitive traders, the difference between the (hypothetical) prices of assets H and L is expected to increase. For our experiment this means that price differences should be larger in *Market* versus *BDM*. Comparing the mean price difference between *Market* (20.26) and *BDM* (14.09) we do indeed find evidence in line with the former prediction (Mann-Whitney U test, $p < 0.001$).

To the extent that bid-ask feedback facilitates social comparisons we should also see a difference between prices across these variations. However, within the *Market* treatments we do not find a significant effect of bid-ask feedback on mean price differences (NoBAF: 20.43, BAF: 20.08; Mann-Whitney U test: $p = 0.596$). Figure E1 splits Figure 1 by the bid-ask feedback dimension and illustrates that such feedback seems to make little difference, and the regressions reported in Table D4 confirm this.[20] Hence, despite the fact that adding social comparison information should make the type of considerations discussed above more salient we do not find significant treatment differences. Based on this evidence it seems unlikely individuals' sensitivity to social comparisons is a key driver of our results.

4.2.2 | Differences in strategic behavior

A second class of alternative explanations we discuss are based on differences in strategies. As we do not see price differences with public information, any explanation based on differences in strategic behavior needs to rely on some assumption as to why strategies are different enough to cause price differences with private but not public information.

How could strategic behavior affect prices, though? Note first that in the *BDM*, subjects have no influence on the price they pay or receive for the asset. If traders are risk neutral this will lead (as we show in Appendix C) to an initial price in the interval [103.1, 112.5) for asset *H* and in the interval (87.5, 96.9] for asset *L*. Further, for each asset, three units will be traded (hypothetically given bids and asks). Unlike in the *BDM*, in the call market traders can influence the price at which they are buying or selling: buyers like to lower the price and sellers like to increase the price. Subjects in the market, therefore, have an incentive to shade their bids and asks by bidding a bit lower and asking a bit more than the expected value. If we assume participants shade their bids and asks, but not by "too much," this will lead (as we show in Appendix C2) to a price in the interval [114.0625, 118.75) for asset *H* and in the interval (93.75, 98.4375] for asset *L*. For both assets, two units will be traded.

Based on this, strategic behavior should lead to higher prices for asset *H* in the market relative to the *BDM*, and fewer units to be traded. Table 3 shows our findings in this regard. In the public information setting, we find, consistent with this, a slightly higher price for asset *H*, but a slightly lower price for asset *L*; however, both difference are not statistical significant (see coefficient β). For the private information setting, we find for both assets significantly lower prices in the market (see coefficient $\gamma + \delta$), which does not point to strategic behavior being a dominant factor. In terms of units traded, we find that actually fewer units are traded under the *BDM* compared to the market treatment (see Table D5).[21] With strategic behavior we would expect the opposite result. Taken together these pieces of evidence suggest to us that it is unlikely that strategic trading causes the difference between the *BDM* and market treatment.

4.2.3 | Differences in cognitive strain

One difference between the *BDM* setting and the *Market* setting is that, while in the *BDM* the price (*group value*) has a purely informational role, in the *Market* it also enters participants' payoff calculations directly. This double role of the price is one way in which differences in cognitive strain between the two treatments could come about. Similarly, there could be differences in cognitive strain between the treatments differing in bid-ask feedback, since in the treatments with bid-ask feedback there is more information available to process for participants. There are several factors which suggest to us that differences in cognitive strain are not a key driver of our results. First, note that there is no difference between the *BDM* and *Market* settings in the public information case (see coefficient γ in Tables 2 and 3). Hence, if differences in cognitive strain are behind the differences observed with private information, they must come from an interaction between the informational role of the price (which is identical) and the price mechanism. Second, we can compare noise levels across the two institutions. If cognitive strain is higher under the *Market* condition, this could be reflected in higher levels of noise in the *Market* compared to the *BDM*. We do not find evidence for this in the data. In fact, the coefficient of variation ($\frac{\sigma}{\mu}$ ratio) for market prices is, if at all, higher in the *BDM* compared to the *Market* (0.32 vs. 0.30 for asset *H* and 0.39 vs. 0.27 for asset *L*). Third, for those participants who are price-sensitive there is no difference between the two institutions, suggesting that if cognitive strain matters, it matters only for some participants. Fourth, we do not see a difference between the treatments with bid-ask feedback and those without, which should arguably also differ in terms of cognitive strain. While none of these elements by itself constitutes proof, their combination suggests to us that differences in cognitive strain are not of key importance in driving our results.

5 | CONCLUSIONS

We conducted a lab experiment to study information aggregation in markets. The innovative aspect of our work is that we assess the quality of information aggregation in the market relative to a comparable non-market institution. To this purpose, participants in our lab experiment are randomly assigned to different institutional environments. In treatments with market interaction (the market treatments), assets are traded via a call auction mechanism. In the non-market treatments, prices of assets are determined via a BDM mechanism. Treatments are designed in such a way that the information available to participants across the market and non-market variations is exactly identical. The only difference is how prices are determined.

We find that markets do worse compared to the non market institution. In particular prices are further away from the public information benchmark in the market compared to the BDM mechanism. The difference is driven by price-insensitive traders who seem unable to learn from market prices. Because of this, they perceive a wedge between their subjective prior and the market price, which they cannot rationalize. This leads them to perceive ambiguity in the market which then affects their bids and asks. Price-sensitive traders, by contrast, learn equally well in the market as they do under the BDM mechanism. They seem, hence, able to extract information from the price despite the noise generated by price-insensitive traders.

Our results caution against the naive belief that markets will always successfully aggregate information. Further research could study which properties of markets lead to better or worse outcomes in this regard. Our results in Appendix D suggest that bid-ask feedback might play a role with over-the-counter markets potentially more affected.[22] Another property worth exploring further in this context is the volume of trades. While in our experiment volumes traded were low it would be interesting to see how markets and the BDM mechanism compare under high volume trading.

There are two further directions for future research that seem obvious. First, the robustness of our findings could be studied more extensively including for settings with more traders and more assets with positively correlated risk. While we have documented robustness across some information conditions, more could be done in this direction as well, both in terms of feedback structures and initial information available (including asymmetries with informed and uninformed agents). Second, while our treatments and explorative analysis have suggested one possible mechanism (and ruled out some others), more research needs to be done to understand the role of price-insensitive traders and how they learn across different settings.

ACKNOWLEDGMENTS

We thank Leonard Wolk and seminar participants in Maastricht and Auckland for very helpful comments and suggestions. The Netherlands Organisation for Scientific Research (NWO) is gratefully acknowledged for its support.

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ENDNOTES

[1] Using a lab experiment allows us to determine exactly the relevant public and private information held by traders and to assess to what extent, all information is embodied in market prices. It also allows us to compare our results to existing evidence in directly comparable markets.

[2] We do not find differences in asset prices between the market and the non-market institution in the case of public information, which is in line with Crockett et al. (2020) where behavior is found to be invariant to prices being form exogenous or endogenous.

[3] While we do not directly elicit neither priors nor posteriors from traders and hence cannot prove this point, it seems very unlikely to us that a trader whose bids and asks do not react to the market price would be making inference on the return distribution from the price. As the price changes over time there must be a wedge between fixed priors and the changing price.

[4] Plott et al. (2003) study the ability of parimutuel betting systems in aggregating information under two specific environments. The difference lies on the "precision" of the private information hence, on the difficulty to learn the state of the world. While the simpler environment advocates for the RE equilibrium, in the more complex situation the most accurate model predicts that individuals decide according to their private information.

[5] The impact of information being public or private is also addressed in some of the experimental common-value auction literature (Brocas et al., 2015; Grosskopf et al., 2018), though there are many differences between these and our settings.

[6] We conducted the private information sessions in 2014 and the public information sessions between late 2016 and early 2017.

[7] Hence, technically, the show-up served as an endowment; though, this was not explicitly presented as such to the participants.

[8] In Appendix C, we derive predictions for the case where agents consider a more general state space and in particular where they deem it possible that probabilities are defined on a grid finer than $\frac{1}{5}$.

[9] Note that in the experiment we did not provide a prior to participants.

[10] Under the more general setting presented in Appendix C, we find that more than one period of trading is needed to reveal all private information, but that one period is sufficient for all agents to learn to rank the assets correctly. Further, note that this results is not particular to the chosen signal distribution ρ_1, and would hold for all signal distributions (including ρ_2) that reflect the exact probability distribution over the asset outcomes.

[11] This differs from the results obtained in Bohm et al. (1997)'s artificial market, suggesting that the design of experimental markets is important.

[12] In theory it could also be that they are price-insensitive because they have very special preferences. Any such explanation is essentially ruled out by the evidence from our public information treatments, see Section 3.

[13] The reason Asparouhova et al. (2015) use asymmetric cutoffs is a well known simultaneous-equation bias in estimating price-sensitivity. Because total changes in holdings of assets must balance out across participants, slope coefficients must sum to zero and OLS estimates will be biased upwards.

[14] Note that, by design, the variation in asset holdings between periods is relatively small in our experiment. This might be one reason why slightly more participants are classified as price-insensitive in our study compared to Asparouhova et al. (2015). Broadly, though, the results are very similar.

[15] Reported results do not change if we would classify participants as price-sensitive or price-insensitive based on their behavior in Repetition 1, and restrict the regression to their bids and asks in Repetitions 2 and 3.

[16] Note that it is entirely plausible that some traders who are classified as "price-sensitive" do perceive some amount of ambiguity and act accordingly.

[17] Appendix Figure E2 shows a simulated price path for price-sensitive traders only. The figure shows that for these traders the difference between prices under public and private information is much smaller compared to the full sample.

[18] Essentially these assumptions are that agents who perceive ambiguity entertain at least one posterior that implies a worse expected asset return than the correct posterior of an agent who does not perceive ambiguity.

[19] Theoretically, in the presence of ambiguity-averse agents equilibrium prices may fail to reflect all the available information (Caskey, 2009; Condie & Ganguli, 2017). See Epstein and Schneider (2010) and Guidolin and Rinaldi (2013) for a review of the theoretical literature.

[20] For the situation without (with) bid-ask feedback, the differences between the market and the BDM are in Table D4 captured by γ (τ) for public information and by $\gamma + \delta$ (ϕ) for private information. For both situations, there is no significant difference with public information and are for both assets prices lower in the market with private information. Hence, there is no sign of the results reported in Section 3 being driven by one of the bid-ask feedback conditions only.

[21] Of course under the *BDM* no units are actually traded at all. In Table D5, we compare the amount of units that would be traded hypothetically under the *BDM* given bids and asks with those actually traded in the market.

[22] In a companion paper (Mengel & Peeters, 2021), we find that bid-ask feedback causes a substantial difference in risk-taking behavior.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Albertazzi, A., Mengel, F. & Peeters, R. (2021) Benchmarking information aggregation in experimental markets. *Economic Inquiry*, 1–17. Available from: https://doi.org/10.1111/ecin.13010