



Overweighting of public information in financial markets: A lesson from the lab

Alba Ruiz-Buforn^a, Eva Camacho-Cuena^a, Andrea Morone^b, Simone Alfarano^{a,*}

^a University Jaume I, Spain

^b Università degli Studi Aldo Moro di Bari, Italy



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ABSTRACT

We study the information aggregation process in a laboratory financial market where traders have access to costly private and free public imperfect information. The public disclosure provokes (i) a crowding-out effect on traders' information demand, (ii) a market overreaction to the public signal, and (iii) a deterioration in price informativeness. We show that the reduction in price informativeness is a direct consequence of the overweighting of public information when aggregated in prices. Moreover, we provide experimental evidence for the theoretical conjecture that the overweighting effect and the subsequent market overreaction to public disclosures are directly related to traders' second- (or higher) order beliefs. From an economic policy perspective, we provide support that when deciding on a communication strategy, regulatory institutions can smooth the market overreaction by properly setting the level of transparency of their disclosures.

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1. Introduction

The idea that a price system based on competitive markets can aggregate information dispersed in the economy dates back to the 1940s (Hayek, 1945). Economists have understood that in properly designed asset markets, prices can aggregate and disseminate the information possessed by traders, although this is not necessarily done efficiently. Instead of leaving the market operating alone, public disclosures might facilitate the information aggregation and dissemination process. We ask whether and how the presence of a regulatory institution that releases public information can be beneficial for market performance. If it is assumed that public information simply accumulates with the information already present in the market, it seems quite natural that more information should be valuable for decision makers.

However, the theoretical literature has shown that, when there exist strategic interactions among decision makers, public disclosures may lead to unintended consequences: (i) Public disclosures might reduce the production of private information (the *crowding-out effect*). (ii) Public disclosures might be weighted above and beyond their precision (the *overweighting effect*), contrary to the pre-

scription of the Bayesian rule, which states that each signal should be weighted proportionally to its precision. What would be an intuitive reason for the emergence of the overweighting effect? Let us assume that a financial trader has access to public and private information, both providing an equally valuable prediction for the asset's return. Differently from private information, public information is common knowledge among traders (Aumann, 1976); that is, all traders know it, and all traders know that the others know it, etc. Let us further assume that this trader gives some importance to the average opinion of the other traders in deciding her investment strategy. She knows that everyone observes the same public information, which becomes a relevant predictor of the average opinion. Therefore, she will put more weight on public information than on private information. If a significant fraction of traders follows this behavior, public information turns out to be a focal point for the coordination of traders' expectations, exerting an excessive influence on market prices. The crucial aspect for the emergence of the overweighting effect lies in the direct influence that public information exerts on what traders believe about the other traders' beliefs. The purpose of this article is to experimentally analyze how public information affects traders' beliefs, and thereby to explore the extent of the overweighting phenomenon. Can we identify the overweighting effect? Is it empirically relevant? Can we smooth the undesirable consequences of public disclosures?

* Corresponding author at Economics Department, University Jaume I, Avenida Sos Baynat s/n 12071, Castellón, Spain

E-mail address: alfarano@uji.es (S. Alfarano).

An extended line of research explores the primitives to observe the detrimental effects of public disclosures and their consequences in coordination games based on the influential Keynes' beauty contest metaphor of financial markets. Note that the presence of an explicit incentive for traders to coordinate reinforces the effectiveness of public information in aligning expectations, facilitating the emergence of the overweighting effect. In [Morris and Shin's \(2002\)](#) seminal paper,¹ they show that public information can be considered a double-edged instrument, conveying information about the fundamentals (the informational component) and at the same time, providing information about what the other traders believe about the fundamentals (the commonality component). The authors conjecture that financial markets overreact to public disclosures, because public information is extremely effective (*too effective* using the words of [Morris and Shin \(2002\)](#)) in coordinating traders' beliefs. Therefore, even a "small noise" in public information can be amplified at the aggregate level, driving the economic system far from fundamentals and possibly damaging social welfare.²

Other papers analyze the consequences of public disclosures in a market environment, without introducing an explicit coordination motive.³ [Allen et al. \(2006\)](#) are the first to directly connect the overweighting of public information with traders' excessive reliance on public disclosures. They illustrate how the role of second-order beliefs, i.e., beliefs that a trader forms about other traders' beliefs, generates the overweighting effect. Specifically, [Allen et al. \(2006\)](#) show that asset prices overweight public information relative to private information when traders' willingness to pay is related to their beliefs about others' average opinion on the future evolution of the asset price.

Despite the extensive theoretical literature on market overreaction to public disclosures, there is no empirical evidence supporting its relevance beyond an anecdotal narrative (see [Blinder et al., 2008](#)). Thus, the laboratory provides a suitable platform to investigate the unintended consequences of public disclosures in markets in general and in financial markets in particular. It is possible to control and to observe all information in the hands of subjects, together with their trading activity.

This paper contributes to the literature by experimentally testing whether the adverse effects of public disclosures are general phenomena to be observed in a market context beyond the coordination environment. We investigate the impact of releasing an imperfect, public, and costless signal into an asset market where traders have access to imperfect and costly private information about the future prospect of the asset. This setting allows us to examine under which conditions the presence of public information may act as a sort of disciplining mechanism, promoting the aggregation of information or in contrast, systematically distorting the market performance, driving the price far from the fundamentals.

We analyze under which conditions the overweighting of public information reduces price informativeness and constitutes the source of the market overreaction to public dis-

closures. Several authors, such as [Ackert et al. \(1997, 2004\)](#), [Middeldorp and Rosenkranz \(2011\)](#), [Ferri and Morone \(2014\)](#), and [Halim et al. \(2019\)](#), investigate the impact of a public signal in a laboratory financial market. When public information is released, they consistently report a reduction in price informativeness, which they attribute to the lower acquisition of information. In contrast, our results suggest that the overweighting effect is the main determinant of the deterioration in price informativeness. To the best of our knowledge, our paper is the first experimental contribution to detect and quantify the overweighting effect in a market context that, contrary to coordination settings, does not provide traders with any explicit coordination motive to align their expectations.

Unlike the theoretical literature on the overweighting of public information, we show that traders' bounded rationality is responsible for the emergence of this phenomenon in our experiment. Full rationality in our setting implies either an absence of trading activity or a market price that weights each signal, private and public, according to its precision. In both cases, public information is never overweighted compared to its precision. Thus, the observation of a systematic deviation toward the public signal challenges the current *rational* view of the overweighting effect as in the [Morris and Shin \(2002\)](#) framework, posing new theoretical and experimental questions on how to release public information. Moreover, we provide experimental support for [Allen et al.'s \(2006\)](#) conjecture about the role of second-order beliefs as the main driver of the emergence of the overweighting phenomenon. Finally, we observe that lowering the precision of public disclosures, interpreted as the level of transparency, reduces the overweighting effect. Our finding supports the idea that releasing public information can be harmful for the performance of a financial market if the information is not properly tailored to the market conditions.

Instead of being limited to an academic debate, the excessive impact of public information has become a cause of concern for regulatory institutions. The 2008 financial crisis is a good example of excessive impact if one takes into account the influence that credit rating agencies' valuations had on investors' financial decisions, who blindly followed what turned out to be misleading advice ([European Commission, 2010](#); [Scalet and Kelly, 2012](#); [Amtenbrink and Heine, 2013](#); [Cavallaro and Trotta, 2019](#); [Hu et al., 2019](#)). Besides the excessive reliance on ratings, the agencies' presence might have given to investors fewer incentives to search for independent and alternative sources of information for evaluating innovative financial products. To avoid such adverse effects, regulatory institutions proposed new measures to improve market participants' internal risk management capabilities and reduce the excess reliance on external credit ratings ([European Commission, 2009](#)). In the same line, the Dodd-Frank Wall Street Reform and the Consumer Protection Act of 2010 were approved by the U.S. Congress ([Chaffee, 2010](#)). The adverse effects of releasing public information are also relevant for regulatory institutions such as central banks when setting the level of transparency in their forward guidance activity or communicating stress-tests results for the banking system. In recent years, central banks have included in their research agenda the study of how public communications and disclosure policies affect agents' behavior and incentives ([Bank of England, 2015](#)).

The rest of the paper is organized as follows. In [Section 2](#), we describe the experimental design, and in [Section 3](#), we discuss the competing benchmarks employed to account for the asset market outcomes. In [Section 4](#), we present the experimental findings. In [Section 5](#), we discuss the behavioral insights of our experimental findings. Finally, in [Section 6](#), we present concluding remarks, with particular emphasis on policy implications for regulatory institutions.

¹ Several generalizations of the original framework have been proposed by [Angeletos and Pavan \(2004, 2007\)](#), [Myatt and Wallace \(2011\)](#), and [Colombo et al. \(2014\)](#).

² See the classical papers by [Hirshleifer \(1971\)](#) and [Hakansson et al. \(1982\)](#). See also more recent papers such as [Colombo et al. \(2014\)](#), [Vives \(2014\)](#), and [Goldstein and Yang \(2017\)](#), among others.

³ See also [Bacchetta and Van Wincoop \(2008\)](#), [Amador and Weill \(2010\)](#), and [Goldstein and Yang \(2019\)](#). Another strand of literature (e.g., [Kim and Verrecchia, 1991](#); [Barron and Karpoff, 2004](#)) explores the relation among public announcement precision, traders' beliefs, and trading volume.

Table 1

Experimental design and parameters. The parameter p denotes the precision of private signals, and P stands for the precision of the common or public signal.

	Treatment	p	P	Number of markets
Baseline	B	0.8	-	20
Public information	PS80	0.8	0.8	20
	PS70	0.8	0.7	20
Common information	CS80	0.8	0.8	20

2. Experimental design and procedure

2.1. Experimental design

Our experimental setting is similar to other contributions in the literature on laboratory financial markets with Arrow-Debreu assets.⁴ Each market (labeled with “ m ”) consists of a three-minute trading period, and it is populated by 15 traders.⁵ At the beginning of the trading period, each trader is endowed with $C^0 = 1,000$ units of experimental currency (ECU) and $A^0 = 10$ Arrow-Debreu assets. Each asset pays a dividend $D_m \in \{0, 10\}$ at the end of the market with 50–50 chances, which is common knowledge among traders. Assets live only for a single trading period, that is, one market, and they are worthless apart from the dividend paid out.⁶ The value of the dividend is randomly determined by the experimenter before the market starts, but it is not revealed to the traders until the end of the market, when the traders’ payoff is determined. The asset market is implemented as a double auction, where traders are free to introduce their bids and asks for assets or directly accept any other trader’s outstanding bid or ask. Every bid, ask, or transaction concerns only one asset, although each trader can handle as many assets as desired as long as she has enough cash or assets (no short sales are allowed).

Parallel to the asset market, we implement an information market where, at any moment during the trading period, traders can acquire imperfect private signals at a price of 4 ECU per signal. Private signals are independent realizations conditional on the dividend value, and they are presented to traders with a value of 10 or 0. Specifically, we define as p the probability of getting a signal suggesting a dividend 10 when the state of the world is $D_m = 10$, and with $q = 1 - p$ the probability of getting a signal suggesting a dividend 0. *Mutatis mutandis* for the state of the world $D_m = 0$. We refer to p as the precision of the signal. As the objective of our paper is to examine whether disclosing a public signal distorts market prices, we give the market the opportunity to correct possible distortions. To do so, we allow traders to acquire private information conditional on the observed dynamics of prices, implementing an information market parallel to the asset market. This particular setting should provide the market the best chances to prevent the distortive effects of public information. We are implicitly assuming that the market can recognize the distortion and eventually, correct it with a flow of new private information.

Table 1 summarizes the implemented treatments. In the baseline treatment (B), traders have access only to costly private information. To investigate the impact of public information on market performance, we introduce the public information treatments (PS80 and PS70). In these treatments, traders can acquire private signals and have free access to a *public signal*, which is released

⁴ See, for example, Ackert et al. (1997, 2004), Hey and Morone (2004), Deck et al. (2013), Fellner and Theissen (2014), Ferri and Morone (2014), Asparouhova et al. (2017), Page and Siemroth (2017, 2020), and Halim et al. (2019).

⁵ In the baseline treatment, group 1 is populated by 13 traders.

⁶ The cash, dividends, prices, and profits during the experiment are designated in ECU and converted into € at the end of the session. One ECU is equivalent to 2 cents.

at the beginning of each market. This signal is identical for all traders and is common knowledge. The realization of the public signal might take a value of 10 or 0 with precision P . We do not provide the institution releasing the public signal with a pay-off or target function. The public signal is the realization of a binary random variable with a given correlation with the fundamentals, and it does not emerge out of a micro-funded strategy of the regulatory authority releasing the signal. Comparing treatments PS80 and PS70 allows to test whether by acting at the level of precision of the released information, we might enhance or mitigate the crowding-out effect and the market overreaction to public disclosures.

To disentangle the two components that render public information a double-edged instrument, we implement the common information treatment (CS80) in which traders receive a costless signal whose realization is identical for all of them, but it is not common knowledge. In other words, they know only that each trader receives one signal with the same precision, but they do not know that the realization of that signal is identical for all traders. We refer to this signal as the *common signal*. The common signal is released at the beginning of each trading period, and it is presented to traders with a value of 10 or 0 with precision $P = 0.8$. The common signal is equally informative about the dividend value for all traders, but the signal is no longer a predictor of the opinion of the other traders as the public signal is.⁷ Thus far, the impact of a common signal on asset markets has not been analyzed in the theoretical and experimental literature.

Comparing the PS80 and CS80 treatments allows to understand whether the commonality component of public information serves as the main driver of the overweighting, as suggested by the theoretical literature. In the PS80 and CS80 treatments, the first-order beliefs are identical, whereas the second-order beliefs are markedly different. To illustrate this important point, let us assume that trader i observes a released signal whose value is 10. She infers that the expected value of the dividend conditional on the released signal is 8 (first-order belief of trader i). Moreover, in the PS80 treatment, trader i knows that the first-order belief of each one of the other traders is also 8 (second-order belief of trader i). The common knowledge of the public signal allows trader i to unequivocally estimate the others’ beliefs. Conversely, in the CS80 treatment, trader i does not know whether the other traders observe a signal valued at 0 or 10. Therefore, to estimate the others’ beliefs, trader i has to take into account the probability distribution of the realizations of the signal among other traders, creating a higher degree of uncertainty in the estimation of others’ beliefs. Therefore, if traders base their trading strategies on their second-order beliefs, we expect to observe that the overweighting effect in the CS80 treatment will exhibit a significantly different magnitude compared to the PS80 treatment.

2.2. Experimental procedure

The experiment was programmed using Z-Tree software (Fischbacher, 2007), and it was conducted at the *Laboratori d’Economia Experimental* at University Jaume I in Castellón. A total of 118 undergraduate students in the Economics, Finance, and Business Administration degree in at least their second year were recruited. When subjects arrived at the laboratory, the instructions were distributed and explained aloud using a PowerPoint presentation.⁸ This was followed by one practice period so that the subjects became familiar with the software and the trading mechanism. After the instructions were explained and during the practice period,

⁷ When it is not necessary to specify whether the released signal is public or common signal, we refer to it as the *released signal*.

⁸ Translated instructions are available in Appendix A.1.

subjects could privately ask questions about the experiment. Each subject could participate in only one session, which consisted of 10 markets. At the end of every market, dividends were paid out, and the subjects' profit was computed as the difference between the cash held at the end of the market and their initial cash endowment. Each subject's final payout was computed as the accumulated profit in the 10 markets, and each subject was paid in cash at the end of the session. The average payout was about 20 €, and each session lasted around 90 minutes. Note that the subjects could incur losses. To avoid some of the problems associated with subjects making real losses in experiments, we endowed all subjects with a participation fee of 3 €, which could be used to offset losses. No subject earned a negative final payout in any session.

3. Competing benchmarks

We propose three competing benchmarks as possible explanations for the dynamics of prices in the asset market: i) the "no information acquisition - no trade equilibrium" as an equilibrium based on the assumption of full rationality; ii) the fully revealing benchmark as a result of efficient aggregation of public and private information, inspired by the strong version of the efficient market hypothesis; and iii) the public information benchmark as an alternative explanation for the behavior of prices, implicitly assuming the existence and relevance of the overweighting effect.

3.1. No information acquisition - no trade equilibrium

The experimental setting can be characterized by a "no information acquisition - no trade equilibrium" (hereafter "no-trade equilibrium"). If all traders are rational and risk neutral, or share the same beliefs and risk aversion, we should observe no transaction in the asset market and no information acquisition. The basic element underlying this equilibrium lies in the constant-sum nature of the setting. Essentially, it means that a trader would have incentives to acquire a private signal just in case she expects to recover the acquisition cost, making profits at the expense of some other traders. Thus, the other traders who have not acquired private signals would not trade with her. Therefore, the incentive for the first trader to acquire private information disappears, and there will be no activity in the information and asset markets. As we see in Section 4, this equilibrium is never achieved. Conversely, we always observe a sustained level of trading activity and acquisition of information.

3.2. Fully revealing benchmark

An alternative to the no-trade equilibrium is the fully revealing benchmark, defined as the expected price conditional on all information present in the market. Note that whereas no-trade equilibrium is an equilibrium in the strict economic sense, the fully revealing benchmark is not. Grossman and Stiglitz (1980) show the impossibility of the existence of equilibrium in a competitive market with fully informative prices and contemporaneous access to costly information. They resolve this paradox by introducing exogenous noise to provide incentives for the acquisition of costly information.

Addressing the Grossman-Stiglitz paradox experimentally, Sunder (1992) finds that the fully revealing benchmark is a reasonable predictor to describe price behavior in a laboratory asset market. He suggests that the double auction mechanism creates enough *endogenous* noise to prevent an instantaneous revelation of information, creating incentives for traders to acquire information even in the absence of *exogenous* noise. Therefore, we can rely on Sunder's conjecture to consider the fully revealing benchmark as a possible predictor of the level of prices. We compute the fully

revealing benchmark (FR) as the Bayesian conditional probability ($Pr(\cdot|\cdot)$) of $D_m = 10$, given all information available at time t in a given market m :

$$FR_{mt} = Pr(D_m = 10|H_{mt}, S_m) = 10 \left[1 + \left(\frac{q}{p} \right)^{H_{mt}} \left(\frac{Q}{P} \right)^{S_m} \right]^{-1}, \quad (1)$$

where H_{mt} refers to the net private signals available until time t , and S_m denotes the realization of the released signal.⁹ Employing Eq. (1) as a benchmark implies that the information is fully incorporated into the price, independently of its nature (public or private). Moreover, each signal, including the released signal, has an impact on the market price proportional to its precision. Essentially, we rely on the efficient market hypothesis in its strong form (Fama, 1970). Thus, if the information present in the market is sufficient to discover the dividend value, prices should converge to the dividend, independently of the realization of the public signal and its precision.

Nevertheless, many experimental contributions to laboratory financial markets find that information aggregation is imperfect, and therefore, prices are just partial indicators of the fundamental value.¹⁰ In particular, several experiments analyze information aggregation in Arrow-Debreu asset markets with acquisition of imperfect information, finding limited evidence that prices efficiently aggregate all information. Considering this experimental literature, we expect to observe some deviations from the fully revealing benchmark. The main goal of our paper is to evaluate whether those deviations systematically point to the public signal.

3.3. Public information benchmark

We define that a public signal is overweighted when it accounts for the market price more than justified by its precision. Contrary to the efficient market hypothesis, we conjecture that the efficiency of information aggregation depends on the nature of the information, namely, whether the incoming information is private or public. In this paper, we explicitly test whether public information is overweighted in the market price with respect to its precision.

Most laboratory contributions related to overweighting of public information are limited to stylized game theoretical coordination models based on Morris and Shin (2002)' seminal paper. Cornand and Heinemann (2014) and Shapiro et al. (2014) show that the overweighting phenomenon can be observed, although it is milder than predicted by the theory. Note that, in this class of experiments, the overweighting effect is the strongest under full rationality and weaker under bounded rationality. The lower-than-predicted overweighting of public information renders this effect a second-order issue, at least in a coordination framework (Baeriswyl and Cornand, 2016). Ackert et al. (2004) and Middeldorp and Rosenkranz (2011) are the only contributions studying the market overreaction to public disclosures in laboratory financial markets. Recently, Page and Siemroth (2020) use a meta-analysis of experimental data to show that public information is almost completely incorporated into prices, while little private information is reflected in prices. Their finding is compatible with the overweighting phenomenon, although they did not explicitly mention this effect in their paper.

Our experimental setting exhibits the key elements suggested by the theoretical literature to observe overweighting of public information on market prices: (i) access to private and public information, (ii) heterogeneous expectations because of the endogenous

⁹ See Appendix B for the derivation of the fully revealing benchmark. Note that there is no released signal in the B treatment; thus, we pose $S_m = 0$.

¹⁰ See Sunder (1995), Plott (2000), and Noussair and Tucker (2013) for surveys of experimental asset markets.

acquisition of noisy private information, and (iii) the beauty contest element following the Keynes' metaphor in describing a financial market (see Section 5 for an illustrative example). Considering those three points, we rely on Allen et al.'s (2006) result that prices overweight public information if traders take into account the average belief of the other traders when deciding their trading strategy.

To operatively detect the overweighting phenomenon, let us first define the public information benchmark (PB) as the expected price conditional only on public information:

$$PB_m = Pr(D_m = 10|V_m) = 10 \left[1 + \left(\frac{Q}{P} \right)^{V_m} \right]^{-1}, \tag{2}$$

where $V_m = 0$ in the B and CS80 treatments, whereas $V_m = S_m$ in the PS80 and PS70 treatments. We consider as a public signal the announcement, stated in the instructions, that the two states of the world are equally probable in the B and CS80 treatments. In those treatments, $PB_m = 5$ in all markets. Note that the fully revealing benchmark of Eq. (1) and the public information benchmark of Eq. (2) take into account the public signal. The main difference is that the fully revealing benchmark based on the Bayesian rule weights all signals according to their respective precision, whereas the public information benchmark assigns a zero weight to private information.

4. Results

Figs. C.8 through C.15, included in Appendix C, illustrate the trading activity in all markets for all treatments. A simple inspection of market activity shows that the no-trade equilibrium is not a meaningful description of traders' behavior in any treatment. This empirical finding is in line with many experiments on laboratory financial markets. Several recent papers examine under which conditions subjects trade in the laboratory despite the theoretical incentives not to do so (Angrisani et al., 2008; Carrillo and Palfrey, 2011). A fraction of the trading activity in the market might be also accounted for by the active participation hypothesis (Lei et al., 2001), based on the lack of an alternative incentivized task for the subjects rather than just participating in the asset market.

4.1. Information acquisition

Fig. 1 displays the distribution of the number of acquired signals in the experiment. On average, almost 40% of traders acquire no signals, while more than 25% of traders acquire one signal. From

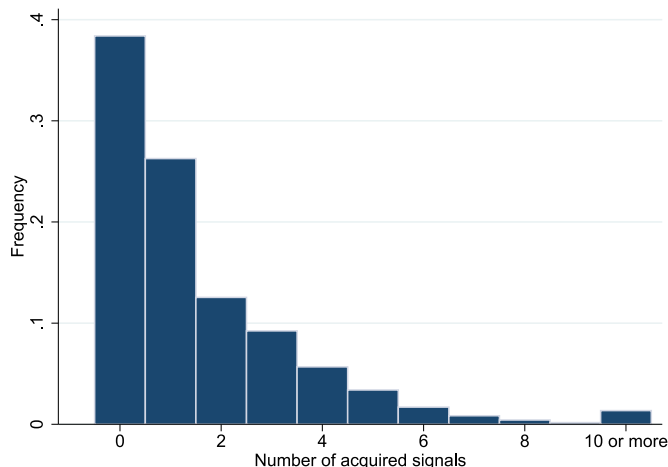


Fig. 1. Distribution of the number of acquired signals by each trader in a market; 1180 observations.

Table 2

Average number of acquired signals at different time intervals (in seconds) by treatment. The number of acquired signals is averaged across markets.

Seconds	[0,10]	(10,30]	(30,60]	(60,120]	(120,180]
B	22.9	3.0	3.1	3.3	1.6
PS80	13.5	5.0	3.8	2.4	1.8
PS70	10.9	3.2	1.7	1.3	1.0
CS80	12.4	5.2	4.5	4.1	2.6

another perspective, Table 2 shows that the acquisition of information monotonically decreases over time; most of the activity is concentrated at the beginning of the market (the first 10 seconds). Note that the overall quantity of information is roughly invariant in the last trading minute. Therefore, we can consider the fully revealing benchmark approximately constant during that time interval.

Fig. 2 illustrates the per-capita acquisition of signals per treatment. At first sight, the number of per-capita acquired signals is larger in the B treatment than in the other treatments. This suggests that the released signal crowds out the demand for private information. To formally analyze traders' information acquisition choices, we estimate a Poisson regression of the number of acquired signals (*AcqSign*) on the period of the session and treatment dummy variables (*PS80treat*, *PS70treat*, *CS80treat*), using the B treatment as the default condition. We run a Poisson regression because *AcqSign* is a count variable. We further evaluate whether the initial transactions affect the number of the acquired signals. One can expect that initial transactions biased toward one of the dividend values might affect incentives to acquire information. We include the dummy variable *AvgPrice15* or *AvgPrice20* that takes a value of 1 when the average price, computed within the first 15 or 20 seconds, is lower than 3 or higher than 7. We compute the average price within the first 15 or 20 seconds, because the trading activity within the first 10 seconds is scarce or absent in some markets. Results in Table 3 show that traders acquire significantly fewer private signals when a signal is released. Intuitively, releasing a signal helps investors forecast the fundamentals, reducing the marginal value of private information and therefore, crowding out its demand. Performing a post-regression analysis, we find no significant differences among treatments where a signal is released (Wald test, $p = 0.36$ and $p = 0.32$ comparing the PS80 and PS70 treatments, and the PS80 and CS80 treatments, respectively). The

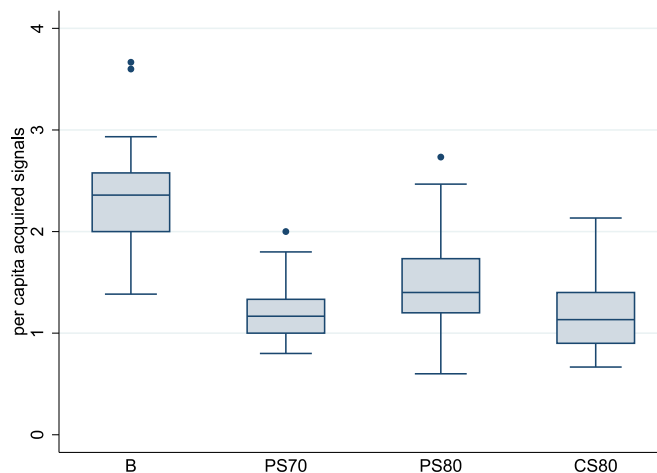


Fig. 2. Per-capita demand for private information in each treatment. The figure displays the distribution of the per-capita number of acquired signals at the market level.

Table 3

Poisson regression of the number of acquired signals (*AcqSign*). *PS80treat*, *PS70treat*, and *CS80treat* are dummy variables indicating the treatment. The baseline is the B treatment. *AvgPrice15* and *AvgPrice20* are dummy variables, indicating that the average price in the first 15 or 20 seconds of the market is lower than 3 or higher than 7. One observation in the PS80 treatment is omitted, because one trader acquired a large number of signals in period 10. The regressions also include the period of the session. Clustered standard errors on a subject level are given in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	AcqSign	AcqSign	AcqSign
PS80treat	-0.44* (0.26)	-0.45* (0.26)	-0.44* (0.26)
PS70treat	-0.69*** (0.25)	-0.70*** (0.25)	-0.69*** (0.25)
CS80treat	-0.70*** (0.24)	-0.69*** (0.24)	-0.68*** (0.24)
AvgPrice15		-0.06 (0.06)	
AvgPrice20			-0.05 (0.08)
Period	-0.04*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)
Constant	1.20*** (0.19)	1.11*** (0.20)	1.10*** (0.20)
Observations	1,179	1,179	1,179
Clusters	118	118	118
Log pseudolikelihood	-2271.12	-2270.45	-2270.63

variable period in a session has a negative effect on the number of acquired signals, suggesting some sort of learning effect of traders in better reading the price dynamics. Furthermore, we find that the number of acquired signals is not significantly affected by the initial transactions.

Result 1. Releasing a free signal reduces incentives to acquire costly signals, crowding out private information.

The experimental literature on information acquisition in asset markets is extensive. Related to the crowding-out, the few experimental contributions in the literature consistently report a reduction in acquisition of private information in the presence of public disclosures. Middelorp and Rosenkranz (2011) are the first to find that releasing a public signal reduces the quantity of acquired information. Page and Siemroth (2017) recently examined different aspects of information acquisition in a prediction market similar to our setting. They report that traders acquire more information when their initial information is inconclusive, similarly to Ruiz-Bufo et al. (2021), who additionally observe a crowding-out effect when the public disclosures are conclusive. Implementing the information network in a laboratory prediction market, Halim et al. (2019) find that social communication crowds out information production.

4.2. Market informativeness

After having analyzed how a public disclosure affects the demand for private information, we address whether the public signal compensates for the reduction in private information. To evaluate the impact of public information on the potential to discover the true state of the world, we introduce the market informativeness indicator. We define market informativeness as the mean absolute deviation (MAD) of the fully revealing benchmark about the dividend, averaged during the last minute of the market:

$$MI_m = \frac{1}{60} \sum_{t=120}^{180} \frac{|FR_{mt} - D_m|}{10} \tag{3}$$

The label *m* indicates the given market. We divided by 10 to normalize all distances to be bounded between 0 and 1. The maximum level of market informativeness is reached when $MI_m = 0$. The higher the value of MI_m , the lower the market informativeness. Thus, a value of MI_m close to zero indicates that the information present in the market is sufficient to discover the dividend value.¹¹

As one can infer from Figs. C.8 through C.15, market informativeness always satisfies the condition $MI_m < 0.05$.¹² This indicates that the information present in the market is always sufficient to discover the dividend value at a reasonable confidence level. Despite the crowding-out effect on the demand for private information, the potential of the market to discover the true state of the world is not affected by the released signal, independently of its realization. Even in markets where disclosures are misleading, the overall private information is sufficient to discover the dividend value. Therefore, the crowding-out effect is beneficial in reducing the overall cost of acquiring information, without affecting the potential of the market to discover the dividend value.

Result 2. The crowding-out effect leaves invariant the potential of the market to discover the true state of the world, reducing the cost of acquisition of information.

4.3. Price informativeness

We explore whether releasing a public signal affects the aggregation of information into prices. We measure price informativeness by computing the mean absolute deviation of the market price (PR_{mt}) about the fully revealing benchmark, averaged among all markets ($M = 20$), for each treatment at a given time:

$$MAD_t^{FR} = \frac{1}{M} \sum_{m=1}^M \frac{|FR_{mt} - PR_{mt}|}{10} \tag{4}$$

The maximum level of price informativeness is given when $MAD_t^{FR} = 0$. Significant deviations from the lower bound indicate a low level of price informativeness. In Fig. 3, the evolution of the price informativeness is plotted over time for each treatment. We observe a downsloping trend for all treatments, which suggests that prices tend to gradually aggregate information; consequently, the forecasting accuracy of the prices about the dividend improves.¹³ Given Result 2, one would expect that the prices converge to the dividend in most of the markets, independently of the realization of the released signal. Instead, none of the treatments shows full convergence of the prices to the dividends.

Result 3. Prices imperfectly aggregate the information present in the market.

This finding is in line with the behavior observed in previous contributions on laboratory asset markets with endogenous costly private information (see, for example, Sunder, 1992; Corngnet et al., 2018). Nevertheless, differences among treatments are evident. Although the prices in the B treatment quickly converge toward the dividend, eventually reaching 90% forecasting accuracy, treatments with a public disclosure exhibit a smoother improvement in price

¹¹ The choice of averaging over the last trading minute is a compromise between having sufficient statistics for the market informativeness indicator and having low activity in the information market (see Table 2). In the last minute, either zero or a few signals are acquired, and therefore, the fully revealing benchmark is almost constant over time. Moreover, traders should have enough time to aggregate the information present in the market, giving the fully revealing benchmark its “best shot” as Plott and Sunder (1988) state.

¹² Except for market 9 of group 1 in the PS80 treatment, which is equal to 0.14.

¹³ We define the price accuracy as the mean absolute distance between the price and the dividend across markets. Note that, considering Result 2, price informativeness and price accuracy are almost identical over the trading period.

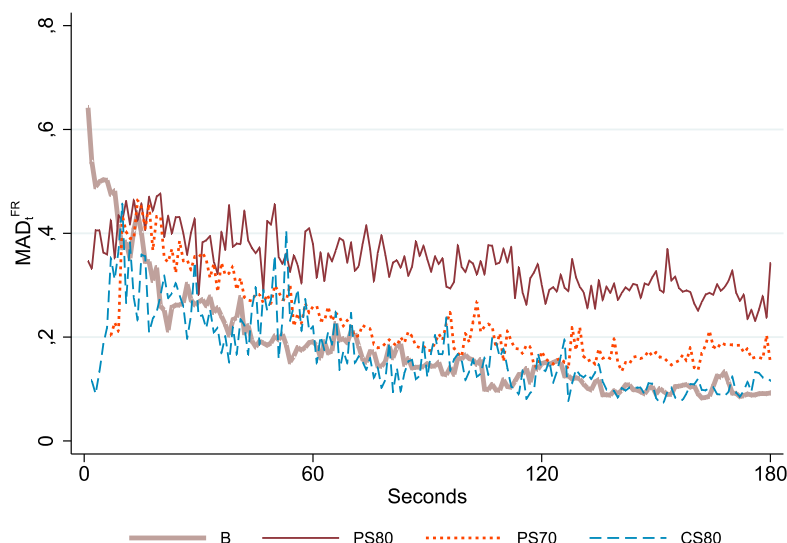


Fig. 3. Average price informativeness over time for each treatment, computed as the mean absolute deviation of prices about the fully revealing benchmark (MAD_m^{FR}).

informativeness. Prices reach approximately 70% and 80% forecasting accuracy in the PS80 and PS70 treatments, respectively. Differently, price informativeness exhibits similar values in the CS80 and B treatments. Fig. 3 suggests that public disclosures worsen the dissemination and aggregation of information, leading to a deterioration in price informativeness compared to the B treatment.

To formalize this finding, we estimate a Beta regression of the price informativeness on the treatment dummy variables and the period of the session. We chose to employ a Beta regression because the dependent variable takes values in the interval (0,1), and it is markedly skewed around its median. We compute the dependent variable as the mean absolute deviation of the prices from the fully revealing benchmark averaged in the last minute of each market (MAD_m^{FR}), defined as:

$$MAD_m^{FR} = \frac{1}{60} \sum_{t=120}^{180} \frac{|FR_{mt} - PR_{mt}|}{10} \tag{5}$$

We find that the distance between the prices and the fully revealing benchmark significantly increases in the PS80 and PS70 treatments. Conversely, in the CS80 treatment price informativeness is significantly higher than in the B treatment. In the period, the deviations of the prices from the fully revealing benchmark are also reduced. The results suggest that public disclosures deteriorate price informativeness, while a common signal favors aggregation of information into prices.

Result 4. Public disclosures worsen price informativeness.

One might think that the reduction in price informativeness is exclusively due to the misleading public disclosures. However, when we consider only the markets with a correct released signal in specification (2), price informativeness still exhibits a deterioration in the PS80 treatment and an improvement in the CS80 treatment. Interestingly, the reduction in price informativeness is accompanied by an increase in the level of trading activity. Public disclosures might distort prices, creating potential profit opportunities and consequently, increasing the trade volume (see Table D.7 in Appendix D).

Result 5. Public disclosures increase trade volume.

Remark. One might wonder whether the deterioration in price informativeness is exclusively caused by the crowding-out effect, as suggested by the literature. If this is the case, MAD_m^{FR} should be the

Table 4

Beta regression of price informativeness (MAD_m^{FR}), considering all markets (1) and only markets with a correctly released signal (2). $PS80treat$, $PS70treat$, and $CS80treat$ are dummy variables indicating the treatment. The baseline is the B treatment. The regressions also include the period of the session. Clustered standard errors on the group level are given in parentheses. We have a total of eight clusters, given there are two independent groups per treatment. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1) MAD_m^{FR} (All markets)	(2) MAD_m^{FR} (With correct signal)
PS80treat	0.94*** (0.22)	0.80** (0.40)
PS70treat	0.29*** (0.08)	-0.05 (0.13)
CS80treat	-0.67*** (0.23)	-1.09*** (0.21)
Period	-0.10*** (0.04)	-0.12*** (0.03)
Constant	-1.26*** (0.23)	-1.46*** (0.21)
Observations	80	66
Clusters	8	8
Log pseudolikelihood	92.89	108.56

lowest in the B treatment, and of similar magnitude in the PS80, PS70, and CS80 treatments, as the number of acquired signals is not statistically different (see Table 3). Instead, we find that price informativeness worsens in the PS80 and PS70 treatments, while it improves in the CS80 treatment, despite the crowding-out effect. Note further that the deterioration in price informativeness is statistically different in the PS80 with respect to the PS70, indicating a further deviation from the nexus crowding-out/price informativeness (Wald test, $p < 0.01$). We provide evidence that the reduction in price informativeness is not in a one-to-one relation with the crowding-out effect. The results imply that a larger number of acquired private signals is not *per se* a condition for increasing price informativeness. More information does not always improve price informativeness.

Result 6. The crowding-out effect is not the main determinant of the deterioration in price informativeness.

Contrary to the efficient market hypothesis, the results show that the nature of the released signal, public or common, plays a crucial role in determining the efficiency of the market.

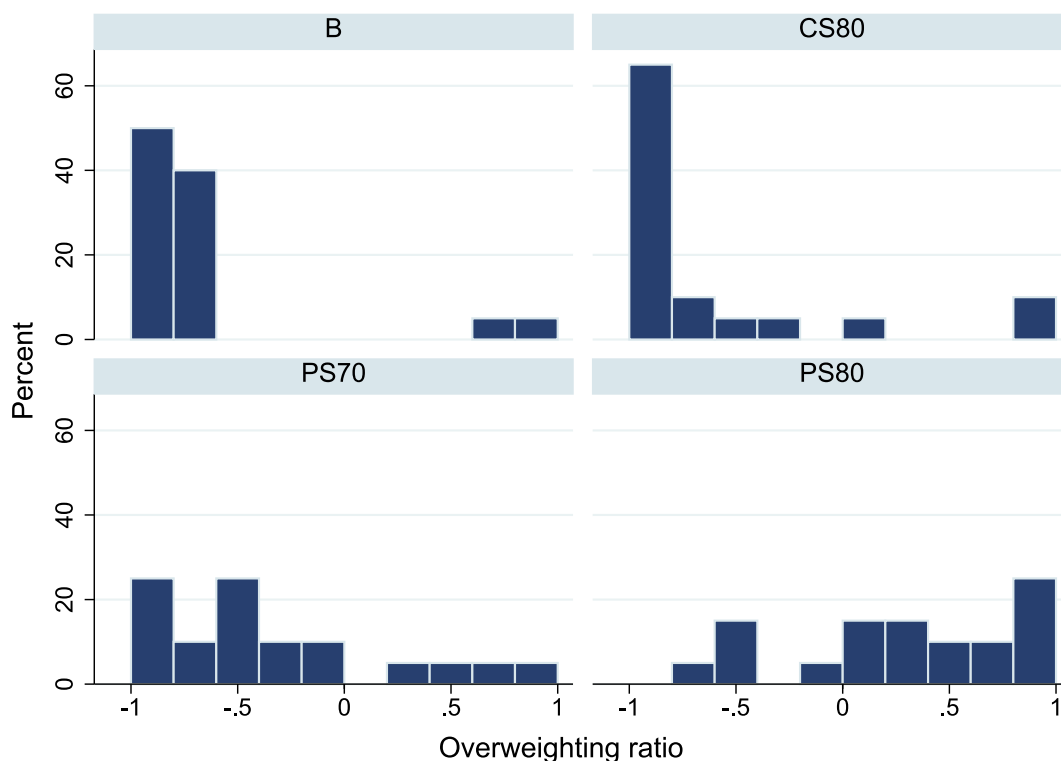


Fig. 4. Distribution of the overweighting ratio (ϕ) in each treatment, computed with Eq. (7).

4.4. Overweighting of public information

Why does price informativeness improve when a common signal is released, although private information is crowded out? We show that prices systematically overweight public information, leading to a reduction in price informativeness. To detect whether public information is overweighted, we compare the goodness of fit of the fully revealing benchmark and the public information benchmark in describing the behavior of prices. Let us introduce the mean absolute deviation of prices from PB, defined as:

$$MAD_m^{PB} = \frac{1}{60} \sum_{t=120}^{180} \frac{|PB_m - PR_{mt}|}{10} \tag{6}$$

When MAD_m^{PB} is close to zero, prices fluctuate around the public information benchmark. Recall that the announcement of equiprobable states of the world constitutes the public information in the B and CS80 treatments, so that $PB = 5$ in those treatments.

Using Eqs. (5) and (6), we define the overweighting ratio as:

$$\phi_m = \frac{MAD_m^{FR} - MAD_m^{PB}}{MAD_m^{FR,PB}} \tag{7}$$

where $MAD_m^{FR,PB} = \frac{1}{60} \sum_{t=120}^{180} \frac{|FR_{mt} - PB_m|}{10}$ represents the mean absolute distance between the two benchmarks. The variable ϕ measures the difference between the benchmarks' goodness of fit in units of their mutual distance; ϕ is bounded between -1 and 1. When $\phi = 1$, the public benchmark perfectly accounts for prices. This case represents the extreme situation of complete overweighting of public information when, essentially, private information is totally disregarded in accounting for price behavior. Conversely, the case $\phi = -1$ indicates that prices converge to the fully revealing benchmark; that is, we have no overweighting effect. To interpret the overweighting ratio, we have to consider that the closer ϕ is to 1, the stronger the overweighting effect; that is, the higher the weight of the public signal with respect to private information in accounting for price behavior.

Fig. 4 displays the distribution of ϕ in each treatment. At first glance, Fig. 4 shows that the distribution of the overweighting ratio in the B treatment concentrates on values close to $\phi = -1$, which means that the prices reflect (almost) all available information, weighted according to its precision. Instead, we observe a markedly different pattern in treatments with a released public signal. The values of ϕ are scattered within the entire interval of variability, with a positive bias in the PS80 treatment and a negative bias in the PS70 treatment. This pattern suggests that public information is weighted more than is justified by its precision, with a stronger effect in the PS80 treatment. When the signal is common instead of public, the distribution of ϕ is highly concentrated at the value $\phi = -1$, similarly to the B treatment scenario.

To formalize the visual impression, we estimate a Beta regression of the overweighting ratio on the treatment dummies and the period. Specification (1) in Table 5 considers all markets, while specification (2) considers only markets with a correct released signal. We observe that the overweighting ratio significantly increases in the PS80 treatment in both specifications. This effect reverses in the CS80 treatment, although it is significant only in specification (2).¹⁴ Considering the effect of releasing a public and common signal on price informativeness (see Table 4), we find that the price informativeness variations mirror the variations in the overweighting ratio across treatments. Putting it differently, a deterioration in price informativeness goes along with a stronger overweighting effect. Furthermore, an improvement in price informativeness accompanies a reduction in the overweighting effect. Instead of provoking a "generic" reduction in price informativeness, the release of a public signal yields systematic deviations of prices toward the public signal.

¹⁴ To evaluate the robustness of the results, we introduce an alternative benchmark that replaces the public signal with the common signal in Eq. (2). The strong reduction in the overweighting effect persists when we consider this new benchmark (see Appendix E).

Table 5

Beta regression of the overweighting ratio considering all markets (1) and only markets with a correct released signal (2). To run the Beta regression, we transform the variable ϕ into a new variable bounded between 0 and 1, i.e. $\frac{1+\phi}{2}$. *PS80treat*, *PS70treat*, and *CS80treat* are dummy variables indicating the treatment. The baseline is the B treatment. The regressions also include the period of the session. Clustered standard errors on the group level are given in parentheses. We have a total of eight clusters, given there are two independent groups per treatment. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	ϕ -Overweighting (All markets)	ϕ -Overweighting (With correct signal)
PS80treat	1.34*** (0.43)	2.00** (0.79)
PS70treat	0.40*** (0.15)	-0.11 (0.17)
CS80treat	-0.56 (0.42)	-1.24*** (0.17)
Period	-0.18*** (0.05)	-0.19*** (0.04)
Constant	0.40 (0.35)	0.29 (0.35)
Observations	80	66
Clusters	8	8
Log pseudolikelihood	73.00	73.57

Result 7. Prices overweight public disclosures, reducing price informativeness.

Looking again at Table 4, releasing the common signal in the CS80 treatment significantly improves price informativeness compared with the PS80 treatment (Wald test, $p < .01$), and even compared to the B treatment. The overweighting effect is strongly attenuated in the CS80 treatment compared to the PS80 treatment, because the prices converge to the dividend in most markets. When the commonality component is eliminated, the released signal does not constitute the main determinant of market prices. Contrary to the public signal, the common signal accumulates with the private information when aggregated into prices, without distorting the dissemination and the aggregation process.

Result 8. The commonality component of the public signal causes the overweighting effect.

4.5. The role of the precision of the public signal

Interpreting the relative precision of the public signal as its transparency, we provide evidence in favor of the possibility that controlling the transparency of the released information allows to smooth the market overreaction to public disclosures. In specification (1) of Table 5, releasing a public signal in the PS70 treatment has a significant positive effect on the overweighting ratio; however, this effect is significantly lower than in the PS80 treatment (Wald test, $p = .03$). Furthermore, such an effect is not significant when we consider only markets with a correct signal in the PS70 treatment. This suggests that reducing the public signal's precision softens the overweighting effect as well as reduces the deterioration in price informativeness.

Result 9. The magnitude of the overweighting effect is influenced by the relative precision of the public signal with respect to a single private signal.

Concerning the optimal communication of monetary authorities, several authors, such as Myatt and Wallace (2014) and Baeriswyl and Cornand (2014), propose to use the transparency of public information as a control variable when designing the central bank information disclosure policy. Result 9 supports the conjecture that setting the transparency of public disclosures constitutes an effective control instrument at the disposal of regulators.

4.6. The role of second-order beliefs

Although in the experiment we did not elicit subjects' beliefs, we can indirectly infer their beliefs by analyzing the behavior of the market prices across the treatments. To do so, we focus on the finding that price informativeness is significantly higher in the CS80 treatment than in the PS80 treatment. We argue that this difference is due to the role that the commonality component of the public signal exerts on traders' second-order beliefs. We start classifying subjects' beliefs following the "taxonomy" typically adopted in the k-level thinking framework (Nagel, 1995; Camerer et al., 2004).

Let us first assume that subjects' trading strategies depend only on their first-order beliefs. When devising their trading strategy, subjects consider irrelevant whether the released signal is public, common or iid because they only consider its expected value. Therefore, we should not observe any significant difference between PS80 and CS80 price informativeness. This argument suggests that a first-order belief bias (i.e., the subjects already overweight the released signal in their first-order beliefs) does not determine the overweighting effect. Although we cannot exclude its existence, we do exclude that it is the primary cause of the reduction in price informativeness.

Let us alternatively assume that subjects' trading behavior depends on their first- and second-order beliefs. We have to distinguish whether subjects believe that the released signal in the CS80 treatment is (i) iid or (ii) the same for all subjects. In the latter case, we should not observe any difference between the CS80 and PS80 treatments, because the subjects' first- and second-order beliefs are the same.

Let us now assume that the subjects believe that the released signal in the CS80 treatment is iid. As explained in Section 2, the (iid) common signal creates a certain degree of uncertainty when the subjects form their second-order beliefs. Such uncertainty prevents the common signal from becoming a focal point for the subjects' beliefs, favoring the dissemination and aggregation of information in the market. Conversely, the public signal ensures that all subjects possess the same signal, allowing a more precise estimation of their second-order beliefs. The public signal, then, becomes a focal point for the alignment of the subjects' beliefs, restraining the information dissemination and its aggregation into prices (see Section 5). Concluding our reasoning, our experimental results are compatible with the assumption of trading strategies based on

Table 6

OLS regression of centered net profits by treatment. *InfLevel1*, *InfLevel2*, and *InfLevel3* are dummy variables indicating that a trader has acquired one, two, or three or more signals. The baseline is a trader who has acquired no signals. Clustered standard errors on the subject level are given in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	NetProfit B	NetProfit PS80	NetProfit PS70	NetProfit CS80
InfLevel1	3.95 (5.62)	-11.15** (4.65)	-6.16 (4.69)	-11.64 (9.44)
InfLevel2	6.99 (5.67)	5.07 (8.69)	6.37** (2.84)	1.76 (4.77)
InfLevel3	-7.05* (4.00)	-12.30 (9.45)	-1.88 (6.97)	-0.63 (5.32)
Constant	43.77*** (3.20)	50.37*** (3.64)	46.87*** (2.01)	44.32*** (2.17)
Observations	280	300	300	300
Clusters	28	30	30	30
R-squared	0.05	0.03	0.02	0.02

second-order beliefs and that the subjects consider the released signal as iid in the CS80 treatment.

The identified difference between the PS80 and CS80 treatments can be also cast into the framework of third-order beliefs: Subjects consider their own information together with the first- and second-order beliefs of the other subjects. Within this framework, we can devise more complex scenarios where the common or public nature of the released signal plays a role in the implementation of the trading strategies. However, based on the literature on k-level thinking, we can safely state that this scenario is highly improbable. This literature points out that first- and second-order beliefs are the most frequent cognitive levels observed in laboratory or field data (Bosch-Domenech et al., 2002; Nagel, 2008).

To the best of our knowledge, this is the first contribution to the literature that observes and measures the overweighting effect of public information in a market environment. Furthermore, we are the first to provide empirical evidence compatible with the conjecture that traders' strategic pricing concerns trigger the overweighting of public information beyond coordination experiments directly reproducing the Morris and Shin (2002) framework.

4.7. Traders' profits

We analyze traders' profit as a function of their information acquisition and the characteristics of the released signal. To that aim, we compute the net profit (π) of trader i in market m as:

$$\pi_{mi} = (C_{mi}^{180} - C^0) + D_m \text{Assets}_{mi}^{180}, \tag{8}$$

where $(C_{mi}^{180} - C^0)$ is the cash held at the end of the market after paying back the initial endowment, and Assets_{mi}^{180} denotes the number of assets held at the end of the market. To compare the markets with dividends 0 and 10, we redefine net profit by centering them; that is, $(\pi_{mi} + 50)$ if $D = 0$, and $(\pi_{mi} - 50)$ if $D = 10$. The value 50 is the expected value of the portfolio of the assets at the beginning of the market.

We perform an Ordinary Least Squares (OLS) regression analysis for each treatment separately, clustering errors at the subject level. For explanatory variables, we define dummy variables according the number of signals acquired by traders: *InfLevel1*, *InfLevel2*, and *InfLevel3* indicate that a trader acquires one signal, two, or three or more signals, respectively. *InfLevel0* indicates that a trader does not acquire a signal, uninformed trader.

In Table 6 there are some differences across treatments. In the B treatment, traders with *InfLevel1* and *InfLevel2* and uninformed traders do not exhibit significantly different performances. Instead,

traders with *InfLevel3* cannot recover the costs of acquiring information, performing significantly worse than uninformed traders. This pattern changes in markets with a released signal. A general tendency across treatments seems to favor traders who acquire two signals, while the decision to acquire one or three (or more) signals does not outperform the choice of being uninformed. One can infer the following from Table 6:

Result 10. Releasing information at the beginning of the market changes the pattern of the traders' net profit, favoring the decision to acquire two signals.

A general conclusion we can draw is that, intuitively, acquiring too many signals has a negative impact on traders' performance. However, corroborating the released information by acquiring two signals might help to outperform the market. The introduction of a released signal leads to a non-monotonic relationship between net profits and the number of acquired signals. Huber (2007) and Huber et al. (2011) observe an analogous non-monotonic relationship between profits and information.

5. Bounded rationality, overweighting, and higher-order beliefs

Following Allen et al. (2006), public information may have an excessive impact on prices when higher-order beliefs play a role in the determination of prices, because a public signal provides information about the dividend and information on the other traders' beliefs.

Let us introduce a qualitative idea on how traders could have the incentive to forecast other traders' expectations in our financial market. Inspired by the notion of prior-information traders introduced by Plott and Sunder (1988), we assume that the market is populated by bounded rational traders. An informed trader whose private signals suggest a dividend of 10 is willing to buy assets at any price equal to or lower than her expected dividend. She expects to make a profit by buying the asset at a low price. In particular, if this trader believes that there is a non-marginal fraction of uninformed traders (i.e., a trader who does not acquire a signal), she has an incentive to bid around her belief of uninformed traders' expected dividend, that is, the public information benchmark. Uninformed traders could be willing to buy and sell their assets around their expected dividend, determined solely by the public signal.

When the proportion of uninformed traders willing to trade with informed traders is high enough to provide sufficient liquidity and/or assets, market prices fluctuate around the expected dividend conditional on the public signal. Therefore, prices do not

flect traders' private information. Prices reflect mostly the expectations for and about uninformed traders' beliefs, which are biased toward public information. In this case, the public information benchmark better predicts the market price than the fully revealing benchmark does.

What we have just sketched could be a simple mechanism behind the overweighting of public information, based on the impact of public information on traders' second-order beliefs. Further research is necessary to experimentally investigate the microstructure details of this process and account for the results we identified in our experiment. Specifically, ongoing research is exploring the behavior of traders in an environment with exogenous allocation of information. Although losing some degree of realism, this simplification of the experimental setting allows for a detailed analysis of traders' trading behavior as a function of the level of information, which is invariant over time.

The previous reasoning essentially rests on traders' bounded rationality. In contrast, the literature has introduced the overweighting effect as an equilibrium outcome of coordination models with fully rational agents, as in Morris and Shin (2002). Cornand and Heinemann (2014) and Shapiro et al. (2014) provide two contributions that analyze the impact of different degrees of rationality on the overweighting phenomenon within the boundedly rational behavioral framework introduced by Nagel (1995). They show that the higher the level of bounded rationality, which is measured as the degree of inductive reasoning, the lower the overweighting phenomenon. Note, however, that we observe the opposite relationship between the level of rationality and the overweighting of public information. In our setting, full rationality implies either a no-trade equilibrium or a noisy rational expectation equilibrium, following Sunder's (1992) argument. In both cases, we should not observe the overweighting effect, because we have either no trade or the price reflects the information according to its precision. Therefore, the bounded rationality of traders seems to be a necessary condition to detect the overweighting of public information in our market environment. As we do not explicitly introduce a coordination setting, the experimental results generalize existing literature, showing that the overweighting effect is a relevant phenomenon in a market setting with bounded rational traders rather than being a marginal effect observed in coordination environments.

In the literature, several elegant frameworks account for deviations from full rationality, such as Camerer et al.'s (2004) cognitive hierarchy model or Eyster and Rabin's (2005) cursed equilibrium. In particular, Eyster et al. (2019) apply the cursed equilibrium to a financial market, showing that public information is overweighted when aggregated into market prices. Similar to that theoretical contribution, our paper provides experimental support for the overweighting effect within the framework of bounded rationality.

We can find other important contributions in modeling bounded rationality in the literature on noise traders. A cornerstone is De Long et al.'s (1990) paper on noise trading. They theoretically show that the interaction between informed traders (arbitrageurs) with a limited trading horizon and noise traders could give rise to an equilibrium price that deviates from the fundamentals. To obtain such a result, they exogenously imposed a correlation among noise traders, justified by the presence of an optimistic market mood or market sentiment. In De Long et al.'s (1990) original paper, this correlation is introduced assuming that the representative noise trader's misperception is a normal random variable with mean ρ^* . Without being too rigorous and based on our experimental results, the existence of such a systemic correlation can be alternatively related to the presence of public information, systematically influencing the formation of noise traders' beliefs.

6. Conclusions

The main purpose of this paper is to experimentally examine the aggregation of information in financial markets as a function of traders' access to different sources of information, namely, costless public and costly private information. Such an informational setting has been used extensively in the literature to model the intervention of regulatory authorities. The objective of regulatory institutions when releasing public information is essentially to discipline the market, reducing the potential negative effects of asymmetric information. According to the theoretical literature, however, the release of public information might have adverse effects, such as the overweighting of public information and the crowding out of private information.

We show that overweighting of public information on market prices exists, and it is measurable and empirically relevant, heavily affecting market performance. Moreover, in this experimental setting, this effect emerges without an explicit incentive for the subjects to coordinate, as in other experimental studies reproducing the very specific Morris and Shin (2002) theoretical framework. We illustrate that traders' overreaction to public information is a more general phenomenon than conjectured by the literature. By investigating the dual role of public information, we find that the commonality component is mainly responsible for the overweighting phenomenon. Introducing public information negatively affects the aggregation of information into prices, as prices are biased toward the public signal. Conversely, providing a common signal to all traders improves the aggregation of information.

Some general warnings for regulators can be derived from this set of experiments. Policymakers should be aware that the release of public information might have distorting effects on traders' effort to find alternative sources of information and on the aggregation of information into prices. Such effects might be extremely significant, as demonstrated by the role that credit rating agencies had in the spread of the 2008 financial crisis. Far from opposing the activity of public institutions in releasing information to discipline financial markets, we stress the unintended effects of the complex interaction between private and public information on market performance.

As policy advice, we recommend that ongoing reforms of the regulation of financial institutions (for instance, credit rating agencies) should account for the complex interplay, that we identified in the experiments. In particular, the reforms should provide incentives for investors (institutional and/or private) to actively search for alternative sources of information. To take stock of the regulatory advantages of releasing public information and smoothing its potential adverse effects, we provide some guidelines for designing public communication and disclosure strategies: (i) More precise public information does not necessarily help the market align with the fundamentals, as public information does not cumulate; but it substitutes private information because of crowding-out and overweighting effects. (ii) It is not always optimal to reveal all the information possessed by public institutions. In this respect, it might be more effective to release an informative signal that is not perceived as too precise by investors to avoid market overreaction. The level of transparency of public information should be tuned considering the precision of the private information at the disposal of traders. Therefore, it is advisable to use econometric techniques for developing some proxies for the precision of traders' private information, based, for instance, on survey data. Interestingly, if we interpret the common information setting as a disclosure strategy, the most effective measure we have identified to enhance market efficiency and at the same time, reduce the cost of gathering private information, is whispering in the ears of investors, that is, spreading common information among investors without being common knowledge. However, we understand that it is unrealis-

tic to expect this measure could be implemented in real financial markets.

Finally, we strongly believe that the laboratory setting can be used as a realistic testbed for evaluating the performance of different policy instruments, without relying on specific behavioral assumptions and/or ad hoc coordination mechanisms. As a result, our conclusions can be more robust than those based on experimental settings currently used. Several other measures can also be tested, such as sequentially releasing public information, reducing the level of publicity, or increasing the number of regulatory institutions (Ruiz-Bufo et al., 2021). Examining the effects of these measures is the focus of ongoing research.

Declaration of Competing Interest

None.

CRedit authorship contribution statement

Alba Ruiz-Bufo: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Data curation. **Eva Camacho-Cuena:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition. **Andrea Morone:** Conceptualization, Investigation, Software. **Simone Alfano:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition.

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Appendix A. Material of the experiment

English translation of instructions as well as English translation of the computer screens as seen by the subjects in each treatment.

A1. Instructions of the experiment

Welcome. This is an economic experiment on decision making in financial markets. The instructions are simple and if you carefully follow them, you can earn a considerable amount of money. Your earnings will be personally communicated to you and paid in cash at the end of the experiment.

During the experiment your gains will be measured in experimental units (ECU) that will be translated into Euro at the end of the experiment using an exchange rate of 1 € for every 50 ECU accumulated, plus a fixed amount for participating 3 €. The corresponding amount in € will be paid in cash at the end of the experiment.

At the beginning of the experiment, it has been assigned a number to each one of you. From now on, that number will identify you and the rest of the participants. Communication is not allowed among the participants during the session. Any participant who does not comply will be expelled without payment.

THE MARKET

You are in a market together with 14 other participants.

At the beginning of each period, your initial portfolio consists of 10 assets and 1000 ECU as cash. Each participant has the same initial portfolio.

The experiment consists of 10 periods of 3 minutes each. In each period, you and the other participants will have the opportunity to buy and sell assets. You can buy and sell as many assets as you want, although each bid or ask involves the exchange of a single asset. Therefore, the assets are bought and/or sold one at a time.

INFORMATION AND DIVIDENDS

At the end of each period, you will receive a specific dividend for the assets you hold in your portfolio. **The value of the dividend can be 0 or 10 with the same probability.**

Thus, without additional information, the value of the assets can be 0 or 10 with a probability of 50%.

Moreover, you can **acquire a private signal** on the value of the dividend at the end of the period. The signal you will receive will be 0 or 10.¹⁵

- **A private signal equal to 0** means that with a probability of 80% the value of the dividend will be 0 at the end of the period.¹⁶
- **A private signal equal to 10** means that with a probability of 80% the value of the dividend will be 10 at the end of the period.

The **cost of the signal is 4 ECU**. During each period, you can buy as many signals as you wish. This will be your private information and therefore you will be the only one able to see it.

[Only in the public information treatments:] In addition, you will have a public signal that will be correct with a probability of 80%, that is:

- **A public signal equal to 0** means that with a probability of 80% the value of the dividend will be 0 at the end of the period.
- **A public signal equal to 10** means that with a probability of 80% the value of the dividend will be 10 at the end of the period.

[Only in the common information treatments:] In addition, you will have a free signal that will be correct with a probability of 80%, that is:

- **A signal equal to 0** means that with a probability of 80% the value of the dividend will be 0 at the end of the period.
- **A signal equal to 10** means that with a probability of 80% the value of the dividend will be 10 at the end of the period.

At the end of each period, your profit will be the cash you have at the end of the period plus the dividends for the assets you own, minus the cash you had at the beginning of the period, that is, 1000 ECU.

Your payment at the end of the session corresponds to the accumulated profit during the 10 periods.

If at any time you have any questions or problems, do not hesitate to contact the experimenter. Remember that it is important that you understand correctly the operation of the market, since your earnings depend both on your decisions and on the decisions of the other participants in the market.

¹⁵ We explained to the subjects that private signals are independent, which means that each acquired private signal is a new draw. Therefore, they may observe different signals.

¹⁶ The values of the different probabilities are changed in accordance to the different treatments.

A2. Screenshots

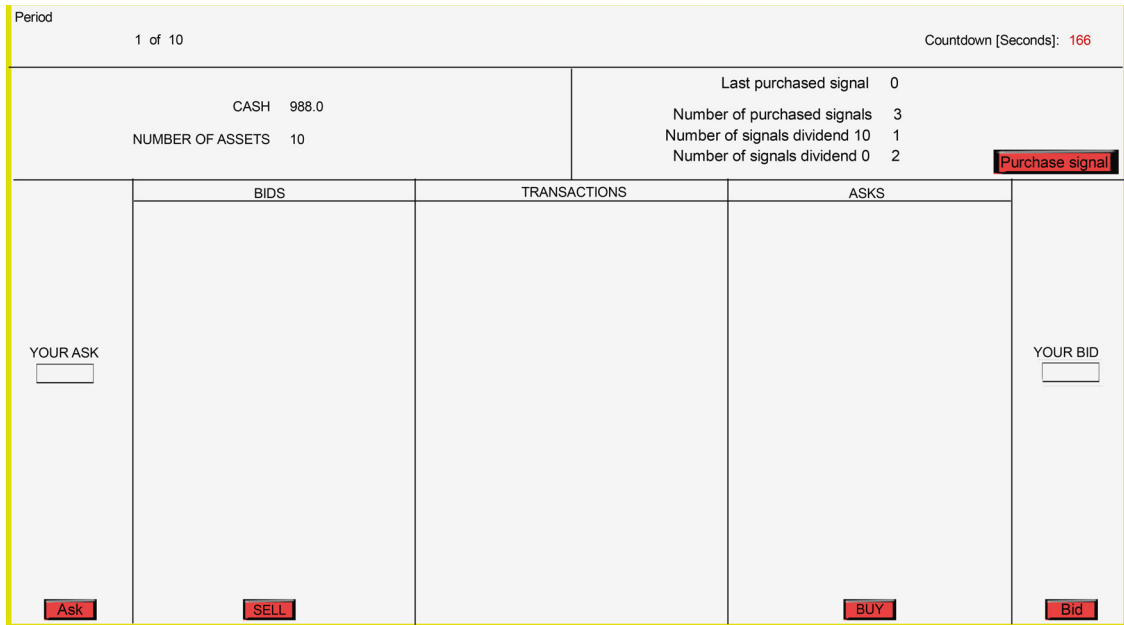


Fig. A.5. Screenshot of the B treatment.

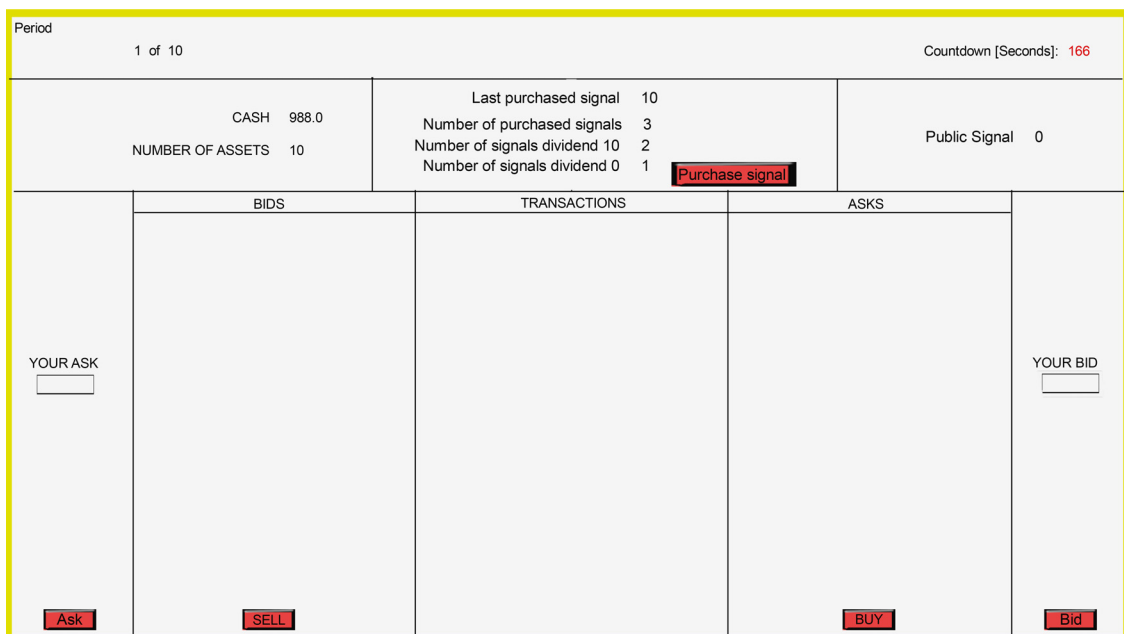


Fig. A.6. Screenshot of the PS80 and PS70 treatments.

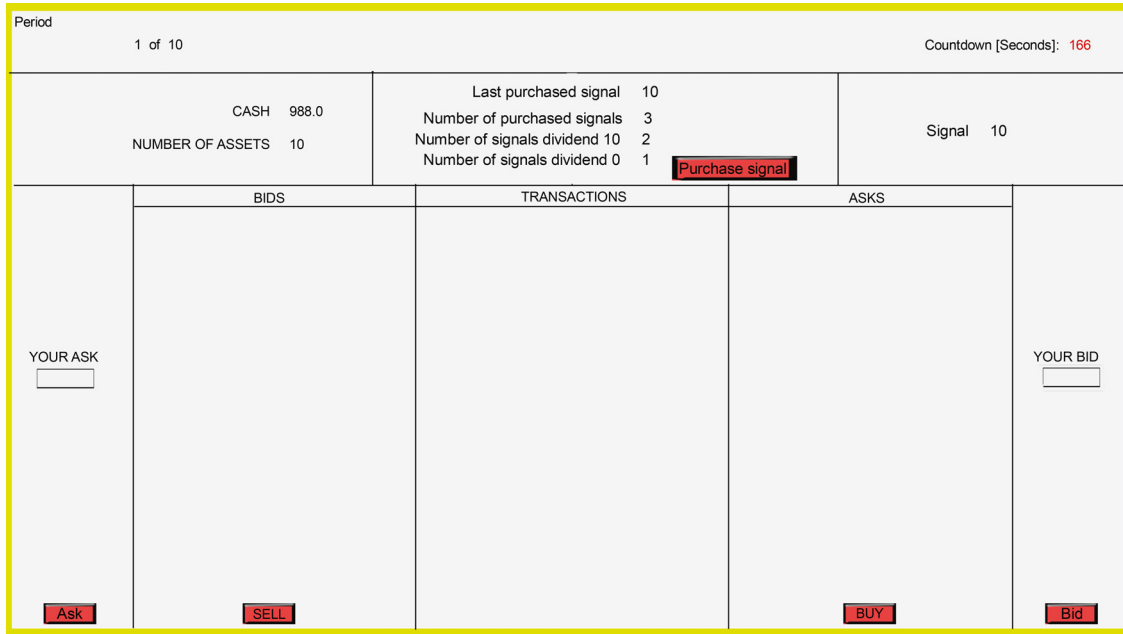


Fig. A.7. Screenshot of the CS80 treatment.

Appendix B. Fully revealing benchmark

Let us compute the fully revealing benchmark in our setting. Using Bayesian inference, we compute the probability that the dividend is equal to 10 ECU conditioned on the series of signals acquired by subjects until time t . We refer to I_t as the market private information set $I_t = \{s_1, s_2, \dots, s_j, \dots, s_t\}$. s_t takes a value of -1 when the private signal indicates that the dividend is 0. Conversely, s_t takes a value of 1 when the private signal suggests that the dividend is 10. Additionally, we introduce the variable $S \in \{-1, 1\}$ in the PS70, PS80, and CS80 treatments. Following the previous reasoning, $S = -1$ when the public or common signal predicts a dividend 0 and $S = 1$ otherwise. $Pr(D = 10|I_t, S)$ denotes the probability of observing a dividend equal to 10 ECU conditioned on the information available at time t :¹⁷

$$Pr(D = 10|I_t, S) = \frac{Pr(I_t|D = 10) \cdot Pr(D = 10|S)}{Pr(I_t, S)}, \quad (B.1)$$

where $Pr(I_t, S)$ is the marginal probability computed as

$$Pr(I_t, S) = Pr(I_t|D = 10) \cdot Pr(D = 10|S) + Pr(I_t|D = 0) \cdot Pr(D = 0|S). \quad (B.2)$$

$Pr(D = 10|S)$ is the prior probability of the event $D = 10$, given the public signal S . $Pr(D = 0|S)$ indicates the prior probability of the event $D = 0$. The values of this conditional probability are defined later on.

Let us now compute the formula of Eq. (B.1) as a function of

- p , the probability that a single private signal is correct, with $q = 1 - p$;
- P , the probability that the public or common signal is correct, with $Q = 1 - P$;
- N_t , the number of signals in the information set available until time t and
- n_t , the number of 1s, and $N_t - n_t$, the number of -1s in I_t .

In the following, when not necessary, we will omit the time variable t from the variables n_t and N_t . Depending on the value of

¹⁷ *Mutatis mutandis*, the probability of observing a dividend equal to 0 ECU is $Pr(D = 0|I_t, S) = 1 - Pr(D = 10|I_t, S)$, as we have two possible states of the world.

S , the numerator of Eq. (B.1) is given by:

$$\begin{aligned} Pr(I_t|D = 10) \cdot Pr(D = 10|S = 1) &= p^n \cdot q^{N-n} \cdot P, \\ Pr(I_t|D = 10) \cdot Pr(D = 10|S = -1) &= p^n \cdot q^{N-n} \cdot Q, \text{ and} \\ Pr(I_t|D = 10) \cdot Pr(D = 10|S = 0) &= p^n \cdot q^{N-n} \cdot \frac{1}{2}. \end{aligned} \quad (B.3)$$

The marginal probability in Eq. (B.2) takes the following form:

$$\begin{aligned} Pr(I_t, S = 1) &= P \cdot p^n \cdot q^{N-n} + Q \cdot p^{N-n} \cdot q^n, \\ Pr(I_t, S = -1) &= Q \cdot p^n \cdot q^{N-n} + P \cdot p^{N-n} \cdot q^n, \\ Pr(I_t, S = 0) &= \frac{1}{2} p^n \cdot q^{N-n} + \frac{1}{2} p^{N-n} \cdot q^n. \end{aligned} \quad (B.4)$$

Combining Eqs. (B.1), (B.2), (B.3), and (B.4) and defining $H_t = \sum_{j=1}^t s_j = 2n_t - N_t$ as the aggregate net private signal available at time t , we obtain the probability that the dividend is equal to 10 as a function of the relevant information present in the market at time t :

$$Pr(D = 10|H_t, S) = \left[1 + \left(\frac{q}{p} \right)^{H_t} \left(\frac{Q}{P} \right)^S \right]^{-1}. \quad (B.5)$$

Finally, using Eq. (B.5), the fully revealing benchmark for the asset price under risk neutrality assumption is given by:

$$\begin{aligned} FR_t &= 10 \cdot Pr(D = 10|H_t, S) + 0 \cdot Pr(D = 0|H_t, S) \\ &= 10 \left[1 + \left(\frac{q}{p} \right)^{H_t} \left(\frac{Q}{P} \right)^S \right]^{-1}. \end{aligned} \quad (B.6)$$

Appendix C. Trading activity

Every panel plots the chart of transactions. The vertical axis shows the price at which the transaction took place, and the horizontal axis shows the time (in seconds) at which the transaction took place. The first number at the caption of each panel identifies the market, and the second one indicates the value of the dividend (either 10 or 0). The solid line is the trading price. Finally, the dotted line indicates the fully revealing benchmark, whereas the dashed line, if present, indicates the public information benchmark.

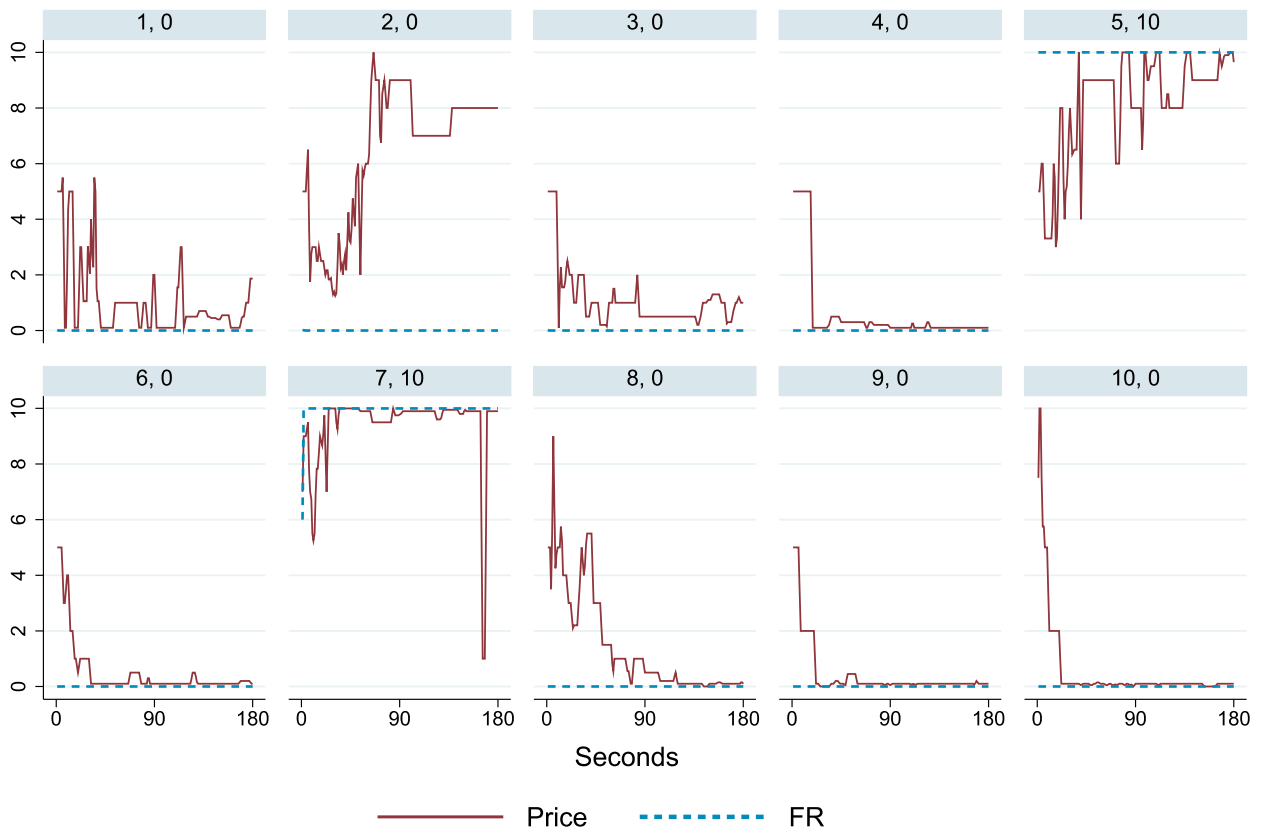


Fig. C.8. Transactions overtime and fully revealing benchmark in each market of the B treatment (Group 1).

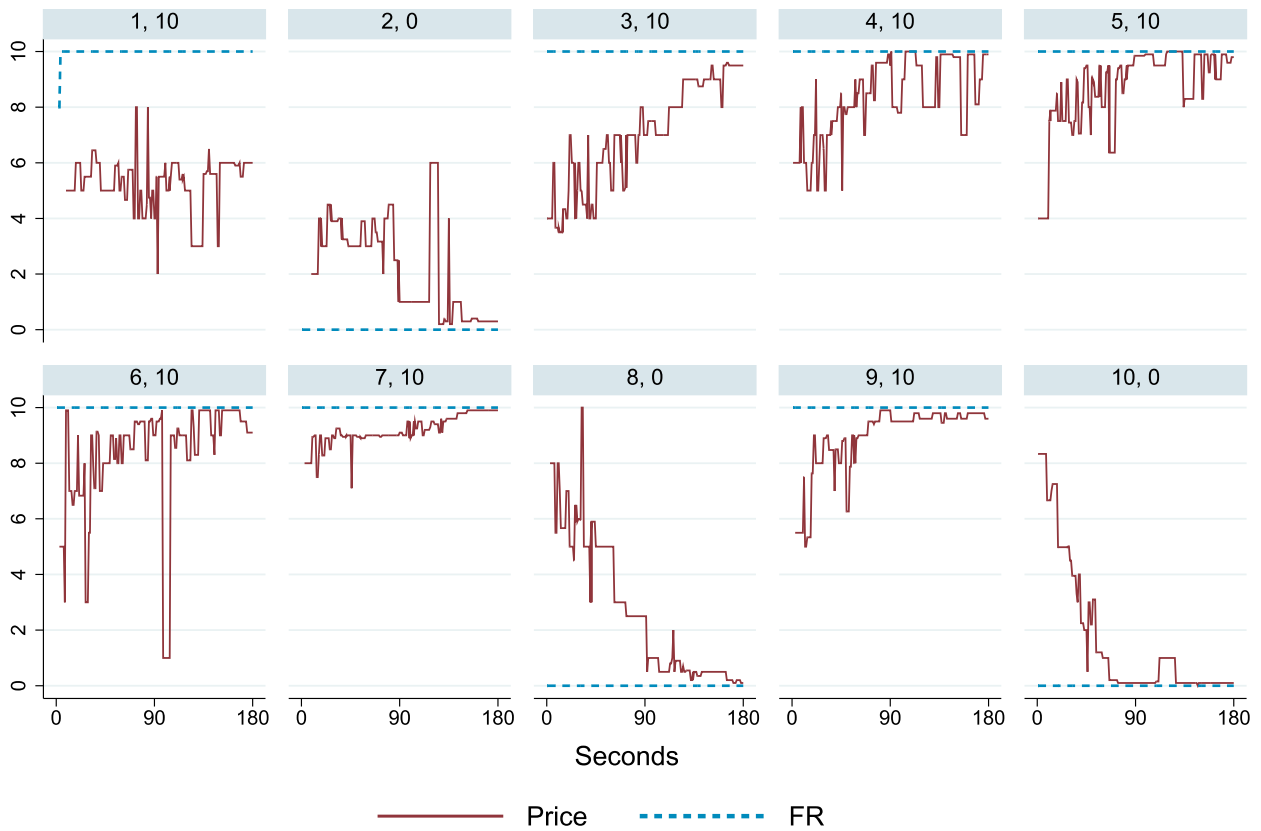


Fig. C.9. Transactions overtime and fully revealing benchmark in each market of the B treatment (Group 2).

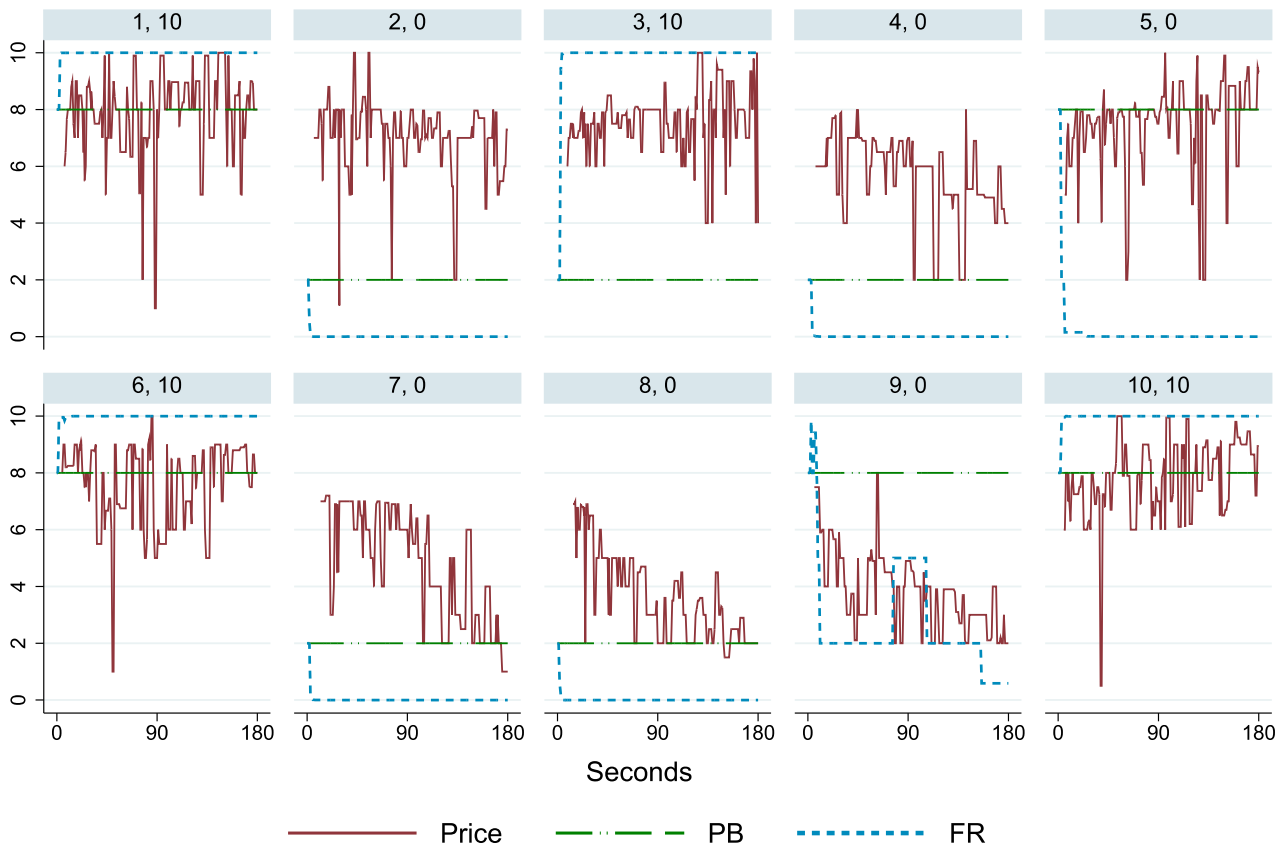


Fig. C.10. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the PS80 treatment (Group 1).

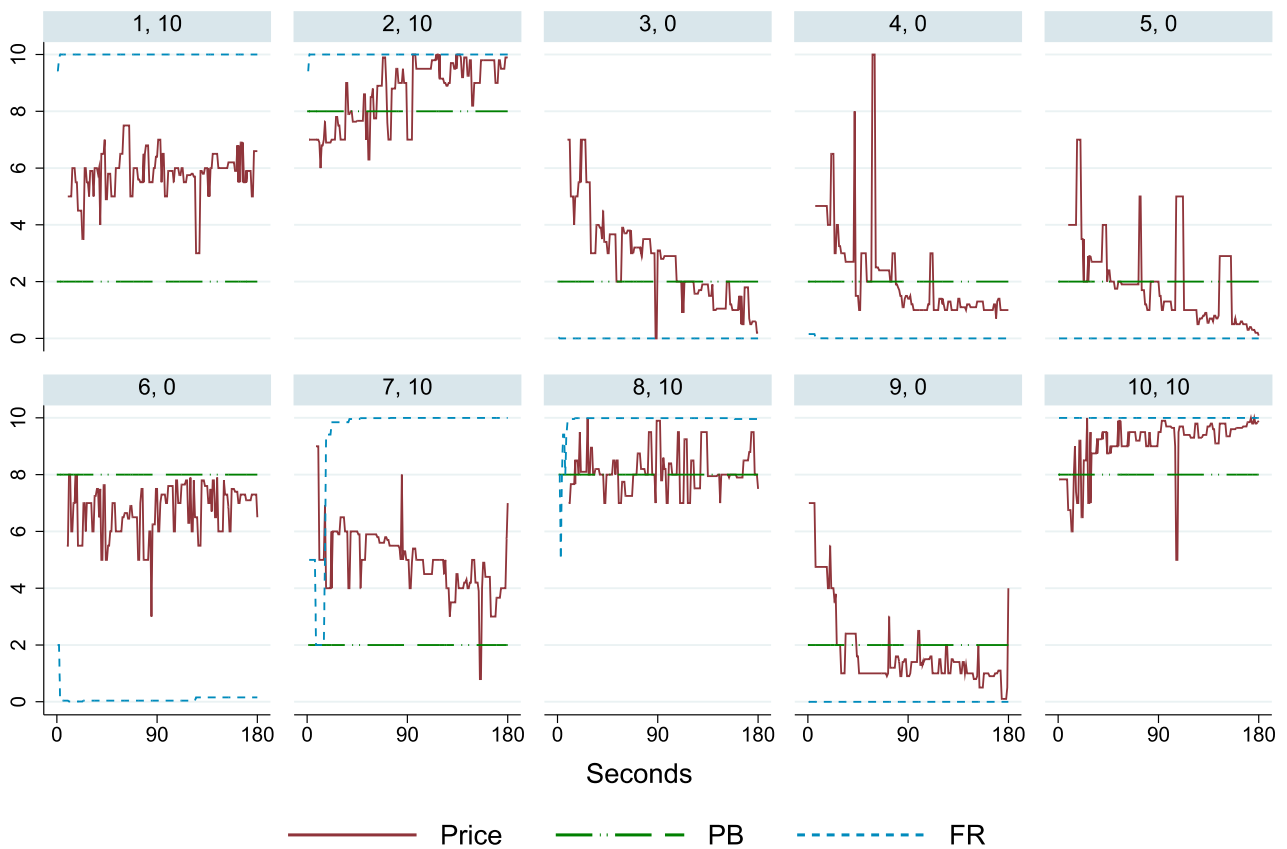


Fig. C.11. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the PS80 treatment (Group 2).

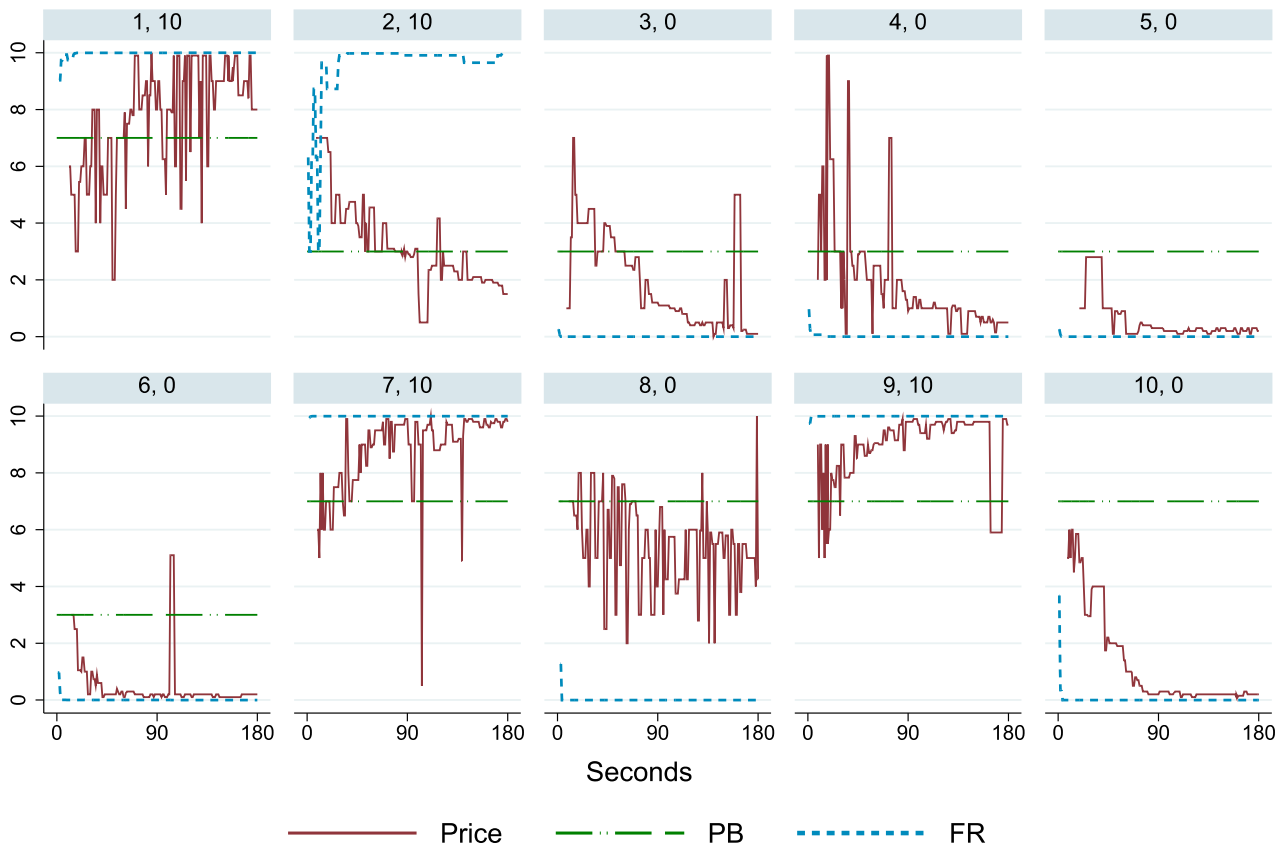


Fig. C.12. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the PS70 treatment (Group 1).

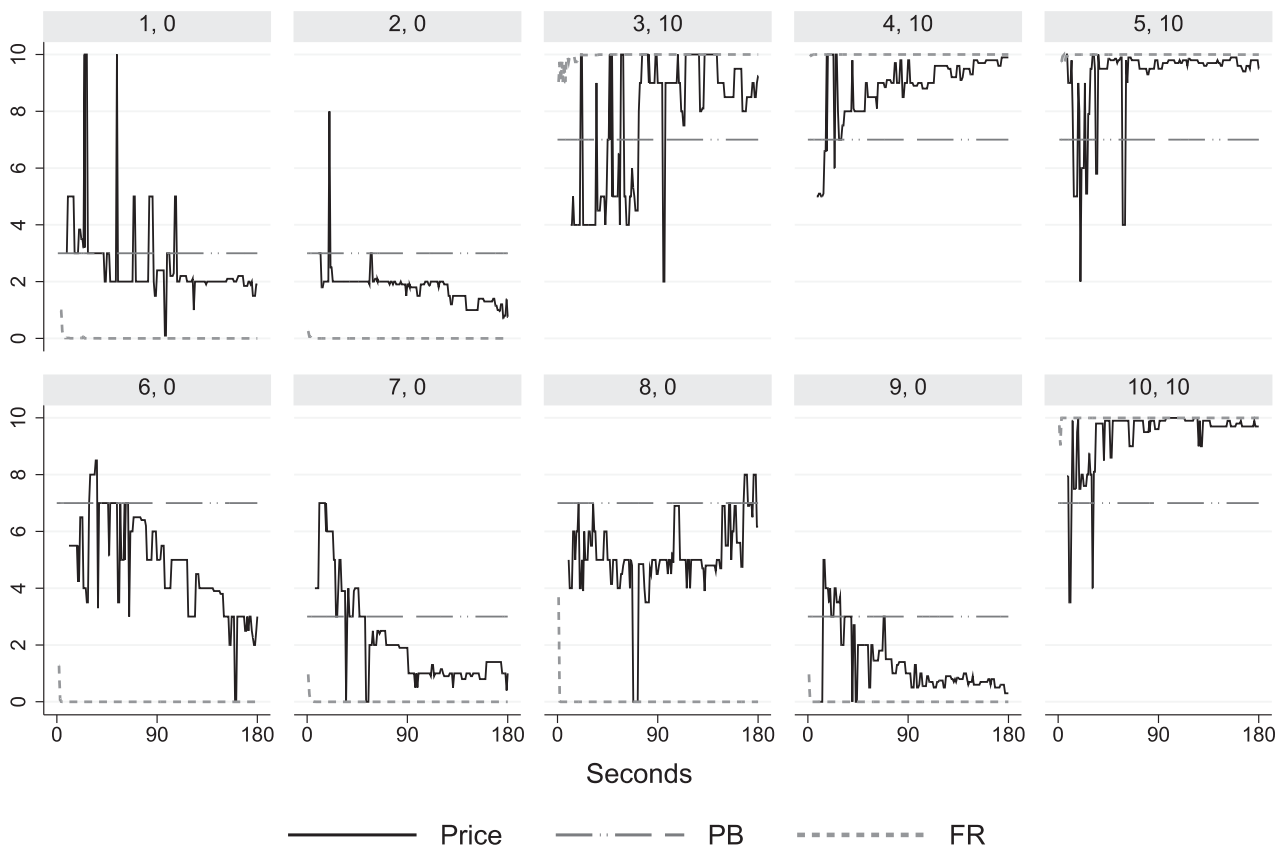


Fig. C.13. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the PS70 treatment (Group 2).

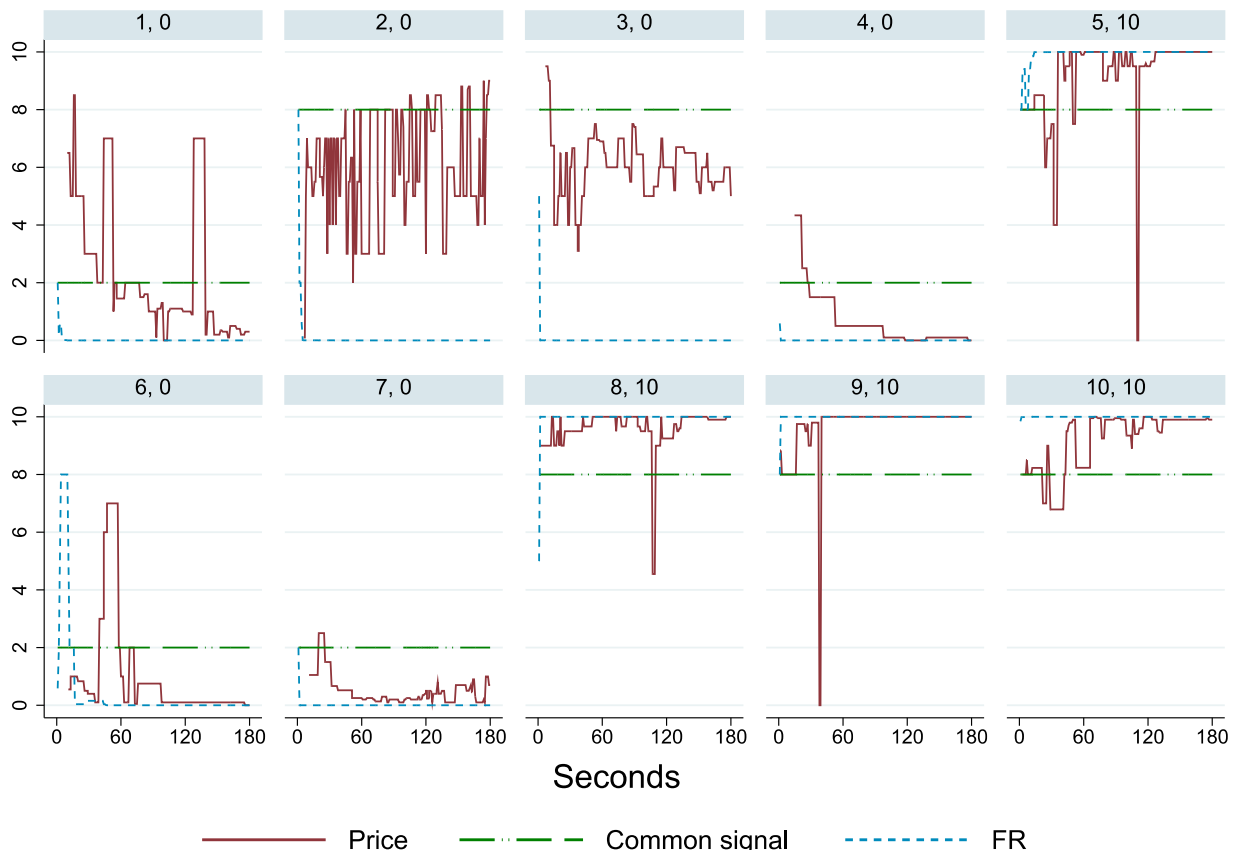


Fig. C.14. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the CS80 treatment (Group 1).

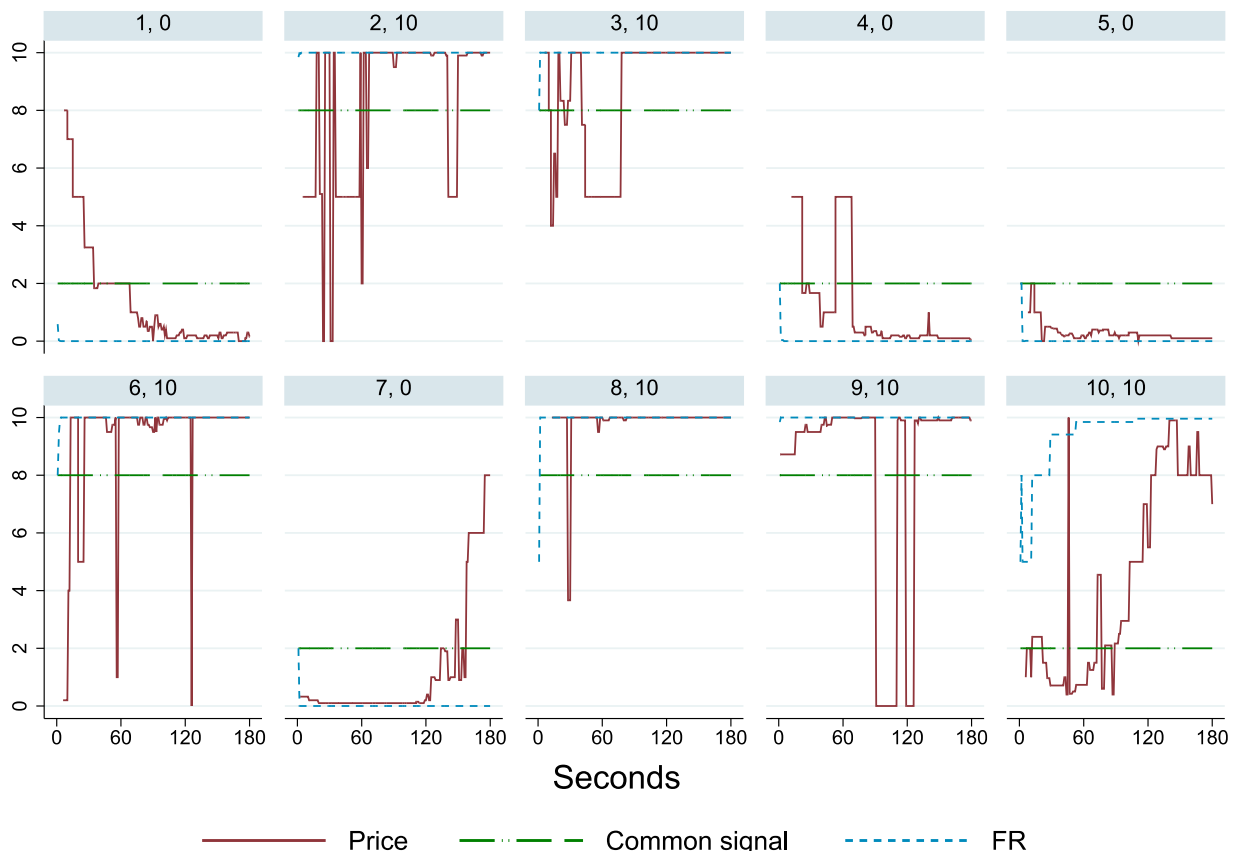


Fig. C.15. Transactions overtime, fully revealing benchmark, and public benchmark in each market of the CS80 treatment (Group 2).

Appendix D. Trade volume

Table D.7 illustrates the results of an OLS regression analysis of market trade volume (measured as number of transaction per markets) on the treatment dummies, period and price informativeness (MAD_m^{FR}). Specification (1) suggests that public disclosures affect positively trade volume, while the common signal does not have a significant effect. When we include MAD_m^{FR} as an additional regressor, we observe a positive and significant effect on trade volume, while the treatment dummies turn out to be not significant. We can infer that the trade volume is mainly related to the efficiency of prices in reflecting the available information. Our analysis suggests that, when the aggregation of information is poorer, there are more profits opportunities and more transactions. A higher degree of price informativeness generates less profit opportunity and, therefore, less trade volume.

Table D.7

OLS regression of trade volume. $PS80treat$, $PS70treat$ and $CS80treat$ are dummy variables indicating the treatment. The baseline is the B treatment. MAD_m^{FR} , which is defined in Eq. (5), stands for mean absolute deviation of prices from the fully revealing benchmark in the last minute of the market. The regressions also include the period of the session. Clustered standard errors on a group level are given in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Trade Volume	Trade Volume
PS80treat	25.75* (11.80)	17.93 (9.61)
PS70treat	7.45** (2.67)	4.89 (2.65)
CS80treat	7.10 (4.71)	6.92 (6.00)
Period	0.87 (0.81)	1.69* (0.84)
MAD_m^{FR}		42.97*** (10.82)
Constant	62.47*** (4.60)	53.37*** (5.76)
Observations	80	80
Clusters	8	8
R-squared	0.19	0.33

Appendix E. Alternative Benchmark

We further analyze the overweighting effect by redefining the overweighting ratio computed in Eq. (7). Instead of using the mean absolute distance between prices and public benchmark, we consider the mean absolute distance between prices and the common signal. We want to find out whether the common signal constitutes a focal point, similarly to the public signal. This change only affects the CS80 treatment, where $PB=5$ is replaced in Eq. (2) by the values 2 or 8 depending on the realization of the common signal. We label the new overweighting ratio as ψ .

We reproduce the analysis of Table 5 with the redefined overweighting ratio ψ . Table D6 displays consistent results compared to Table 5. In particular, we find that the ψ overweighting ratio in the CS80 treatment is always significantly lower than in the B treatment. With this complementary analysis, we demonstrate that the observed differences between the PS80 and CS80 treatments are robust to changes in the reference level when computing the public/common benchmark.

Table E.8

Beta regression of overweighting ratio given the released signal, considering all markets (1) and only markets with a correct released signal (2). To run the Beta regression, we transform the variable ψ into a new variable bounded between 0 and 1, i.e. $\frac{1+\psi}{2}$. $PS80treat$, $PS70treat$, and $CS80treat$ are dummy variables indicating the treatment. The baseline is the B treatment. The regressions also include the period of the session. Clustered standard errors on the group level are given in parentheses. We have a total of eight clusters, given there are two independent groups per treatment. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	ψ -Overweighting	ψ -Overweighting
	(All markets)	(With correct signal)
PS80treat	1.55*** (0.48)	1.97** (0.77)
PS70treat	0.46*** (0.18)	-0.10 (0.17)
CS80treat	-0.77*** (0.23)	-1.06*** (0.19)
Period	-0.18*** (0.05)	-0.19*** (0.04)
Constant	0.35 (0.34)	0.29 (0.35)
Observations	80	66
Clusters	8	8
Log pseudolikelihood	64.88	66.34

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