Price distortions and public information: theory, experiments and simulations

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Abstract

This paper studies the effects on the asset price of the introduction of a public signal in the presence of asymmetric private information in a decentralized market. We introduce an artificial market model populated by boundedly rational agents with heterogeneous levels of reasoning: sophisticated and naive traders. The model captures the main impacts of public information analyzed in the laboratory experiments reported by Ruiz-Buforn et al. (2019). Public information, when correct, coordinates market activity, improving price convergence to the fundamentals. By contrast, unwarranted public information pushes prices away from fundamentals. This strong influence of public information on prices is primarily driven by its common knowledge property.

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1 Introduction

The idea that a price system based on competitive markets is able to aggregate dispersed information in the economy dates back at least to Hayek (1945). A detailed description of the ability of markets in efficiently aggregate information, and the conditions under which this might take place, is found in the theoretical literature of rational expectations and market structure. Grossman and Stiglitz (1980) demonstrate that a paradox exists when in a competitive and efficient market the production of information is costly. Informed traders have no incentive to reveal their private information into the market if not properly compensated by the costs of producing information, and therefore it does not exists an equilibrium price. This problem is solved when prices only partially reveal the information.

There is a large experimental literature dealing with the aggregation and dissemination of information in laboratory financial markets to test the theoretical predictions of rational expectation equilibrium models. Many experimental contributions have shown that centralized asset markets can disseminate private information held by agents (Plott and Sunder, 1982). However, the ability of markets to disseminate (free allocated) information is limited (Plott and Sunder, 1988; Camerer and Weigelt, 1991; Corgnet et al., 2015).

There is another set of models that study the aggregation of information in decentralized markets. These markets are characterized by their opaqueness, where the details of the contracts are only known by the two parties (Duffie, 2012). Several theoretical studies suggest that decentralized markets are able to aggregate dispersed information in the market, although the aggregation process is slowed down with respect to centralized markets (Duffie et al., 2005; Duffie and Manso, 2007; Duffie et al., 2015).

Despite the extensive literature on aggregation of information, not much attention has been paid to the interplay between private and public information and its potential adverse effects on market performance. In addition to the information held privately by traders, one might assume the existence of a disciplining institution that releases public information to improve market efficiency. For instance, the European Central Bank employs the *forward guidance* to manage the expectations of investors and consumers, providing information about future monetary policy targets. Thus, the forward guidance can influence current financial and economic conditions. However, the central bank announcements might influence too much the informativeness of prices and create an overweighting phenomenon, enhancing the volatility of markets. Public information, in fact, provides common priors for the market and "significant market events generally occur only if there is similar thinking among large groups of people..." (Shiller, 2002).

Taking stock of that, it is not trivial to predict the effect of public announcements on market performance. Beyond the information on fundamentals, public announcements provide information about the beliefs of the other market participants. Morris and Shin (2005) state that "The central bank cannot manipulate prices and, at the same time, hope that prices yield informative signals." Another example is the sovereign bonds market where prices are closely tracked to assess the probability of debt default of a country. However, prices may become uninformative when some unwarranted information is publicly announced. This public information may allow self-fulfilling beliefs. Allen et al. (2006) prove that there is an excessive reliance on a public signal even when there is not an explicit coordination motive. Agents use that information to better forecast the aggregate demand and, therefore, they overweight its value above and beyond its role in predicting the liquidation value of the asset.

We address the overweighting of public information phenomenon within a simple trading model. We formalize a decentralized asset market with heterogeneous agents who differ in their level of reasoning and information.[1] Using Monte Carlo simulations and comparing them with the observed experimental data in Ruiz-Buforn et al. (2019), we establish two conjectures. Our first conjecture suggests that the presence of more traders with higher levels of reasoning increases the impact of public information in the aggregate transaction prices. Second, the common knowledge of the public signal is the main responsible of the distortive effect of a misleading public signal. Ruiz-Buforn et al. (2019) study the effects of releasing public information in a laboratory financial market where traders have access to private information.[2] Our model reproduces qualitatively the main patterns observed in the laboratory experiment. Prices are strongly biased toward the public signal independently of its realization, i.e. correct or incorrect prediction on fundamentals. However, the impact of mistaken information lessens when the released signal, even if it is observed by all traders, is not common knowledge.

The rest of the chapter is organized as follows. Section 2 introduces the behavioral trading model and its results. Section 3 describes the laboratory experiment. Section 4 illustrates the model calibration and the finite sample properties of the model, implementing Monte Carlo simulations and comparing them to the observed data. Finally, Section 6 concludes.

2 The model

2.1 Information set

The market is populated by N agents who are endowed with risky assets and cash.[3] The asset is essentially an Arrow-Debreu security, which can take two possible values $D \in \{0, 1\}$ with equal probability. At the beginning of the market, all agents observe a binary public signal $y \in \{-1, 1\}$ that predicts the value of the asset with probability $q \in [\frac{1}{2}, 1]$. A public signal $y = -1$ indicates that $D = 0$ whereas a signal $y = 1$ indicates that $D = 1$. Moreover, each agent receives two binary private signals that predict the value D, each one with probability $p \in [\frac{1}{2}, 1]$. Agent i's private information can take three values: (i) $x_i = 2$ if the agent receives two private signals predicting $D = 1$; (ii) $x_i = 0$ if they receive two opposite signals and (iii) $x_i = -2$ if

[1] Cognitive hierarchical models represent stock markets where some traders believe, incorrectly and over-confidently, that their strategy is the most sophisticated. In such situations, "the players are not in equilibrium because some players' beliefs are mistaken" (Camerer et al., 2004).

[2] Ruiz-Buforn et al. (2018) test the overweighting phenomenon when traders can acquire costly private information.

[3] The amount of cash is a loan that they must give back at the closing of the market.

they receive two private signals predicting $D = 0$. Thus, there are three possible information levels depending on the realization of the private signals. Each level of information is denoted by "i", which indicates *high*, *medium* and *low* $i \in \{H, M, L\}$. Note that y is common knowledge to all agents whereas x_i is private information for each agent and, therefore, not observable by the other agents.

According to the Bayesian inference, agent i's expected dividend is

$$E[D = 1|x_i, y] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{x_i} \left(\frac{1-q}{q}\right)^{y}} . \tag{1}$$

According to the informational levels, there are three possible expected dividend values in the market $D_i \in \{D_H, D_M, D_L\}$.[4] Agent i's expected dividend is *high* (D_H) when his private information is $x_i = 2$. If agent i observes $x_i = 0$, he is privately uninformed and his expected dividend is *medium* (D_M). Finally, if he observes $x_i = -2$, he has a *low* expected dividend D_L.

2.2 Agents' decisions

Once private and public information is revealed, agents decide whether to be sellers or buyers and the price of their offer. Agents have one chance to decide their offer and bargaining is not allowed. Each agent's offer involves one randomly chosen agent as a counterpart. Thus, an agent who observes the offer of another agent in the market decides whether to accept or reject it.

We assume that all agents are risk-neutral and bounded rational since they are not fully aware of the strategic implications of their actions in an asymmetric information environment. Using the concepts of cognitive hierarchy theory, there are two types of agents $\tau \in \{N, S\}$ according to their level of reasoning. A fraction $\theta \in [0, 1]$ of the agents' population is sophisticated (S) while a fraction $1 - \theta$ is constituted by naive traders (N). Agents desire to maximize expected payoffs[5], using their information. Naive traders only consider the information they have about the fundamentals. Sophisticated traders, on the other hand, make use of the public information in order to forecast other agents' beliefs, considering that it also carries information on the asset liquidation value. Unlike naive traders, sophisticated traders compute the probability of acceptance for each offer. Essentially, our market population is characterized by agents trading based on their first-order beliefs (naive) and agents trading based on their second-order beliefs (sophisticated).

An important point should be clarified here. Our market is populated by heterogeneous agents with different time-invariant trading strategies. This means that the agents do not learn from their trading activity, but they follow the same strategy. The market is not centralized since we implement a bilateral trading mechanism between two agents. We use the average price as a measure of central tendency of the whole transactions distribution.

[4] Hereafter, we will denote the expected dividend as $D_i \equiv E[D = 1|x_i, y]$.

[5] The expected payoff denotes the income of the trader after dividend payment.

Naive traders

A naive trader acts as prior information trader considering only his own information without taking into account the zero-sum nature of the game and the strategic implications of his actions.

Naive Proposer: First, we define the features of naive traders' bidding behavior. If he submits a buy offer at price b and it is accepted, he gets an additional unit of the asset and his expected payoff is $\pi^N(b|D_i) = 2D_i - b$. If his sell offer at price a is accepted, he trades his unit and gets a payoff[6] $\pi^N(a|D_i) = a$. Finally, if he does nothing, i.e. there is no trade (nt), his expected payoff is $\pi^N(nt|D_i) = D_i$.

A naive trader takes the action that provides him with the highest expected payoff:

$$s_i = \underset{s \in \{a,b,nt\}}{\text{argsup}}\ \pi^N(s|D_i)\ , \tag{2}$$

where a, b and nt refer to every possible action s of a naive trader: submitting a sell offer at price a, submitting a buy offer at price b and doing nothing, respectively.

Comparing the three possible strategies -submitting a bid, an ask or doing nothing- he prefers submitting bids below his expected dividend and asks above it ($b < D_i < a$). Since he only considers the information on fundamentals, we assume he estimates that the probability of an offer being accepted is exponentially decreasing with the gains from trading. So, he submits bids and asks close to his expected dividend D_i. The naive proposer i, therefore, submits bids $b_i = D_i - \varepsilon$ and asks $a_i = D_i + \varepsilon$ with the same probability, since both actions provide him with the same expected payoff, which is strictly higher than doing nothing. Note that he earns the extra profit ε with respect to doing nothing, which is independent of his type i. The parameter ε is exogenously fixed. We assume that $0 < \varepsilon < min\{D_i\}$. So that all bids and asks are within the range $[0, 1]$ independent of i.

The expected payoff of a naive proposer when submits his optimal offer is

$$\pi^N(a|D_i) = D_i + \varepsilon$$

and

$$\pi^N(b|D_i) = D_i + \varepsilon\ .$$

Since it is the same, he randomizes between the two strategies.

Naive Receiver: Similarly, we assume that a naive trader accepts offers that provide him with a higher expected payoff than no accepting them. If a naive trader receives a bid, the expected payoff of acceptance is b. If he receives an ask and accepts it, he gets an additional asset and his expected payoff is $2D_i - a$. Thus, a naive trader accepts buy offers below and sells offers above his expected dividend:

$$\pi^N(b, D_i) = \begin{cases} b & \text{if he accepts} \\ D_i & \text{if he rejects} \end{cases}$$

[6]The proposer knows with certainty the gains of his action since they do not depend on the liquidation value of the asset.

and

$$\pi^N(a, D_i) = \begin{cases} 2D_i - a & \text{if he accepts} \\ D_i & \text{if he rejects} \end{cases}$$

In conclusion, he accepts a bid if $b > D_i$ and an ask if $a < D_i$.

Sophisticated traders

We assume that a sophisticated trader acts with certain level of strategic reasoning. When deciding her strategy, a sophisticated trader uses her information set (x_i, y) and considers the trading motives of the counterpart to decide her optimal action. We assume that sophisticated traders consider their second-order beliefs based on the assumption that all other traders in the market are naive. As a consequence, sophisticated traders take into account how information (private and public) is distributed across traders in the market. The bounded rationality of this kind of traders stems from the fact that they do not contemplate higher-order beliefs, i.e. they believe that all other traders are naive, without further iteration levels.

In this framework, the public signal enters in the information set of all traders in the market. The public nature of this signal allows sophisticated traders to better characterized other traders' expectations.

Sophisticated Proposer: When a sophisticated trader submits an offer, her expected payoff depends on the selling price a or the buying price b, her information D_i and the probability that her offer is accepted. She faces a trade-off between the transaction payoff and the probability of closing such transaction. If she submits an ask a, her expected payoff is[7]

$$\pi^S(a|D_i) = D_i + (a - D_i) \sum_j Pr[a < D_j|D_i] ,$$

where $Pr[a < D_j|D_i]$ denotes the probability that a sophisticated trader with expected dividend D_i sells her asset at price a. In other words, $Pr[a < D_j|D_i]$ represents the probability to be matched with a trader with an expected dividend $D_j > a$ given her information. Similarly, when submitting a bid b her expected payoff is

$$\pi^S(b|D_i) = D_i + (D_i - b) \sum_j Pr[b > D_j|D_i] ,$$

where $Pr[b > D_j|D_i]$ denotes the probability that a sophisticated trader with expected dividend D_i buys her asset at price b. In case that the sophisticated trader decides to do nothing, her expected payoff is D_i.

A sophisticated trader takes the action that provides her with the highest expected payoff:

$$s_i^* = \underset{s \in \{a,b,nt\}}{\text{argsup}} \; \pi^S(s|D_i) , \tag{3}$$

[7]See appendix A.1 for the extended functions.

where a, b, nt denotes every possible trader's action: selling at price a, buying at price b and doing nothing, respectively. She faces a trade-off between maximizing her payoff and maximizing the potential market demand.

Solving eq. (3), the optimal action for a sophisticated trader with an expected dividend D_H is submitting buy offers at price $b^*_H = D_M + \varepsilon$. If her expected dividend is D_L, she will submit sell offers at price $a^*_L = D_M - \varepsilon$. The trade-off between her transaction payoff and the potential market demand is optimized at the medium-price level. To give some intuition, at that price she satisfies the demand of two out of three types of naive traders. Finally, if she is privately uninformed (D_M), submitting a bid $b^*_M = D_L + \varepsilon$ or an ask $a^*_M = D_H - \varepsilon$ provides her with the highest expected payoff. Note that an uninformed sophisticated trader is not able to exploit the difference between her private information and the public signal. Given that her information is the public signal, it does not help her to characterized other traders' expectations. So, her optimal choice is selling at the highest possible price or buying at the lowest possible price that a trader is willing to accept.

Sophisticated Receiver: In case a sophisticated trader receives an offer, it provides her with new information to be updated. Indeed, the received offer carries information about the proposer's private information. A sophisticated trader knows that traders submit offers that provide them with positive expected payoffs. This means that no trader will submit sell offers below his expected dividend nor buy offers above his expected dividend.[8] The expected payoff of a sophisticated trader when she receives a bid b or an ask a is

$$\pi^S(b, D_i) = \begin{cases} b & \text{if she accepts} \\ \sum_j D_{ij} \quad Pr[D_j | D_j > b] & \text{if she rejects} \end{cases}$$

and

$$\pi^S(a, D_i) = \begin{cases} -a + 2\sum_j D_{ij} \quad Pr[D_j | D_j < a] & \text{if she accepts} \\ \sum_j D_{ij} \quad Pr[D_j | D_j < a] & \text{if she rejects} \end{cases}$$

where D_{ij} denotes the updated expected dividend of the trader i when she infers from the offer that the proposer's expected dividend is D_j.[9] D_{ij} is computed by adding the proposer's private signals $x_j \in \{-2, 0, 2\}$ to her own information set $D_{ij} \equiv E[D = 1 | x_i, x_j, y]$. Finally, $Pr[D_j | D_j > b]$ and $Pr[D_j | D_j < a]$ define the probability of the proposer's level of information given the observed bid and ask, respectively.[10] The optimal action depends on which of the two expected payoffs is higher.

[8] For example, she identifies the proposer as type H when she observes a bid $b > D_M$. In case she observes a buy offer at $b > D_L$, she infers the probability that the expected dividend of the proposer is D_H or D_M. A bid $b < D_L$ does not carry additional information since any trader makes positive expected payoffs buying at a very low price.

[9] Table 3 in Appendix A.2 describes the information revealed in every offer, together with some illustrative examples to explain the computing process of the expected payoffs.

[10] Recall that sophisticated traders believe all other traders are naive.

2.3 Endogenous order flow

Having defined the optimal strategy for each type of trader, we now compute the optimal number of offers submitted by them. In order to do so, we introduce a cost function in the number of offers. This cost function is composed by a quadratic term[11] $c \cdot (z_i^\tau)^2$ and an opportunity cost term D_i. The parameter c is a constant of proportionality. The variable z_i^τ denotes the number of offers submitted by a trader of type τ and with expected dividend D_i. The quadratic term can be understood as some costs to manage all information related to the offers. The opportunity cost denotes trader's expected payoffs if he would not submit any offer. Proposer's cumulative payoff function is

$$\Pi^\tau(s|D_i) = [\pi^\tau(s|D_i) - c\, z_i^\tau - D_i]\ z_i^\tau\ , \tag{4}$$

where $\pi^\tau(s|D_i)$ denotes the proposer's expected payoffs when playing his or her optimal strategy s given her information. The order flow is the optimal number of offers per unit of time and it is computed maximizing eq. (4) with respect to z_i^τ:

$$z_i^\tau = \frac{\pi^\tau(s|D_i) - D_i}{2c}\ .$$

For naive traders, we denote the order flow with $z_i^N = \nu = \frac{\varepsilon}{2c}$, which is independent of their information level. The order flow of sophisticated traders, on the other hand, changes based on their information level. The relative order flow of sophisticated traders with respect to the naive traders is

$$\mu_i = \frac{z_i^S}{z_i^N} = \frac{\pi^S(s|D_i) - D_i}{\varepsilon}\ .$$

Without loss of generality, we can set the value of c in such a way that the order flow of the naive traders is $\nu = 1$, so that $c = \frac{\varepsilon}{2}$.

2.4 Transactions

What we have characterized so far the traders' behavior given their level of reasoning and information. In general, a trade occurs because traders differ in endowments, preferences or beliefs. The latter element takes place in our framework. In this section, we study the tendency of transaction prices as a function of the fraction of sophisticated traders in the market $\theta \in [0, 1]$.

Without loss of generality, Table 1 describes the market transactions assuming $D = 1$. The first column lists the proposer's type according to their level of reasoning and information, the second and the third columns show the optimal strategy of every type of trader. Finally, the last column lists what types of traders accept the offer.

Let us define with $f(\tau_i, \tau'_j)$ the probability per unit of time that a given match between two traders, a proposer τ_i and a receiver τ'_j, turns out in a transaction.[12] If

[11]The quadratic nature of the costs is necessary for having an optimal value for the number of offers.

[12]In order to compute it, we refer to Table 1. Note that $f(\tau_i, \tau'_i) = 0 \quad \forall i$.

Proposer (τ_i)	**Offer**	**Price**	**Receiver** (τ'_j)
S_H	b^*_H	$D_M + \varepsilon$	N_L, N_M S_L
S_M	a^*_M	$D_H - \varepsilon$	N_H
	b^*_M	$D_L + \varepsilon$	N_L
S_L	a^*_L	$D_M - \varepsilon$	N_H, N_M S_H
N_H	a_H	$D_H + \varepsilon$	*No trade*
	b_H	$D_H - \varepsilon$	N_M, N_L, S_L
N_M	a_M	$D_M + \varepsilon$	N_H S_H
	b_M	$D_M - \varepsilon$	N_L, S_L
N_L	a_L	$D_L + \varepsilon$	N_H, N_M, S_H
	b_L	$D_L - \varepsilon$	*No trade*

Notes: In the first and last columns both parts of a transaction, the proposer and the receiver, are described. S (N) denotes the type of traders according to their level of reasoning -sophisticated (naive)-, whereas the subindex H, M and L represent traders' expected dividend. The other two columns of the table show the offers and their corresponding prices.

Table 1 Transactions.

we sum over the index τ' and j, $\sum_{\tau' j} f(\tau_i, \tau'_j)$, we obtain the probability per unit of time that a trader τ_i closes a transaction according to her or his optimal strategy. Introducing the order flow $\omega_i^\tau = \begin{cases} \mu_i & \text{if } \tau = S \\ 1 & \text{if } \tau = N \end{cases}$ we have

$$t(\tau_i) = \omega_i^\tau \sum_{\tau' j} f(\tau_i, \tau'_j) \ , \tag{5}$$

where $t(\tau_i)$ is the expected number of transactions of trader τ_i per unit of time.

Table 2 shows the expected number of transactions per unit of time for each trader of type τ_i. Note that it is already included the corresponding order flow. To give an example, the probability of observing a transaction of a N_H is computed as the probability that a naive with high expected dividend is matched with any trader who is willing to accept his offer $b_H = D_H - \varepsilon$: a sophisticated trader S_L with low expected dividend, an uninformed naive trader N_M or a naive trader N_L with low expected dividend. All the sum is multiplied by the order flow $\nu = 1$. The explicit calculation is the following:

$$t(N_H) = \nu \sum_{\tau' j} f(N_H, \tau'_j) = \nu[\frac{1}{2}(1-\theta)\theta p^2(1-p)^2 + (1-\theta)^2 p^3 (1-p)] + \frac{1}{2}(1-\theta)^2 p^2 (1-p)^2] \ .$$

Let us define a vector $\mathbf{T}$ whose components are $t(\tau_i)$. As a proxy for the tendency of transaction prices, we compute the average price $\overline{P}$ in the market. The vector of

Proposer (τ_i)	**T**
S_H	$\mu_H\theta[(1-\theta)2p^3(1-p)+p^2(1-p)^2]$
S_M	$\mu_M\theta(1-\theta)p^3(1-p)$
	$\mu_M\theta(1-\theta)p(1-p)^3$
S_L	$\mu_L\theta[(1-\theta)2p(1-p)^3+p^2(1-p)^2]$
N_H	$\nu(1-\theta)[(1-\theta)p^3(1-p)+0.5p^2(1-p)^2]$
N_M	$\nu(1-\theta)[p(1-p)^3+p^3(1-p)]$
N_L	$\nu(1-\theta)[0.5p^2(1-p)^2+(1-\theta)p(1-p)^3]$

Table 2 Probability of transaction per unit of time.

prices $\mathbf{P} = (D_M, D_H, D_L, D_M, D_H, D_M, D_L)$ is defined according to the proposer's offers in Table 1.[13] Finally, the average price $\overline{P}$ is computed as the weighted sum of each possible value of the price according to the probability of observing such price over the total feasible transactions, $F = \sum_{\tau_i} T(\tau_i)$. Defining $\mathbf{T}'$ as the transpose of $\mathbf{T}$, the average price is

$$\overline{P} = \frac{\mathbf{T}'}{F}\mathbf{P} \ . \tag{6}$$

3 Laboratory experiment

In this section, we sketch briefly the experimental design of Ruiz-Buforn et al. (2019). The experiment took place in the LEE (*Laboratori d'Economia Experimental*) at University Jaume I in Castellón. Each session consists of ten independent markets lasting 3 minutes each. The asset market is implemented as a double auction where subjects are free to introduce their bids and asks or directly accept other trader's outstanding bid or/and ask. Every bid and ask concerns only one unit of the asset, but subjects can handle as many as desired as long as they have enough cash or assets (no short sale is allowed).

Each market is populated by 15 subjects who are endowed with 1000 units of experimental currency (ECU)[14] and 10 one-period life units of a risky asset. The dividend takes the value 0 or 10 with a 50% probability, which is common knowledge to all subjects. At the beginning of each market, the dividend is randomly determined by the experimenter, but not revealed to the subjects until the end of the same, when the dividend is paid. Additionally, subjects receive noisy signals on the dividend value. Signals are partially but not totally informative and they are presented to the subjects taking the value 10 or 0. If a subject observes a signal

[13] We omit the ε parameter for notational convenience.

[14] During the experiment, earnings and dividends are designated in experimental currency units (ECU) and converted into Euro at the end of the session.

that results to be 10 (0), he can infer that the dividend is expected to be 10 (0) with probability 0.8 and 0 (10) with probability 0.2.

The experiment consists of three treatments depending on the source of information in the market. In the baseline treatment (B), subjects receive two noisy private signals. In the public information treatment (PS), all subjects observe an identical noisy public signal besides the two private signals. In the common information treatment (CS), subjects observe three signals and one of them is identical to all subjects in the market. However, unlike in the PS treatment, this signal is not common knowledge.[15,16]

At the end of each market, dividends are paid out and the subjects' profits are computed as the difference between their initial endowment and the money held at the end of the market. Essentially, profits consist of the gains or losses generated by the trading activity and the dividend. Each subject's final payoff is computed as the accumulated profit in all markets.

4 Model calibration

In this section, we calibrate our model to compare the theoretical mean price $\overline{P}$ and the experimental data (Ruiz-Buforn et al., 2019). It is important to emphasize that this model provides a *post hoc* interpretation of the impact of public information on traders' behavior. Indeed, we did not design the experiment to test this model.

Morris and Shin (2002) claims that public information is a double-edged instrument that simultaneously provides information about the fundamentals and information about other traders' beliefs. The second *edge* is due to the common knowledge of that signal, and it is the reason for the emergence of overreliance on public information above and beyond its information on fundamentals. Our study aims at providing some theoretical insights into the overweighting mechanism. We disentangle the dual role of public information by comparing the mean price when traders observe a public signal and the mean price when they observe an identical signal, which is not common knowledge among traders. In this case, the identical signal carries information on the fundamentals but does not reveal information about the other traders. We refer to that signal as *common signal.* If an incorrect public signal pushes prices away from fundamentals while an incorrect common signal does not exhibit such distorting effect (or has a much lower degree of distortion), we can state that it is the public nature of information the main determinant of traders' overreliance. Stated differently, we find evidence on the overweighting phenomenon if the mean price is biased towards the public signal regardless of its realization, namely whether it is correct or incorrect. Conversely, the mean price should never be biased toward the common signal, independently of its realization. Onward, we will refer to the following scenarios: markets with a public signal are labeled as

[15]Within treatments, we differentiate between two types of markets. Markets with a correct public or common signal are labeled "Correct PS" and "Correct CS", respectively. Markets with an incorrect released signal are labeled as "Incorrect PS" and "Incorrect CS".

[16]In treatment B, one group of subjects participate and, therefore, there are 10 markets. In treatments PS and CS, two groups of subjects participate; we have therefore 20 markets for each treatment.

PS scenario, and markets with an identical signal that is not common knowledge (common signal) as CS scenario.[17] Additionally, we introduce a baseline scenario (B) where there is no identical signal released to the market. Thus, each trader only observes two private signals.

The public information benchmark (PB) represents the theoretical expected dividend considering only the public information and is computed by the following formula:

$$E[D=1|\hat{y}] = \frac{1}{1+\left(\frac{1-q}{q}\right)^{\hat{y}}} \; , \tag{7}$$

where $\hat{y}$ takes values 1 or -1 if the signal is public and $\hat{y}=0$ if the signal is common.[18] $PB=0.8$ when the public signal predicts $D=1$ and $PB=0.2$ when that signal predicts $D=0$. Finally, $PB=0.5$ in the B and CS scenarios.

Recall that, for simplicity, we focus our attention on the case $D=1$ since the model is symmetric in the two states of the world. Thus, the fraction of traders that receive two signals pointing to the dividend and, then, have a high expected dividend D_H is p^2. A fraction of $2p(1-p)$ are uninformed traders whose expected dividend is D_M and a fraction of $(1-p)^2$ are misinformed traders whose expected dividend is D_L. Considering those probabilities, instead of the corresponding frequencies in the population, implies that we neglect the fluctuations in the configuration of the population due to the finite number of traders.[19] Just like the experimental design, we fix the quality of every private, public and common signal at $p=q=0.8$.

4.1 Results

Without loss of generality, Figure 1 shows the mean price in the three scenarios (B, PS and CS) when $D=1$ as a function of the proportion of sophisticated traders in the market population. The mean price is computed separately according to the correctness of the released signal. We use the B scenario as a benchmark for evaluating the impact of releasing a public signal. One can see that the mean price in the B scenario (dashed-dotted line) is biased towards the dividend, although without converging to it. The presence of sophisticated traders drives prices away from the dividend.

Looking at the bottom lines of the figure, it is evident that an incorrect released signal pushes prices away from the dividend $D=1$. However, one can notice several differences between PS an CS scenarios at a glance. An incorrect public signal (thick-solid line) has a stronger distorting impact on price performance. The mean price quickly drops when there are sophisticated traders in the market. In fact, a small fraction of sophisticated traders ($\theta=0.2$) is sufficient to observe that the mean price clearly tends to the incorrect public signal ($PB=0.2$), getting closer to the

[17] In the CS scenario, the procedure for the resolution of the theoretical model is explained in Appendix B.

[18] We denote now the released signal by $\hat{y}$ instead of y like in eq. (1) to unify the three scenarios (benchmark, public signal, and common signal) into a single equation.

[19] We assume that the number of traders is sufficiently large that the fluctuations around the mean can be neglected.

PB as θ increases. The maximum level of overweighting is eventually reached when $\theta = 1$. It is worth noting that this phenomenon is quite a robust outcome. The distance between mean prices and the public signal is, in fact, almost unchanged in the interval $\theta \in [0.2, 0.7]$. This means that, in order to observe the price biased towards the incorrect public signal, it is not necessary a process of fine-tuning the value of θ.

On the other hand, the price behavior in the CS scenario is markedly different. Even though an incorrect common signal distorts the mean price (thin-solid line), this negative effect is less harmful than the negative impact of an incorrect public signal. Interestingly, the presence of sophisticated traders has no impact on the mean price until they make up the majority of the market population. The mean price starts from the middle of range values and remains constant until sophisticated traders reach a percentage close to 80%, which is the large majority of the population.

The top lines of the Figure 1 show the mean price when the released signal points towards the dividend. Mean prices show a lower sensitivity to the presence of sophisticated traders in both scenarios with respect to the case with an incorrect signal. The convergence of the mean price to the $PB = 0.8$ is largely independent of the fraction of sophisticated traders. Surprisingly, there is almost no difference between markets with a public and a common signal. The mean price takes similar values in both scenarios. The mean price gets closer to the dividend with respect to the B scenario. We can claim that releasing an identical signal improves market performance, moving traders' activity at levels closer to fundamentals.

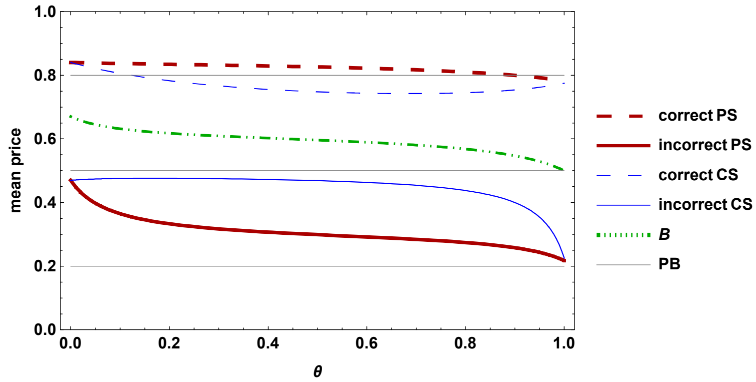


Figure 1 Mean price over the proportion of sophisticated traders, assuming $\varepsilon = 0.025$.

We can deduce from our model that public information is beneficial *per se* when it is correct. Both information on fundamentals and on other traders' expectations help market price to converge to the dividend value. The mean price is almost indistinguishable in the public or common scenario. However, we observe a different impact when there is an identical misleading signal in the market. The fact that traders are aware that they observe an identical signal reinforces the distorting effects. The public signal is overweighted in the aggregation of information into prices due to the overreliance of the traders on public information. Differences between mean prices in scenarios PS and CS, when the released signal is incorrect, indicate the importance of the common knowledge of the public announcements.

We evaluate now whether the released signal has different impacts on the mean price in aggregate terms. Figure 2 plots the mean price for every scenario computed as the weighted probability of occurrence of the signal. Stated differently, the aggregate mean price is computed by the sum of two terms: (i) the mean price when the released signal predicts dividend 1 weighted by the probability of being correct, p, and (ii) the mean price when the released signal predicts dividend 0 weighted by the probability of being incorrect $(1 - p)$. On aggregate, releasing a signal into the market improves mean price performance. The mean prices in both PS and CS scenarios are closer to the dividend than the mean price in the baseline scenario. Figure 2 shows that the effect of the common knowledge is almost indistinguishable in aggregate terms.

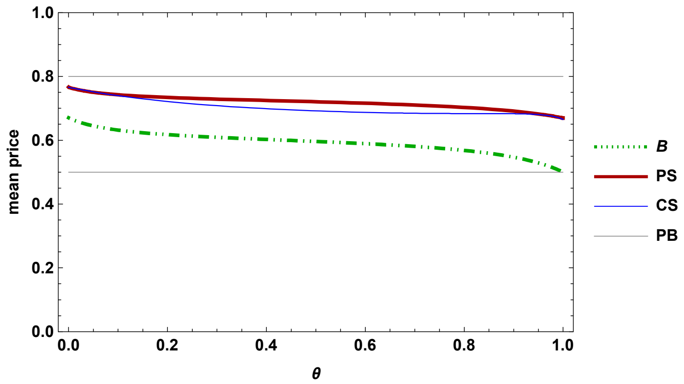


Figure 2 Mean price over the proportion of sophisticated traders, assuming $\varepsilon = 0.025$ in aggregate terms.

4.2 Monte Carlo simulations

Eq. (6) assumes a very large number of traders and encounters, since we replace the frequencies with probabilities. We study now the finite sample properties of our model. We run Monte Carlo simulations based on our theoretical model, assuming 15 heterogeneous traders who have different levels of reasoning. We run 100 market configurations for every realization of the public or common signal given $D = 1$. In each market configuration, 30 private signals are drawn using a binomial distribution and allocated to the traders. Once we fix the distribution of signals among traders, the simulations are initialized with $\theta = 0$, progressively increasing the value of θ in steps of 0.1 until $\theta = 1$. One trader of the whole pool is randomly chosen with equal probability. The probability of being sophisticated or naive depends on the value of θ. Moreover, the number of submitted offers changes depending on the type of the proposer (S,N) and his or her expected dividend. Every offer of a given trader is associated with a counterpart, which is randomly chosen among the rest of traders. The receiver may accept or reject the offer depending on his or her level of reasoning and information. For each value of θ, this operation is repeated 100 times. Finally, the average price of transactions is computed in each case.

Figure 3 shows the mean price obtained in Monte Carlo simulations for PS cases on the panels (a,c) and CS cases on the panels (b,d). We also differentiate between markets where the released signal is correct ($y = 1$) on the panels (a,b) and those where it is incorrect ($y = -1$) on the panels (c,d). One can see that mean price of simulations closely follow the theoretical predictions in all cases. We note further that the mean price dispertion is larger in CS scenario than in PS scenario. This finding indicates that the price is more sensitive to the distribution of signals in CS scenario rather than in the PS scenario.

5 Corroborating evidence: observed vs simulated data

This section compares the computational with the experimental data. The computational data are generated following the process explained in Section 4.2 with a fix value of $\theta = 0.2$. In order to compare the impact of public information on market prices, we evaluate how public information pushes prices away or towards the dividend. We compute the mean absolute deviation of transaction prices PR_{tr} from the dividend value in the laboratory markets:

$$DP_e = \frac{1}{T_r} \sum_{tr=1}^{T_r} \frac{|D - PR_{tr}|}{10} , \tag{8}$$

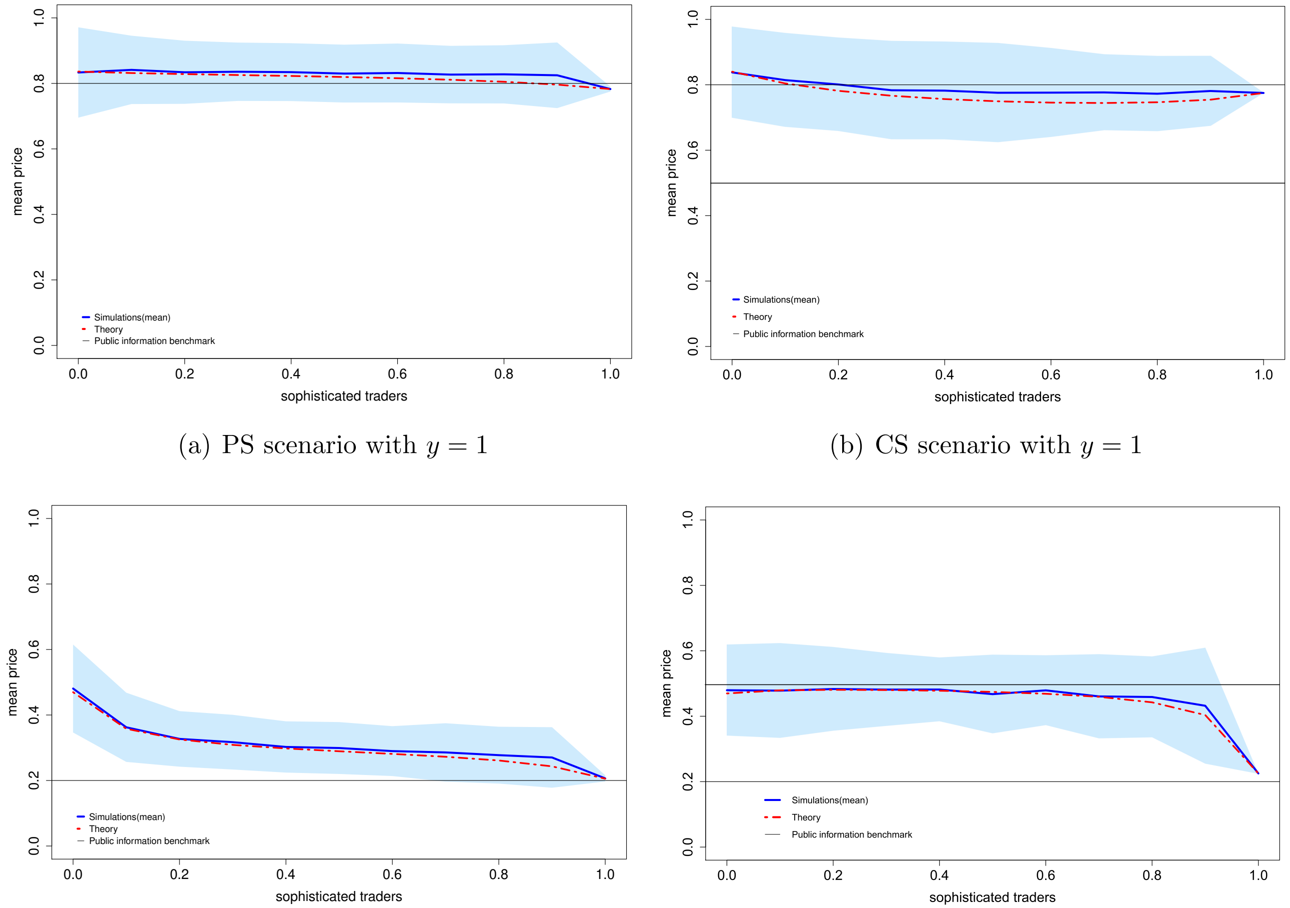
where T_r is the total number of transactions. For the computational data, the formula is

$$DP_s = \frac{1}{M} \sum_{m=1}^{M} |D - \overline{P}_m| , \tag{9}$$

where $\overline{P}_m$ refers to the mean price of every simulated market (m), and M denotes the number of Monte Carlo runs. When $DP_e = 0$ or $DP_s = 0$, prices or mean prices converge to the dividend value.

Figure 4(a) plots the DP_s indicator and Figure 4(b) plots the DP_e indicator. At a first glance, similarities are clear although a higher dispersion is present in the experimental data. Comparing to the B treatment, the release of a correct public signal helps prices to converge towards the dividend (Correct PS). However, an incorrect public signal drives prices far from the dividend (Incorrect PS). The impact of an incorrect common signal is strongly attenuated in some laboratory markets. This result suggests that subjects are able to learn from prices in the laboratory, even when they receive incorrect signals. Note, however, that an incorrect public signal seems to drag this learning process out. We have tested the effect of misleading information assuming that simulated traders are not able to learn. Although this is a weakness of our model, the main results of the laboratory experiment are reproduced.

After analyzing the impact of a correct and incorrect public signal, it remains to answer to the question: What is the aggregate impact of public information? Figure 5 plots the data averaging over the different realizations of the signal. One can see that the release of information, public or common, improves price convergence.



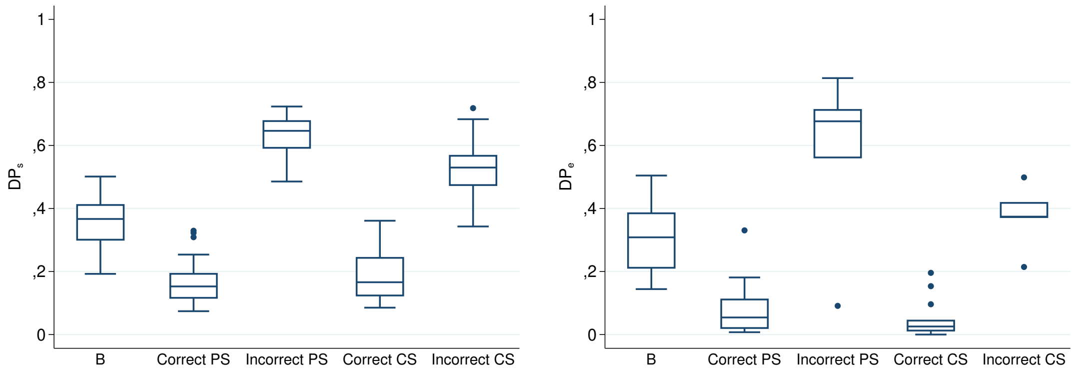
(a) PS scenario with $y = 1$

(b) CS scenario with $y = 1$

(c) PS scenario with $y = -1$

(d) CS scenario with $y = -1$

Figure 3 The results of 100 Monte Carlo simulations with a public signal on the left panels (a,c), and a common signal on the right panels (b,d). The X-axis denotes the proportion of sophisticated traders in the market and Y-axis denotes mean prices. Dashed-blue line describes the theoretical mean price, the solid line represents the average of simulated mean market prices and shaded area shows 2 standard deviations. Horizontal lines represent the $PB \in \{0.2, 0.5, 0.8\}$ depending on the value of the released signal.

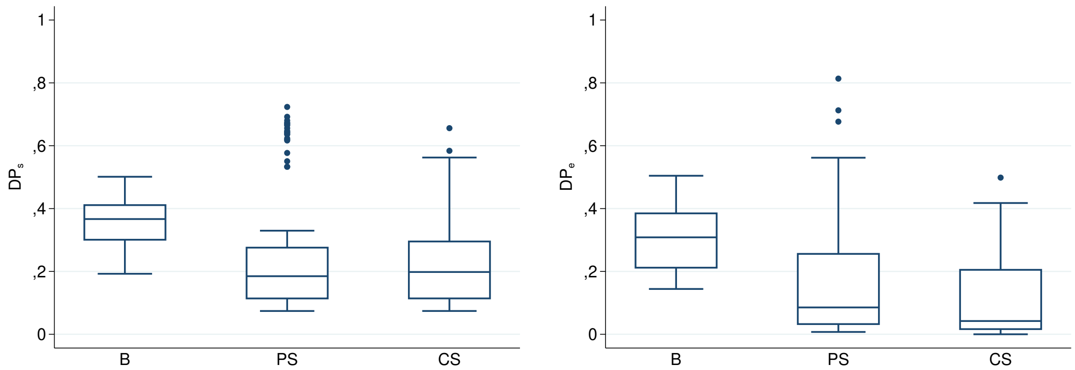


(a) Simulation ($\theta = 0.2$)

(b) Experimental results

Figure 4 Distribution of DP across markets, considering whether the released signal is correct or incorrect.

Therefore, we can conclude that public information is beneficial for market dynamics in the experimental as well as simulated markets.[20]



(a) Simulation ($\theta = 0.2$)

(b) Experimental results of treatments

Figure 5 Distribution of DP across markets.

In conclusion, our model is able to reproduce qualitatively the patterns observed in the experiment, which are i) prices are biased towards the fundamentals when an additional signal is released, ii) the presence of price distortion when the released signal is incorrect and iii) a limited distortion if traders observe the same signal without being common knowledge.

6 Conclusions

We propose a simple decentralized asset market with asymmetric information populated by naive and sophisticated traders. The model aims at identifying the principal

[20]From Figure 3 one can infer that we would obtain similar results if the fixed proportion of sophisticated traders lies in the interval $\theta \in [0.2, 0.7]$.

effects of unwarranted or mistaken public information on prices when it interplays with noisy private information. Under bounded rationality, public information differently affects traders' behavior. Whereas naive traders only consider their own information, sophisticated traders make use of public information to infer the distribution of aggregate demand. We find that a noisy public signal pushes prices away from fundamentals when it predicts the wrong state of the world. A low proportion of sophisticated traders is sufficient to observe that the mean transaction price follows a mistaken public signal.

We also perform Monte Carlo simulations with a finite sample of traders and calibrate the key parameters to match the ones in the laboratory experiment. We compute three scenarios: markets where there is not public information, markets with public information and, markets where one of the signals is observed by all traders but they are not aware of it. An interesting result emerges: the price is biased towards the incorrect public signal rather than the dividend value. Whereas the distorting impact of unwarranted public information emerges, this effect is much lower under the assumption of non-common knowledge about the released signal. In our behavioral model, the common knowledge nature of public information makes traders overrely on public information.

Our simple model qualitatively reproduces the aggregate behavior observed in the laboratory asset markets of Ruiz-Buforn et al. (2019). Heterogeneity combined with bounded rationality generates similar findings to those of the experimental study. Finally, future work should relax some strong assumptions as learning capacity of traders and implement different market architectures.

7 Acknowledgements

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A Public signal scenario

A.1 Sophisticated proposers

The expected payoff function of a sophisticated proposer has two components: (i) the expected payoff if the offer is accepted multiplied by the probability of acceptance and (ii) the expected payoff if the offer is rejected, i.e. D_i. Submitting sell offers:

$$\pi^S(a|D_i) = \sum_j \left(a\ Pr[a < D_j|D_i] + D_i\ Pr[a \geq D_j|D_i]\right)\ .$$

Submitting buy offers:

$$\pi^S(b|D_i) = \sum_j \Big((2D_i - b)\ Pr[b > D_j|D_i] + D_i\ Pr[b \leq D_j|D_i]\Big)\ .$$

A.2 Sophisticated receivers

This section provides some illustrative examples to clarify the computation of expected payoffs when a sophisticated trader receives an offer. Table 3 lists all inferences that a sophisticated trader can make observing a particular offer, assuming all offers are submitted by naive traders.

Observed offer		**Type of the proposer**
	$b \geq D_M$	N_H
bid	$D_L \leq b < D_M$	N_H, N_M
	$b < D_L$	N_H, N_M, N_L
	$a > D_H$	N_H, N_M, N_L
ask	$D_M < a \leq D_H$	N_M, N_L
	$a \leq D_M$	N_L

The first columns describe possible offers. Right column shows receiver's inference about proposers type.

Table 3 Sophisticated receivers' inference about the expected dividend of the proposer.

Receiving buy offers: an example[21]

Let us suppose that a sophisticated trader S_L, whose expected dividend is D_L observes a bid. She updates her beliefs and decides whether accepting or rejecting the offer. For instance, in case she observes a bid $b_{H^-} = D_H - \varepsilon$, she infers the type of proposer is a naive whose expected dividend is D_H.[22]

[21] The intuition to follow when a sophisticated trader receives a sell offer is similar to a buy offer.

[22] We adopt the following notation throughout the examples of received offers. b and a indicate whether the received offer is a buy or a sell offer, respectively; subindex $\{H, M, L\}$ stands for the level of the price, which is equivalent to the expected dividend level; H^- and H^+ are used to denote that the price is slightly below or above the level D_H, namely $D_H - \varepsilon$ and $D_H + \varepsilon$, respectively.

$$\pi^S(b_{H^-}, D_L) = \begin{cases} b_{H^-} & \text{accepting the bid} \\ \sum_j D_{Lj}\ Pr[D_j|D_j > b_{H^-}] & \text{rejecting the bid} \end{cases}$$

where $D_j = D_H$ since a naive trader with a high expected dividend is the only trader submitting this offer without incurring in losses. Thus $D_{Lj} = D_{LH}$ refers to the updated expected dividend, where subindex L means her prior expected dividend and H is the guessed proposer's expected dividend. Her updated expected dividend is

$$D_{LH} \equiv E[D = 1|x_L, x_H, y] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{-2+2} \left(\frac{1-q}{q}\right)^{y}}.$$

In case she observes a bid $b_{M^-} = D_M - \varepsilon$, the type of proposer might be M or H.

$$\pi^S(b_{M^-}, D_L) = \begin{cases} b_{M^-} & \text{accepting the bid} \\ \begin{array}{l} D_{LM}\ Pr[D_M|D_M > b_{M^-}] \\ + D_{LH}\ Pr[D_H|D_H > b_{M^-}] \end{array} & \text{rejecting the bid} \end{cases}$$

where the updated expected dividend is given by

$$D_{LM} \equiv E[D = 1|x_L, x_M, y] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{-2+0} \left(\frac{1-q}{q}\right)^{y}}$$

and

$$D_{LH} \equiv E[D = 1|x_L, x_H, y] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{-2+2} \left(\frac{1-q}{q}\right)^{y}}.$$

The probability assigned to a proposer of type M given that the receiver has an expected dividend D_L is computed by

$$\begin{aligned} Pr[D_M|D_M > b_{M^-}] &= \frac{Pr[b_{M^-}|D_M]\ \ Pr[D_M|D_L]}{Pr(b_{M^-}|D_L)} \\ &= \frac{\frac{1}{4}2pq[(1-D_L) + D_L]}{\frac{1}{4}[D_L(p^2+2pq) + (1-D_L)(q^2+2pq)]} \end{aligned}$$

Conversely, she cannot update her beliefs when she observes a bid $b_{L^-} = D_L - \varepsilon$ because any type of trader could submit that offer.

$$\pi^S(b_{L^-}, D_L) = \begin{cases} b_{L^-} & \text{accepting the bid} \\ \\ D_L & \text{rejecting the bid} \end{cases}$$

B Common signal scenario

The analysis of the common signal scenario follows the same structure as the case of PS scenario. The main difference with the PS scenario lies in the sophisticated traders' strategies. Nonetheless, the lack of common knowledge does not change naive traders' behavior since they evaluate signals according to their precision about fundamentals. This Appendix explains the main differences in the CS scenario and the results of the model.

B.1 Sophisticated traders

Sophisticated traders consider the distribution of information in order to assess market demand. However, contrary to public signal, the common signal does not allow them to better characterized the potential market demand. They estimate the potential demand assuming each trader possesses three independent private signals $\{x_i, y_i\}$ because they are not aware that y_i is identical to all traders. We must redefine, therefore, the expected dividend for a trader of type i as:

$$E[D = 1|x_i, y_i] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{x_i} \left(\frac{1-q}{q}\right)^{y_i}} \tag{10}$$

where $x_i = \{-2, 0, 2\}$ refers to private signals and $y_i = \{-1, 1\}$ refers to the common signal. Notwithstanding the common signal is unique for all traders in the market, the sophisticated traders classify traders in four groups according to the four possible expected dividends $\{D_H, D_{\overline{M}}, D_{\underline{M}}, D_L\}$, corresponding to all the possible combinations of $\chi_i = (x_i + y_i)$.[23] We introduce the notation $\overline{M}$ and $\underline{M}$ to denote the low and high intermediate levels. The variable i takes the values $\{H, \overline{M}, \underline{M}, L\}$. It is important to stress, however that only three are the levels effectively present in the market. For instance, if the common signal is $y_i = 1$, existing types of traders are $\{H, \overline{M}, \underline{M}\}$ and the types of traders are $\{\overline{M}, \underline{M}, L\}$ when common signal is $y_i = -1$. The optimal offer is computed by following the process explained in Section 2.2.

In case a sophisticated trader receives an offer, it provides her with new information to be updated. Unlike markets in the PS scenario, she identifies four possible type of proposers $j \in \{H, \overline{M}, \underline{M}, L\}$, although one of them does not actually exist.

[23]In CS, privately uninformed traders are absent, therefore $\chi_i \in \{-3, -1, 1, 3\}$. Remember that in PS scenario, traders might be informed $x_i \in \{-2, 2\}$ or uninformed $x_i = 0$.

B.2 Transactions

Tables 4 and 5 list the market transactions when the dividend is $D = 1$ and the common signal is correct or incorrect, respectively. The first column denotes the proposer's type according to his level of reasoning and expected dividend. The second and the third columns show the optimal offer of each trader while the last column shows the counterpart of every transaction.

In order to compare the results between common and public signal, one should consider that when the common signal indicates dividend 1, $j = \overline{M}$ corresponds to the M and $j = \underline{M}$ corresponds to L. If the common signal indicates dividend 0, $j = \overline{M}$ corresponds to the H and $j = \underline{M}$ corresponds to M. We rename the type of traders and offers for each prediction of the common signal $y_i = \{-1, 1\}$ for an easier comparison between markets with common signal and markets where the released signal is public. Considering only private signals, the possible types of traders are $\{H, \overline{M}, \underline{M}\}$ if the common signal predicts dividend 1 (Table 4); otherwise $j \in \{\overline{M}, \underline{M}, L\}$ (Table 5). Considering the previous changes, we define a vector of market prices following the proposer's type offer in Table 4, $\mathbf{P} = (D_M, D_L, D_L, D_M, D_H, D_M, D_L)$. The vector of transaction prices when the common signal predicts dividend 0 is $\mathbf{P} = (D_M, D_H, D_H, D_M, D_H, D_M, D_L)$, which is listed in Table 5.

Finally, the expected number of transactions per unit of time is listed in Table 6. The mean price is computed by eq. (6).

Proposer (τ_i)	**Order**	**Price**	**Receiver** (τ_j)	
S_H	b^*_H	$D_{\overline{M}} + \varepsilon$	$N_{\underline{M}}$, $N_{\overline{M}}$	
		$D_{\underline{M}} + \varepsilon$	$N_{\underline{M}}$	
$S_{\overline{M}}$	$b^*_{\overline{M}}$	$D_{\underline{M}} + \varepsilon$	$N_{\underline{M}}$	
$S_{\underline{M}}$	$a^*_{\underline{M}}$	$D_{\overline{M}} - \varepsilon$	N_H, $N_{\overline{M}}$	S_H
N_H	a_H	$D_H + \varepsilon$		*No trade*
	b_H	$D_H - \varepsilon$	$N_{\overline{M}}$, $N_{\underline{M}}$,	$S_{\underline{M}}$
$N_{\overline{M}}$	$a_{\overline{M}}$	$D_{\overline{M}} + \varepsilon$	N_H	S_H
	$b_{\overline{M}}$	$D_{\overline{M}} - \varepsilon$	$N_{\underline{M}}$,	$S_{\underline{M}}$
$N_{\underline{M}}$	$a_{\underline{M}}$	$D_{\underline{M}} + \varepsilon$	N_H, $N_{\overline{M}}$,	S_H, $S_{\overline{M}}$
	$b_{\underline{M}}$	$D_{\underline{M}} - \varepsilon$		*No trade*

Table 4 Transactions when the common signal is 1.

Proposer (τ_i)	Order	Price	Receiver (τ_j)	
$S_{\overline{M}}$	$b^*_{\overline{M}}$	$D_{\underline{M}} + \varepsilon$	N_L, $N_{\underline{M}}$,	S_L
$S_{\underline{M}}$	$a^*_{\underline{M}}$	$D_{\overline{M}} - \varepsilon$	$N_{\overline{M}}$	
S_L	a^*_L	$D_{\overline{M}} - \varepsilon$	$N_{\overline{M}}$	
		$D_{\underline{M}} - \varepsilon$	$N_{\overline{M}}$, $N_{\underline{M}}$,	
$N_{\overline{M}}$	$a_{\overline{M}}$	$D_{\overline{M}} + \varepsilon$		*No trade*
	$b_{\overline{M}}$	$D_{\overline{M}} - \varepsilon$	$N_{\underline{M}}$, N_L	$S_{\underline{M}}$, S_L
$N_{\underline{M}}$	$a_{\underline{M}}$	$D_{\underline{M}} + \varepsilon$	$N_{\overline{M}}$	$S_{\overline{M}}$
	$b_{\underline{M}}$	$D_{\underline{M}} - \varepsilon$	N_L	S_L
N_L	a_L	$D_L + \varepsilon$	$N_{\overline{M}}$, $N_{\underline{M}}$,	$S_{\overline{M}}$
	b_L	$D_L - \varepsilon$		*No trade*

Table 5 Transactions when the common signal is -1.

Proposer (τ_i)	**T** (if $y_i = 1$)	**T** (if $y_i = -1$)
S_H	$\mu_H\theta(1-\theta)p^2(1-p)(p+0.5(1-p))$	$\mu_H\theta p^2 q[(1-\theta)2p + (1-p)]$
	$\mu_H\theta(1-\theta)0.5p^2(1-p)^2$	
S_M	$\mu_M\theta(1-\theta)2p(1-p)^3$	$\mu_M 2\theta(1-\theta)p^3(1-p)$
S_L	$\mu_L\theta(1-p)^2p[p+(1-\theta)2(1-p)]$	$\mu_L 0.5\theta(1-\theta)(1-p)^2p^2$
		$\mu_L\theta(1-\theta)(1-p)^2p[0.5p+(1-p)]$
N_H	$\nu(1-\theta)[(1-\theta)p^3(1-p)+0.5p^2(1-p)^2]$	$\nu(1-\theta)[p^3(1-p)+0.5p^2(1-p)^2]$
N_M	$\nu(1-\theta)[p(1-p)^3+p^3(1-p)]$	$\nu(1-\theta)[p(1-p)^3+p^3(1-p)]$
N_L	$\nu(1-\theta)[0.5p^2(1-p)^2+p(1-p)^3]$	$\nu(1-\theta)p(1-p)^2[0.5p+(1-\theta)(1-p)]$

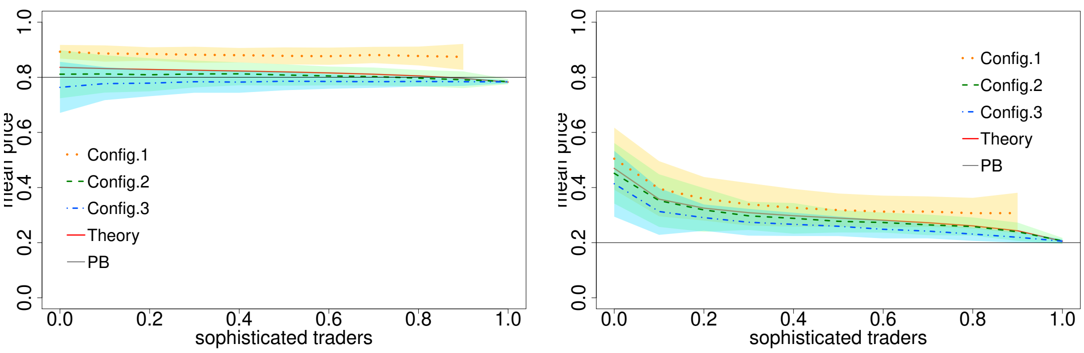
Table 6 Expected number of transactions per unit of time for every type of trader, given $D = 1$ in CS scenario.

C Robustness: Does market configuration matter?

This subsection aims at testing the relevance of the distribution of signals in markets with public information. Intuitively, the proportion of informed traders in the aggregation and dissemination of information matters. For example, an incorrect public signal might largely distort prices when the proportion of informed traders is small. However, an incorrect public signal should be harmless when most of the traders are informed. Since the most concerning case is the impact of an incorrect public signal, we restrict our attention to the PS scenario to assess the importance of market configuration. We define three market configurations based on observed distributions of information across traders in the laboratory experiment. i) Config. 1, markets are populated by 5 uninformed and 10 informed traders. ii) Config. 2, markets are populated by 1 misinformed trader, 7 uninformed traders and 7 informed traders. iii) Config. 3 where markets are populated by 2 misinformed, 5 uninformed and 8 informed traders.

Figure 6 shows that mean prices change depending on the distribution of private information. When the public signal is correct, one can see that the computational mean takes similar values to the theoretical prediction in markets where uninformed and misinformed traders have a large presence (Config.2 and Config.3). For the markets with an incorrect public signal, the public signal always dominates the mean price. The impact is larger when the proportion of informed traders is small (Config.2 and Config.3).

Altogether, we can claim that the market configuration can generate systematic deviations from the theoretical prediction, however "not too large", i.e. the general conclusions still hold. A special case seems to be the configuration where there is absence of misinformed traders. The mean price is noticeably higher than the other market configurations, independently of the prediction of the released signal $y = \{1, -1\}$. Besides, it is interesting to note that there are no transactions when $\theta = 1$. Therefore, if a market where all traders are sophisticated and none is misinformed, we have no transactions.



(a) Correct public signal $y = 1$ (b) Incorrect public signal $y = -1$

Figure 6 Mean price of the market configurations assuming dividend $D = 1$. Shaded area shows 1 standard deviation of the Monte Carlo simulations.