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On the impact of public information in financial markets: an experimental approach

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Abstract

The debate on the "limits of transparency" of the central banks' communication policy is the inspiration of the present thesis. Specifically, this thesis investigates whether it exists an optimal level of information transparency that the central bank can target in order to manage the economic agents' expectations without dominating the evolution of financial markets. In this regard, laboratory methods are used to evaluate the impact of disclosing public information on the price informativeness. The experimental design is based on an Arrow-Debreu asset market where traders have access to imperfect private information about the asset value. The primary research question is whether the disclosure of public information improves or impairs informational efficiency.

Together with beneficial effects, the complex interaction between private and public information leads to detrimental and unintended consequences for market performance. Releasing public information might crowd out private information demand. Furthermore, public information is overweighted beyond its informational content on fundamentals. This overweighting phenomenon is linked to the asymmetric impact of the public information on higher-order beliefs of bounded rational traders.

Introduction

Historically, Economics has been considered an observational science like meteorology. Economists have traditionally used empirical data to understand the functioning of the system, although some relevant elements are not observable like fundamental values or information used by traders. This lack of observable data can be inferred from experiments. Laboratory experiments allow economists to generate data in controlled economic environments where financially motivated subjects make decisions. Thus, experimental economists have been increasingly interested in studying asset markets and improving trading rules.

Financial economics is one of the branches of economics with more available detailed empirical data. Nowadays, financial transactions are constantly recorded in electronic format. Offers, auctions, ratings and forums are available creating a huge amount of easily available data. However, many questions remain unanswered or hard to answer due to the difficulty of observing some important determinants of prices like expectations or the information of investors when trading in the market. In this sense, laboratory experiments complement empirical studies, allowing to monitor such relevant determinants for the behavior of investors in financial markets (Noussair and Tucker, 2013; Sunder, 1995). In laboratory experiments, the experimenter can observe and even control different aspects about the information that every subject receives: the moment, the frequency, the quantity, the precision, the channel and so on. Thus, laboratory experiments produce an environment where flexibility and control of relevant factors are possible. Market participants are free to choose their trading strategies, while confounding factors are held constant across different market settings (Bloomfield et al., 2005).

If we focus on financial markets, one recurring question in the literature is whether markets are efficient. The Efficient Market Hypothesis (EMH) states that prices fully reflect all available information in a market (Fama, 1970). In that case, the trading mechanism must be able to aggregate and disseminate the dispersed information in the market. This implies that traders rationally process the information and, then, prices are always at levels consistent with fundamentals. Grossman and Stiglitz (1980) refine the EMH by proposing a model where prices just partially reflect the information posted by individuals. They claim that if the price system fully reveals the information obtained by informed traders, an equilibrium does not exist. If all information is fully and instantaneously aggregated into prices, no trader has incentives to acquire buy costly information. However, if there is not information in the market, someone should have an incentive to buy and exploit it. For that reason, the presence of an exogenous noise is a necessary condition to have an equilibrium in the information and asset markets, since it allows to recover the costs of acquiring information. However, the accurate control of information at agents' disposal is not feasible in real data. So that the EMH, in its strong form, is a challenging hypothesis to test.

Experimental literature has extensively tested the EMH, specially in its strong form. In particular, a large number of papers have studied the aggregation and dissemination of information in asset markets, being prices the main drivers of information dissemination. Plott and Sunder (1982) implement an asset market where prices can disseminate private information held by traders. Nevertheless, later studies bring forth the limits of the ability of markets to disseminate and aggregate information. Markets informational efficiency is affected by the market structure, the properties of the assets and agents' features (Powell and Shestakova, 2016). In general, markets with homogeneous assets across traders are prone to informational inefficiencies. Plott and Sunder (1988) come to the conclusion that heterogeneous dividends among traders is a necessary condition. Forsythe and Lundholm (1990) further investigate the necessary and sufficient conditions to aggregate and transmit information through prices. They conclude that traders' experience may be a sufficient condition for market prices to reveal dispersed information when the value of the asset is homogeneous among traders.

One particular market inefficiency frequently observed in laboratory experiments[1] is a price bubble in which prices increase over time beyond the fundamentals value followed by a sudden drop in price (Blanchard, 1979; Smith et al., 1988). Another failure of the markets in aggregating information. Camerer and Weigelt (1991) find that agents overreact to uninformative trades when prices behave as if they reveal information that is not actually held by any traders. Whereas bubbles seem to be caused by uncertainty about the rationality of other traders, mirages are caused by uncertainty about information held by others, see Camerer and Weigelt (1991). Closely related to these market inefficiencies is the *herding* phenomenon, which has been largely studied in the theoretical, experimental and computational literature.[2] Agents make their decisions based on the activity of the other market participants instead of relying on their private information (Banerjee, 1992). An example includes the behavior of traders when an asset is subject to some kind bubble and crash that are apparently unrelated to its fundamental values (Hey and Morone, 2004).

In light of those market limitations, an open question emerges: how to promote more informational efficient markets. There is daily evidence that consequences of markets inefficiencies go beyond the mere theoretical concerns. We do not need to

[1] Palan (2013) discusses the experimental literature on bubbles and crashes.

[2] See, for example, the seminal papers of Banerjee (1992) and Bikhchandani et al. (1992). See also experimental studies such as Hey and Morone (2004) and Cipriani and Guarino (2005) and Drehmann et al. (2005) or computational models like Kirman (1993) and Lux and Marchesi (2000).

inquire into recent history to find examples of the consequences of market failures as the dot.com, housing bubble and Sub-prime crisis. Regulatory institutions are concerned about such phenomena and try to face them by regulating the markets trading activity, implementing new market mechanisms or designing communication strategies.[3] For example, the European Central Bank counts on the *forward guidance* to influence market expectations on the future path of interest rates or inflation, as well as its asset purchase program.

Nevertheless, communication strategies may not achieve the desired effects; either because they are not powerful enough or because of market participants can overreact to that information.[4] Some experimental papers have investigated the impact of the released information in a multiple-period life asset market. Gillette et al. (1999) state that prices underreact to the sequential arrival of public information. This underreaction may be explained by the anticipation of future trends by market participants. Palfrey and Wang (2012) find evidence of speculative overpricing in markets with imperfect public information flows. In a more recent experiment, Corgnet et al. (2013) test the impact of ambiguous and sequential public information about fundamentals value.

Up to now, a few papers in the experimental literature have studied the interplay between public and private information. Morris and Shin (2005) make an interesting journey through the importance of public information on the informative capacity of prices: from the earlier ideas of Keynes (1937) and Hayek (1945) to more recent speeches of Bernanke (2004) and Kohn (2005) about the limits of transparency. The original argument of Hayek (1945) about the importance of prices in transmitting information can be reinterpreted in terms of central bank transparency. They posed the problem of how the aim of institutions to *manipulate* market expectations threatens the informational role of prices. The influence of the central bank may lead prices to reflect merely its own information instead of aggregating dispersed information in the market. In fact, Morris and Shin (2005)[p.18] claims that "the more important is the informational role of prices, the greater is the tension between managing market expectations and learning from market expectations". It is reasonable to think that more information helps individuals to make better decisions in an environment characterized by uncertainty. However, public information might trigger negative externalities because of the fact that all traders observe it. In environments such as financial markets, the opinion of most of the market participants affects the individual's incentives (Keynes, 1937; Allen et al., 2006). Indeed, an important set of studies have been developed based on the beauty contests metaphor, with which Keynes draws the intertwined interests of participants in financial markets.

[3]Geraats (2002) provides an overview of the theoretical literature on transparency of monetary policy and compare it to the ways in which central banks have become more transparent.

[4]See, for instance, Baeriswyl and Cornand (2014) who analyze theoretical and experimentally two communication strategies that can control the degree of overreaction.

The payoffs of players in this game depend on the accuracy of guessing the guesses of the other players instead of how accurate is their prediction about the fundamentals.[5]

Even though public announcements might disclose relevant information about the fundamentals of the economy and, then, being beneficial for agents as individuals, it might be detrimental for the society. The mere fact that all market participants receive public information might cause agents to discard their own private information (Morris and Shin, 2002). This effect is even stronger if private information diverges from the principal opinion in the market (Morris and Shin, 2005). Then, public information becomes a focal point and reduces the aggregation of bits of information available in the market. What is more, if one considers an upgrading of the quality of released information, harmful effects could be stronger under certain circumstances. The higher the perception of the quality of the information released by institutions, the greater is the confidence of market participants and, therefore, prices weight more that information (Morris and Shin, 2005). Everything works correctly if communication strategies are well designed. Conversely, if the quality and messages of announcements are not appropriate to the characteristics of the market, public information may lead to detrimental consequences.

Most of the literature on this topic analyses the social value of public information in coordination models, which give a clear incentive to overrely on public information. The present thesis relaxes such restrictive condition and studies the consequences of public information on an asset market experiment. This less restrictive environment carries the study of discussion closer to the reality of financial markets. The main research question of the present thesis: how do public announcements affect traders' behavior? What factors are the main responsible for such effects?

In the first chapter of this thesis, we design an asset market experiment in order to investigate the information aggregation process as a function of different sources of information, namely public and private information. Traders can acquire costly imperfect private information while they also observe an imperfect costless public signal in some markets. The double-auction mechanism provides a favorable framework for flexibility that we need to study the efficacy of announcements when market participants are free to make their decisions. Moreover, its competitive properties help to achieve the competitive equilibrium rapidly (Smith, 1982; Friedman, 1993). Results are two-fold: the release of public information provokes (i) a crowding out effect on the traders' information demand and (ii) a detrimental effect on price informativeness, even though information present in the market is enough to discover the market fundamentals. Despite the absence of an explicit coordination incentive for the traders, we detect the emergence of the overweighting phenomenon. Therefore, we demonstrate

[5]It is worth to mention the theoretical papers of Morris and Shin (2002), Colombo and Femminis (2008), and Colombo and Femminis (2014) and related experimental studies of, for example, Cornand and Heinemann (2008), Cornand and Heinemann (2014), and Baeriswyl and Cornand (2016).

that the adverse effects of releasing public information in a financial market are far more relevant than generally assumed.

In the second chapter, we simplify the previous setting allocating exogenous private information among traders. They get two imperfect private signals and, in some markets, they observe an identical imperfect signal that can be publicly known. We observe that prices quickly converge to the fundamentals when the public signal is correct, while an incorrect public signal drives prices far from fundamentals. The latter effect lessens when the identical signal is non-common knowledge. Additionally, we identify the impact of common knowledge of the public signal on the second-order beliefs as the mechanism responsible for the overweighting phenomenon. We propose a simple reasoning model based on the construction of beliefs about average expectation in the market. This framework does not specify a particular trading mechanism, the purpose of the model is to provide a rationale for the role that public information plays on traders' higher-order beliefs and the impact on their reservation price.

In light of the results obtained in the second chapter, we develop a simple model combined with Monte Carlo simulations. The model aims at identifying the main effects of unwarranted 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 information set, sophisticated traders make use of public information to infer the distribution of aggregate demand. We find that a low proportion of sophisticated traders is sufficient to observe that a noisy public signal pushes prices away from fundamentals when it predicts the wrong state of the world. Heterogeneity combined with bounded rationality and risk neutrality assumptions generates similar findings to those of the experimental study.

Introducción

Históricamente, la economía ha sido considerada una ciencia observacional como lo es, por ejemplo, la meteorología. Los economistas han utilizado principalmente datos empíricos para comprender el funcionamiento de las economías. Sin embargo, algunos elementos clave como los valores fundamentales de los activos o la información en manos de los agentes no son observables. Esta carencia se ha suplido con la introducción de la metodología experimental. Los economistas están cada vez más interesados en estudiar los mercados financieros y mejorar las reglas de su funcionamiento mediante experimentos de laboratorio.

La economía financiera es una de las ramas de la economía con mayor disponibilidad de datos empíricos. En la actualidad, las transacciones financieras quedan registradas electrónicamente. Además, información acerca de ofertas, subastas, valoraciones y foros son fácilmente accesibles. A pesar de ello, muchas preguntas continúan sin respuesta o son complicadas de responder debido a la dificultad de observar algunos determinantes importantes de los precios, como por ejemplo las expectativas o la información privada. En este sentido, los experimentos de laboratorio pueden complementar los estudios empíricos, permitiendo implementar y modificar tales determinantes relevantes en los mercados financieros (Noussair and Tucker, 2013; Sunder, 1995). Por ejemplo, los experimentalistas pueden observar e incluso controlar diferentes aspectos de la información que recibe cada sujeto: el momento, la frecuencia, la cantidad, la precisión, el medio de transmisión, etc. Por esta razón, los experimentos propician un entorno donde la flexibilidad y el control de factores de interés son posibles. Concretamente, los participantes del mercado experimental son libres de elegir sus estrategias de compra y venta, mientras que las condiciones del entorno se mantienen constantes en las diferentes configuraciones de mercado (Bloomfield et al., 2005).

Si nos centramos en el estudio de los mercados, una pregunta recurrente en la literatura es si son realmente eficientes. La hipótesis de mercado eficiente (HME) afirma que los precios de un activo reflejan eficientemente toda la información disponible que existe en el mercado (Fama, 1970). En ese caso, el mecanismo de precios debe ser capaz de agregar y diseminar la información que se encuentra dispersa en el mercado. Esta afirmación implica que los inversores procesan racionalmente la información y, por consiguiente, los precios siempre están en niveles consistentes con los valores fundamentales. Más adelante, Grossman and Stiglitz (1980) pulen la idea de la HME proponiendo un modelo en el que los precios reflejan parcialmente la información transmitida por los individuos. Ellos afirman que, si el sistema de precios revela completamente la información obtenida por los inversores, no puede existir un equilibrio. De hecho, si toda la información se reflejara completa e instantáneamente en los precios, ningún inversor estaría dispuesto a adquirir información costosa. Pero si no hay información en el mercado, alguien debería tener incentivos para comprarla y explotarla. Por este motivo, una condición necesaria para la existencia de equilibrio en los mercados de información y de activos es la presencia de un ruido exógeno que permita a los inversores recuperar los costes de la adquisición de información. Sin embargo, dada la imposibilidad de recoger de forma precisa la información de que disponen los inversores, la demostración de la hipótesis fuerte de la HME continúa siendo un desafío.

La literatura experimental ha analizado extensamente la HME, especialmente en su forma fuerte. En particular, numerosos artículos han estudiado la agregación y difusión de información en los mercados de activos, siendo los precios los principales impulsores de la difusión de información. Por ejemplo, Plott and Sunder (1982) implementan un mercado de activos donde los precios son capaces de diseminar la información privada en manos de los inversores. Sin embargo, estudios posteriores ponen en evidencia los límites de la capacidad de los precios para difundir y agregar información. La eficiencia informativa de los mercados se ve afectada por la estructura del mercado, las características de los activos y de los inversores (Powell and Shestakova, 2016). En general, los mercados donde la valoración de los activos entre los inversores es homogénea son propensos a generar ineficiencias informativas. Plott and Sunder (1988) llegan a la conclusión de que una valoración heterogénea de los activos entre los inversores es una condición necesaria para la existencia de mercados informacionalmente eficientes. Forsythe and Lundholm (1990) investiga en mayor profundidad las condiciones necesarias y suficientes para que los precios sean capaces de agregar y transmitir la información del mercado. Concluyen que la experiencia de los inversores puede ser una condición suficiente para la transmisión eficiente de información cuando el valor del activo es homogéneo entre todos los participantes del mercado.

Una de las ineficiencias de mercado que se observa frecuentemente en los experimentos de laboratorio son las burbujas,[6] las cuales se caracterizan por un incremento de los precios muy por encima del valor fundamental, seguidos de una brusca caída de los mismos (Blanchard, 1979; Smith et al., 1988). Otro fallo de mercado es el fenómeno del espejismo informacional. Camerer and Weigelt (1991) observan que los inversores sobrerreaccionan a transacciones carentes de información cuando los precios se comportan como si revelaran información que realmente no posee ningún inversor. Mientras que las burbujas parecen ser causadas por la incertidumbre sobre la racionalidad de los otros inversores, los espejismos informacionales surgen como consecuencia de la incerteza sobre la información en manos del resto de inversores (Camerer and Weigelt, 1991). Estrechamente relacionado con estas ineficencias de

[6]Palan (2013) revisan la literatura experimental que estudia las burbujas y crisis financieras.

mercado se encuentra el fenómeno *herding*, el cual ha sido ampliamente estudiado en la literatura teórica, experimental y computacional.[7] Los inversores optimizan sus decisiones en función de la actividad del resto de individuos en lugar de basarse en la información de la que disponen (Banerjee, 1992). Un ejemplo lo encontramos en las burbujas y las crisis a las que algunos activos financieros están sometidos; fenómenos que aparentemente no están relacionados con los valores fundamentales de dicho activo (Hey and Morone, 2004).

A la luz de estas limitaciones de los mercados, una cuestión permanece latente: como fomentar una mayor eficiencia informativa en los mercados. Diariamente existen evidencias de que las consecuencias de las ineficiencias de los mercados van más allá de los debates teóricos. No necesitamos buscar exhaustivamente en la historia reciente para encontrar algunos ejemplos de estos fallos de mercado como las burbujas de los dot.com o la inmobiliaria y la crisis financiera. Las instituciones tratan de prevenir estos fenómenos mediante la regulación de la actividad en los mercados, implementando nuevos mecanismos de mercado o diseñando nuevas estrategias de comunicación.[8] Por ejemplo, el Banco Central Europeo utiliza la herramienta de *forward guidance* para influir las expectativas de los mercados sobre la evolución futura de los tipos de interés o la inflación, al igual que de su programa de compra de activos.

Sin embargo, las estrategias de comunicación pueden no alcanzar los objetivos propuestos, bien porque no son lo bastante potentes o porque los participantes del mercado sobrerreaccionan a dicha información.[9] Algunos artículos experimentales han investigado el impacto de la información pública en mercados de activos con múltiples periodos de vida. Por ejemplo, Gillette et al. (1999) afirma que los precios infrarreaccionan a la llegada secuencial de este tipo de información. Esta infrarreacción puede deberse al hecho que los inversores se anticipan a las tendencias futuras del valor de los activos. Palfrey and Wang (2012) encuentran evidencia de la existencia de un sobreprecio especulativo en mercados con flujos de información pública imperfecta. En un experimento más reciente, Corgnet et al. (2013) evalúan el impacto de la emisión secuencial de información pública ambigua acerca de los valores fundamentales.

Sin embargo, hasta ahora pocos estudios de la literatura experimental se han centrado en la interacción entre información pública y privada. Morris and Shin (2005) llevan a cabo un interesante viaje sobre la importancia de la información pública sobre

[7] Banerjee (1992) and Bikhchandani et al. (1992) son dos de los modelos teóricos más influyentes. Ver, además, estudios experimentales como son Hey and Morone (2004) and Cipriani and Guarino (2005) y Drehmann et al. (2005) o computacionales como Kirman (1993) and Lux and Marchesi (2000).

[8] Geraats (2002) aporta una visión general de la literatura teórica sobre la transparencia de la política monetaria y la compara con las diversas formas en las que los bancos centrales se han vuelto más transparentes.

[9] Por ejemplo, Baeriswyl and Cornand (2014) analizan teórica y experimentalmente como dos estrategias de comunicación distintas pueden reducir la reacción de los inversores a la presencia de información pública.

la capacidad informativa de los precios: desde las ideas iniciales de Keynes (1937) y Hayek (1945) hasta discursos más recientes como los de Bernanke (2004) y Kohn (2005) sobre los límites de la transparencia. La idea original de Hayek (1945) acerca de la importancia de los precios como transmisores de información puede ser reinterpretada a día de hoy en términos de transparencia de un banco central. Morris and Shin (2005) plantean el problema de como la intención de las instituciones de *manipular* las expectativas del mercado puede amenazar el papel informativo de los precios. La influencia del banco central puede llevar a que los precios reflejen la propia información de la institución en lugar de agregar la información que se encuentra dispersa en el mercado. De hecho, Morris and Shin (2005)[p.18] afirman que conforme a mayor transcendencia del papel informativo de los precios, mayor es la tensión entre influir en las expectativas del mercado y a prender de las expectativas del mismo. Es razonable pensar que una mayor cantidad de información ayuda a los individuos a tomar mejores decisiones en entornos caracterizados por la incertidumbre. En cambio, la información pública puede desencadenar externalidades negativas debido a que es observada por todos los inversores. En entornos como los mercados financieros, la opinión de la mayoría de los participantes del mercado influye sobre los incentivos del individuo (Keynes, 1937; Allen et al., 2006). Un importante conjunto de estudios se ha desarrollado basándose en la metáfora del "beauty contest", con la que Keynes representa los intereses interconectados de los participantes de los mercados financieros. Los pagos de los jugadores en este juego dependen de la precisión de sus predicciones de las expectativas del resto, en lugar de como la precisión de sus predicciones acerca de los valores fundamentales.[10]

Aunque los anuncios públicos pueden divulgar información importante sobre la situación económica y, por tanto, ser beneficiosa para el inversor como individuo, al mismo tiempo puede ser perjudicial para la sociedad como conjunto. El mero hecho de ser observada por todos los participantes del mercado puede provocar que los mismos descarten su información privada en favor de la pública (Morris and Shin, 2002). Este efecto es incluso mayor si su información privada disiente de la opinión principal del mercado (Morris and Shin, 2005). De esta forma, la información pública se convierte en un foco de atención, reduciendo la agregación de la información que se encuentra dispersa. Además, si se considera un aumento de la calidad de la información pública, los efectos negativos podrían intensificarse bajo ciertas circunstancias. Cuanto mayor es la percepción de la calidad de la información publicada por las instituciones, mayor es la confianza de los participantes del mercado y, por lo tanto, los precios reflejan todavía más dicha información (Morris and Shin, 2005). Todo funciona correctamente siempre y cuando las estrategias de comunicación estén bien diseñadas. Por el contrario, si la precisión y el mensaje de la información pública no son los adecuados para las características del mercado, la información pública puede provocar consecuencias

[10]Es importante señalar algunos trabajos teóricos como Morris and Shin (2002), Colombo and Femminis (2008), and Colombo and Femminis (2014) y estudios experimentales relacionados como, por ejemplo, Baeriswyl and Cornand (2016), Cornand and Heinemann (2008), Baeriswyl and Cornand (2014), and Cornand and Heinemann (2014).

severas.

La mayor parte de la literatura centrada en este tema analiza el valor social de la información pública mediante modelos de coordinación, los cuales inducen claramente a la sobrerreacción de la información pública. Esta tesis relaja dicha condición y estudia los efectos de la información pública mediante experimentos que generen un entorno más próximo a la realidad de los mercados financieros. Las preguntas principales a responder son: ¿Cómo afectan los anuncios públicos en el comportamiento de los agentes? ¿Qué factores son los principales responsables de tales efectos?

En el primer capítulo de la tesis, diseñamos un mercado experimental con el objetivo de investigar el proceso de agregación de la información en función de diferentes fuentes informativas, principalmente pública y privada. Los inversores pueden adquirir información privada a un coste y, además, recibir información pública en algunos tratamientos. El mecanismo de subasta doble genera un entorno flexible necesario que permite estudiar la eficacia de los anuncios en las decisiones de los inversores. Por otro lado, sus propiedades competitivas ayudan a alcanzar rápidamente el equilibrio competitivo (Smith, 1982; Friedman, 1993). Los resultados obtenidos son dos: la información pública provoca (i) una reducción de la demanda de información privada y (ii) un deterioro de la capacidad informativa de los precios, a pesar de que la información disponible en el mercado siempre es suficiente para descubrir el valor fundamental del activo. A pesar de la ausencia de un incentivo explícito a la coordinación de los inversores, detectamos el fenómeno de sobrevaloración de la información pública. De este modo, demostramos que los efectos adversos de difundir información pública en los mercados financieros son más relevantes de lo que se ha supuesto generalmente.

En el siguiente capítulo, simplificamos el diseño experimental y distribuimos exógenamente la información privada a los participantes. Cada inversor recibe dos señales privadas y una señal idéntica para todos, pública o no, en función del tratamiento experimental. Observamos que los precios convergen rápidamente al valor fundamenta cuando la señal pública es correcta, pero cuando es incorrecta, esta señal dirige a los precios lejos del valor fundamental. Este último efecto es atenuado cuando los inversores no saben que la señal idéntica no es común para todos. Adicionalmente, identificamos el efecto que produce el conocimiento de la existencia de una señal idéntica para todos los inversores sobre las creencias de segundo orden, que consideramos como el mecanismo responsable de la sobrevaloración de la información pública. Finalmente, proponemos un modelo simple de razonamiento basado en las creencias sobre las expectativas medias del mercado. En el no especificamos un mecanismo de mercado concreto, puesto que el objetivo de nuestro modelo es aportar una lógica al papel que la información pública desempeña en las creencias de orden superior de los inversores y el efecto sobre su precio de reserva.

A la luz de los resultados obtenidos en los capítulos previos, desarrollamos un modelo que combinamos con simulaciones de Monte Carlo. El modelo busca identificar los principales efectos de la información pública sobre los precios cuando esta interactúa con información privada. Bajo el supuesto de racionalidad limitada, la información pública afecta de forma diferente el comportamiento de los inversores dependiendo su nivel de racionalidad e información privada. Mientras que los inversores *nave* simplemente consideran la información que disponen, los inversores más sofisticados utilizan la información pública para estimar la distribución de la información agregada. Encontramos que es suficiente una pequeña proporción de inversores sofisticados para observar como la señal pública conduce los precios lejos de los valores fundamentales cuando su predicción es incorrecta. Por tanto, asumiendo heterogeneidad en el mercado, combinada con racionalidad limitada y neutralidad al riesgo generan resultados similares a los de nuestro experimento de laboratorio.

Chapter 1

Crowding out effect and overweighting of public information in financial markets: a lesson from the lab

The idea that the price system based on competitive markets is able to aggregate different pieces of information dispersed in the economy dates back to the 50's (Hayek, 1945). Economists have understood that prices, in properly designed asset markets, can aggregate and disseminate disperse information possessed by traders, although they not necessarily do it efficiently. Instead of leaving the market operating alone, the release of public information might constitute an option that can facilitate the aggregation and dissemination process. We can ask whether and how the presence of a disciplining institution that releases public information can be beneficial for the market performance. Intuitively, if it is assumed that public information simply cumulates to the information already present in the market, more information should be valuable for decision makers. Although this is certainly true when an economic agent acts in isolation from others, it might not be the case when there is strategic interaction among decision makers.

The theoretical literature has shown that, in an economic system where agents have access to private information, noisy public information might be weighted above and beyond its accuracy. Thus, public information might drive the economic system far from fundamentals and eventually damages social welfare.[1] Overreliance on public information has become a cause of concern to regulatory institutions. The 2008 financial crisis is a good example of the overweighting phenomenon if one takes into account the influence that the valuation of rating agencies had on the investors' financial decisions, who blindly followed what turned out to be misleading advice. Beside overrelying on ratings, it might be possible that their presence gave to the traders fewer incentives to search for independent and alternative sources of information to evaluate innovative financial products. The information provided by the rating agencies might have reduced the information gathering activity of investors, *crowding out* valuable information at their disposal. In order to avoid such perverse effects of ratings, regulatory institutions have proposed new measures to incentivize market participants to improve their internal risk management capabilities and reduce overreliance on

[1] See, for example, Morris and Shin (2002) and Colombo et al. (2014).

external credit ratings. In this line, the CRA III Regulation includes a set of measures to strengthen own credit assessment by relevant actors and reduce the sole reliance on credit ratings (European Commission, 2009). In the US market, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 was approved by the US Congress to avoid the overreliance to credit ratings by investors and institutions (Chaffee, 2010).

The release of public information is not only related to the activity of credit rating agencies, but it also includes regulatory institutions as central banks, especially considering their forward guidance activity. In the recent years, central banks include and promote in their research agenda the study of how public communications and disclosure policies affect agents' behavior and incentives. In particular, they wonder how disclosure policies can be designed to maximize their impact on desired forms of behavior, such as accurate pricing of risk and proper formation of expectations of inflation (Bank of England, 2015). In this respect, Morris and Shin (2005) illustrate with great clarity how the central bank management of expectations might lead to adverse effects on the informational efficiency of prices. They pointed out that the central bank faces the risk of dominating the dynamics of prices if it ignores the complex interplay between the precision of the released information and the degree of traders' overreliance. Concerning the optimal communication of the monetary authorities, several authors, for example Myatt and Wallace (2014) and Baeriswyl and Cornand (2014), consider the transparency of public information as a control variable when designing the optimal central bank information disclosure policy. They conclude that it is never optimal full transparency nor full opacity. They assert, in fact, that it exists an optimal level of transparency in order to maximize the effectiveness of the communication strategy.

Despite the awareness of regulatory institutions on the role of public information in market efficiency, the adverse effects of releasing public information are essentially conjectures derived out of simplistic game theoretical models based on restrictive assumptions on the information set and the behavior of players. The few existing experimental evidences are based on those models and, therefore, have limited external validity. Such experiments show that the overweighting effect does exist, although it is milder than predicted by the theory. In fact, in this class of experiments, the *overweighting* effect is maximum under full rationality and significantly milder under bounded rationality (Cornand and Heinemann, 2014). The lower-than-predicted overweighting of public information renders this effect a second order issue (Baeriswyl and Cornand, 2016).

The aim of this chapter consists in testing experimentally whether the adverse effects of public information, namely crowding out of private information and overweighting of public information, are general phenomena to be observed beyond the coordination environment. Using laboratory experiments, 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. In particular, this setting allows us to study under which conditions the presence of public information may act as a sort of disciplining mechanism in the asset market and promote the aggregation of information, or by contrast, may distort the market performance, driving the price far from fundamentals. Furthermore, we study how the demand for information responds to the presence of a public signal.

Despite the absence of an explicit coordination incentive to the traders, we demonstrate that those adverse effects are experimentally measurable and empirically relevant. Moreover, we show that such effects have a strong negative impact on market performance, although traders are not full rational. Contrary to the present literature, it seems that the bounded rationality of traders is one of the main features responsible for the emergence of those phenomena in our setting. This is an important result which challenges the current view, posing new theoretical as well as experimental questions to the problems of how to release public information into financial markets. Finally, our contribution gives a robust back-up to the idea that releasing public information can be harmful for the performance of a financial market, if not properly tailored to the market conditions.

The chapter is organized as follows. Section 1.1 describes the experimental design and Section 1.2 discusses the theoretical background together with the related literature. Section 1.3 presents a detailed analysis of the results in the information and asset market. Finally, concluding remarks are given in Section 1.4, with particular emphasis to the policy implications for regulatory institutions.

1.1 The experimental design

Our experimental setting is similar to Hey and Morone (2004) and Ferri and Morone (2014). Each market consists of a 3 minute trading period and it is populated by 15 subjects. At the beginning of the market, each subject is endowed with 1000 units of experimental currency (ECU)[2] and 10 one-period life risky assets that pays a dividend D at the end of the market. The value of the dividend can be either 0 or 10 ECU with equal probability, which is common knowledge among subjects. The value of the dividend is randomly determined by the experimenter before the market starts, but not revealed to the subjects until the end of the market when the subject's payoff is determined. Apart from the dividend paid out, assets are worthless. The asset market is implemented as a single-unit double auction. Subjects are free to introduce their bids and asks for assets or directly accept any other subject's

[2]Cash, dividends, prices and profits during the experiments are designated in experimental units (ECU) and converted into € at the end of the session. One experimental currency unit is equivalent to 2 cents of €.

outstanding bid or ask.[3] The reason for adopting this trading mechanism is due to its competitive properties: allocations and prices should rapidly converge to levels near the competitive equilibrium (Smith, 1982).

Parallel to the asset market, we implement an information market where, at any moment within the trading period, subjects can purchase partially informative private signals at a price of 4 ECU per signal. They can purchase as many signals as they wish, as long as they have sufficient available cash. The purchased signals are private in the sense that they are not observable by the others (Morris and Shin, 2002). The values of all private signals are independent realizations conditional on the dividend value. Signals are presented to the subjects taking the value 10 or 0. More precisely, the probability of getting a signal suggesting a dividend 10 is p when the state of the world is $D = 10$ and the probability of getting a signal suggesting a dividend 0 is $q = 1 - p$.[4] For example, if a subject purchases a signal whose realization is 10, she can infer that the dividend is expected to be 10 with probability p and 0 with probability q. The values of $p > q > 0$ are common knowledge.

Table 1.1 summarizes the different treatments as well as the treatment parameters and the number of markets. The treatments where subjects have access only to private information constitute our baseline treatments,[5] i.e. $\mathrm{T}_B(0.6)$ and $\mathrm{T}_B(0.8)$. In order to study the impact of public information on the market performance, we introduce the public information treatment where subjects can purchase private signals and have free access to a *public signal*. In those treatments, a public signal is released at the beginning of each market and its realization is common knowledge. Just like private signals, the realization of the public signal might take the value 10 or 0 and it is positively correlated with the dividend. For example, if subjects observe a public signal equal to 10, they can infer that the dividend is expected to be 10 with probability P and 0 with probability $Q = 1 - P$.[6] We aim at studying how the mere presence of public information impacts the performance of the information and asset markets. So, we do not provide the institution releasing the public signal with any pay-off or target function. The public signal in our setting is, in fact, a binary random variable with a given correlation to the fundamentals and it is not emerging out of a micro-funded strategy of the public authority releasing the signal.

The theoretical literature on coordination setting models hypothesizes the existence of an optimal level of transparency for the public information based on the

[3]Every bid, ask or transaction concerns only one unit of the asset, although every subject can handle as many as desired as long as she has enough cash or assets (no short sale is allowed).

[4]The value of p represents the precision of a single private signal.

[5]The notation $\mathrm{T}_B(\cdot)$ indicates the baseline treatment and the corresponding precision of a single private signal.

[6]The value of $P > Q > 0$ is common knowledge among subjects and it represents the precision of the public signal.

Setting	Treatment	p	P	♯ of markets
Baseline	$\mathrm{T}_B(0.6)$	0.6	-	20
	$\mathrm{T}_B(0.8)$	0.8	-	20
Public information	$\mathrm{T}_P(0.6,0.8)$	0.6	0.8	20
	$\mathrm{T}_P(0.8,0.8)$	0.8	0.8	20
	$\mathrm{T}_P(0.8,0.7)$	0.8	0.7	20
Common information	$\mathrm{T}_C(0.6,0.8)$	0.6	0.8	20
	$\mathrm{T}_C(0.8,0.8)$	0.8	0.8	20

Notes: In $\mathrm{T}_B(0.8)$, markets in group 1 are populated by 13 subjects. In $\mathrm{T}_P(0.6,0.8)$, markets in group 2 are populated by 10 subjects. The main results of the paper are not affected by the different number of subjects in those markets.

Table 1.1 Experimental design and parameters.

trade-off between its informative role and its potential distortion effects.[7] Taking stock of it, we implement a set of treatments with different relative precision of the public signal with respect to a single private signal: (i) a public signal more precise than a single private signal, $\mathrm{T}_P(0.6,0.8)$,[8] (ii) a public signal with the same precision as a single private signal, $\mathrm{T}_P(0.8,0.8)$ and (iii) a public signal less precise than a single private signal, $\mathrm{T}_P(0.8,0.7)$.[9] Our experimental setting allows to test whether such trade-off exists in a non-coordination environment. In particular, we can test whether regulatory authorities can enhance or mitigate the crowding out effect that a public announcement has on the traders' acquisition of private information and the overweighting of public information.

Morris and Shin (2002) states that is the *double-edged* role of public information (providing information on the fundamentals and coordinating the agents' expectations) that might be responsible for its overweighting in the aggregation of information, at least in a coordination setting with strategic complementarities. In order to disentangle the two elements that renders public information a double-edged instrument, we implement the common information treatment[10] where subjects observe a free signal that is identical to all of them. However, this feature is not common knowledge. In other words, they only know that each subject receives one free signal with the same precision, but they do not know that the realization of that signal is identical. Hereafter, we will refer to this signal as *common signal*. The common signal is, therefore, equally informative to all subjects about the dividend value, but it is not

[7] See Colombo and Femminis (2008), Cornand and Heinemann (2008), and Baeriswyl and Cornand (2014).

[8] The notation $\mathrm{T}_P(\cdot,\cdot)$ indicates the public information treatment; the first number indicates the precision of the single private signal while the second number indicates the precision of the public signal.

[9] One should consider that each subject can buy several private signals in a way that his/her aggregate private information might be more accurate than the single public signal.

[10] The notation $\mathrm{T}_C(\cdot,\cdot)$ indicates the common information treatment; the first number indicates the precision of a single private signal whereas the second number indicates the precision of the common signal.

any more a predictor of the opinion of the other subjects. As in the case of a public signal, it is released at the beginning of each trading period and it is presented to the subjects taking the value 10 or 0 with precision P. Comparing the results of the treatments with public and common signal allows us to better understand whether it is the commonality nature of public information the main driver of its potential distorting effect on market prices, as suggested by the theoretical literature. It is worth noting that first-order beliefs of subjects do not change between common and public information treatments since the information is the same for all subjects. However, the absence of common knowledge about the free signal in the common information treatment changes subjects' second-order beliefs comparing to the public information treatment.

The experiment is programmed using the Z-Tree software (Fischbacher, 2007). The experiment takes place in the LEE (*Laboratori d'Economia Experimental*) at University Jaume I in Castellón. A total of 203 undergraduate students from Economics, Finance and Business Administration in at least their second year of study are recruited. When subjects arrive at the laboratory the instructions are distributed and explained aloud using a Power Point presentation.[11] This is followed by one practice period, so that, subjects get familiar with the software and the trading mechanism. Each subject can only participate in one session, which consists of 10 markets. At the end of every market, dividends are paid out and the subject's profit is computed as the difference between their initial money endowment and the money held at the end of the period. Each subject's final payoff is computed as the accumulated profit in the 10 periods, and paid cash at the end of the session. The average payoff is about 20 € and each session lasts around 90 minutes.[12]

1.2 Theoretical background and related literature

1.2.1 Do nothing equilibrium

Our experimental setting can be characterized by a "do nothing" equilibrium. If all traders are risk neutral or share the same beliefs and risk aversion, we should observe no transaction in the asset market and no purchase of private signals in the information market. The basic reasoning underlying the "do nothing" equilibrium lies in the constant-sum-game nature of our framework. Essentially, it means that a trader would have incentives to purchase a private signal just in case he expects to recover the purchasing cost, making profits at the expense of some other traders. Taking stock of this, the other traders, who have not bought private signals, would

[11]In Appendix 1.A, we show the translated instructions.

[12]Note that subjects can make losses. To avoid some of the problems associated with subjects making real losses in experiments, we endow all subjects with a participation fee of 3 €, which can be used to offset losses. No subject earns a negative final payoff in any session.

not trade with him and, therefore, the incentive for the first trader to purchase private information disappears. Under these assumptions, there will be no activity in the information as well as in asset markets.

As we will see in the results section, this equilibrium is never achieved. Conversely, we always observe a sustained level of activity in the information market as well as in the asset market. This equilibrium turns out not to be empirically relevant, leaving us with the need of considering other possible benchmarks to shed some light on the trading activity observed in our experiment.

1.2.2 Crowding out of private information

Considering that in our experimental setting the information acquisition process is endogenous and in perfectly elastic supply, we can characterize the information market analyzing how the demand for private information varies as a function of the information set at the disposal of subjects.

Several authors, for example Hellwig and Veldkamp (2009), Myatt and Wallace (2011) and Colombo et al. (2014), propose a theoretical model that generalizes the Morris and Shin (2002)'s coordination setting introducing the acquisition of costly and noisy private information. Hellwig and Veldkamp (2009) study the role of information choice in price-setting models finding that the incentive of agents to acquire costly information is stronger when others also acquire information and their strategies are complementary. Myatt and Wallace (2011) go one step further and introduce endogenous costly attention chosen by agents. They find that agents pay attention to the clearest signal available, even if its precision is the lowest. If the complementarity of agents' actions rises, the acquired information is more public in nature. In a quite different study, Kool et al. (2011) use a rational expectations asset market model to prove that, for intermediate levels of precision, public information crowds out costly private information. As a consequence, prices become less informative about future interest rates. Colombo et al. (2014) demonstrate the existence of a crowding out effect of public information on the equilibrium acquisition of private information.[13] The intuition behind this result is simple: the presence of a public signal helps investors to better forecast the fundamentals, reducing the marginal value of private information and, then, its demand.[14]

Our experimental setting does not provide the traders with an explicit coordination motive as in Colombo et al. (2014). Indeed, we cannot sharply characterize our setting within the strategic complementarity or substitutability framework. Nevertheless,

[13]See Corollary 1 in Colombo et al. (2014).

[14]Other important contributions in the area include Colombo and Femminis (2008) and Demertzis and Hoeberichts (2007).

we consider their predictions useful to shed some light on our experimental results concerning the traders' behavior in the information market. Following Colombo et al. (2014), we expect to observe a reduction in the acquisition of private information whenever we introduce a free signal into the market.

Hypothesis 1. *The release of a free signal crowds out demand for private information.*

Comparing the public and common information treatments, we can infer the role of the commonality of public information on traders' higher-order beliefs and its impact on information demand. Note that in $\mathrm{T}_C(\cdot,\cdot)$, the common knowledge of the free signal is absent and, therefore, the common signal does not carry information on the other traders' expectations. In those treatments, the crowding out is due solely to the information about the fundamentals provided by the free signal. We hypothesize that if the common and public information treatments exhibit the same reduction in information demand, it is the informative role of the free signal the main driver of the crowding out effect. Significant differences, instead, point to the existence of a strategic interaction among traders in the acquisition of information (Hellwig and Veldkamp, 2009; Page and Siemroth, 2017). We introduce the hypothesis of absence of strategic interaction in the acquisition of information:

Hypothesis 2. *The crowding out effect is caused by the informativeness on fundamentals of the free signal. Thus, there are not differences in the magnitude of the crowding out in the public and common treatments.*

In an economy with an endogenous information structure, the release of a public signal may crowd out private information, so that public and private information turns out to be substitutes rather than cumulatives. Public information might just partially compensate for the crowding out of private information, leading in some cases to a significant reduction in the overall market informativeness. Colombo et al. (2014), in a coordination setting, theoretically identify the primitives for determine under which conditions the information remains invariant. Following them, we introduce the working hypothesis of informational neutrality of the crowding out:

Hypothesis 3. *The free signal leaves invariant the market informativeness.*

1.2.3 Fully revealing benchmark

We introduce the fully revealing benchmark as the expected price conditional on all information present in the market. Note that, whereas the "do nothing" is an equilibrium in a strict economic sense, the "fully revealing" is not. Grossman and Stiglitz (1980) show the impossibility of the existence of an equilibrium in a market with fully informative prices and contemporaneously access to costly information.

If the information is instantaneously incorporated into the market price as stated by the efficient market hypothesis, traders have no incentive to purchase private information. However, if no trader purchases information, it immediately appears a profit opportunity and, therefore, an incentive to gather information. Grossman and Stiglitz (1980) resolve this paradox by introducing an exogenous noise in order to provide incentives for the acquisition of costly information. The presence of the exogenous noise compensates the costs of purchasing information, so that, it is possible to define an equilibrium in both the assets and the information market.

Sunder (1992) shows experimentally that the fully revealing benchmark is a reasonable predictor to describe price behavior in a laboratory asset market. Indeed, he suggests that the double auction mechanism creates enough *endogenous* noise to prevent an instantaneous revelation of information; creating incentives for the subjects to purchase information even in absence of an exogenous noise. Taking into account that we use a double auction as trading mechanism in the asset market and that traders have access to costly imperfect information, we can rely on Sunder's results to consider the fully revealing benchmark as a possible predictor of the level of prices in our experimental financial markets.

Hypothesis 4. *Prices aggregate efficiently the information dispersed in the market as implied by the efficient market hypothesis.*

In other words, if the information present in the market is sufficient to discover the dividend value, prices converge to the dividend value independently of the realization of the public signal. Let us compute the fully revealing benchmark in our setting. Using the Bayesian inference, we compute the probability that the dividend is equal to 10 ECU conditioned on the series of signals purchased by subjects up to time t. We refer to I_t as the market private information set $I_t = \{s_1, s_2, ..., s_j..., s_t\}$. s_t takes value -1 when the private signal indicates that the dividend is 0. Conversely, s_t takes value 1 when the private signal suggests that the dividend is 10. Additionally, we introduce the variable $S \in \{-1, 1\}$ in the public information and common information treatments. Following the previous reasoning, $S = -1$ when the public or common signal predicts a dividend 0 and $S = 1$ otherwise.[15]

$Pr(D = 10|I_t, S)$ denotes the probability of observing a dividend equal to 10 ECU conditioned on the information available at time t:[16]

$$Pr(D = 10|I_t, S) = \frac{Pr(I_t|D = 10) \cdot Pr(D = 10|S)}{Pr(I_t, S)} \;, \tag{1.1}$$

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

[15] Note, however, that there is no free signal in the baseline treatment, and then $S = 0$.

[16] *Mutatis mutandis*, the probability to observe a dividend equal to 0 ECU is $Pr(D = 0|I_t, S) = 1 - Pr(D = 10|I_t, S)$ since we have just two possible states of the world.

$$Pr(I_t, S) = Pr(I_t|D = 10) \cdot Pr(D = 10|S) + Pr(I_t|D = 0) \cdot Pr(D = 0|S). \quad (1.2)$$

$Pr(D = 10|S)$ is the prior probability of the event $D = 10$ given the public signal S.[17] The values of this conditional probability are defined later on.

Let us now compute the expression for the different terms of eq. (1.1) 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 $Q = 1 - P$.

  In this sense, treatments in the private information setting, i.e. $\mathrm{T}_B(0.6)$ and $\mathrm{T}_B(0.8)$, can be considered a case where the public information does not bias the traders towards any of the two states (and therefore $P = Q = 1/2$), whereas in all the other treatments the public or common signal biases the uniform prior towards one of the states depending on the realized value.
- N_t, the number of signals in the information set available up to time t;
- n_t is the number of 1s and $N_t - n_t$ is the number of -1s in the 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 S, the numerator of eq. (1.1) is given by:

$$\begin{aligned} Pr(I_t|D = 10) \cdot Pr(D = 10|S = 1) &= p^n \cdot q^{N-n} \cdot P\ , \\ Pr(I_t|D = 10) \cdot Pr(D = 10|S = -1) &= p^n \cdot q^{N-n} \cdot Q\ , \\ Pr(I_t|D = 10) \cdot Pr(D = 10|S = 0) &= p^n \cdot q^{N-n} \cdot \frac{1}{2}\ . \end{aligned} \quad (1.3)$$

The marginal probability in eq. (1.2) takes then form:

$$\begin{aligned} Pr(I_t, S = 1) &= P \cdot p^n \cdot q^{N-n} + Q \cdot p^{N-n} \cdot q^n\ , \\ Pr(I_t, S = -1) &= Q \cdot p^n \cdot q^{N-n} + P \cdot p^{N-n} \cdot q^n\ , \\ Pr(I_t, S = 0) &= \frac{1}{2} p^n \cdot q^{N-n} + \frac{1}{2} p^{N-n} \cdot q^n\ . \end{aligned} \quad (1.4)$$

Combining eqs. (1.1), (1.2), (1.3) and (1.4), 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 information present in the market at time t:

[17] $Pr(D = 0|S)$ indicates the prior probability of the event $D = 0$.

$$Pr(D = 10|I_t, S) = \left[1 + \left(\frac{Q}{P}\right)^S \left(\frac{q}{p}\right)^{H_t}\right]^{-1} . \tag{1.5}$$

Finally, using eq. (1.5), the fully revealing benchmark for the asset price under risk neutrality assumption is given by:

$$FR_t = 10 \cdot Pr(D = 10|I_t, S) + 0 \cdot Pr(D = 0|I_t, S) = 10 \left[1 + \left(\frac{Q}{P}\right)^S \left(\frac{q}{p}\right)^{H_t}\right]^{-1} . \tag{1.6}$$

1.2.4 Overweighting of public information

Morris and Shin (2002) and Allen et al. (2006) have been the first to point out that if higher-order expectations play a role in pricing an asset, public information will be overweighted with respect to its precision. Morris and Shin (2002), in particular, illustrate the overweighting phenomenon within the framework of a beauty contest game assuming full rationality of players. In such a game, players make a double account of the public information, considering its informational content as well as its role in second-guessing the expectations of the other players (commonality). The incentive to coordinate renders public information a predictor of the expectations of the other players and therefore they overrely on public information with respect to its informational role. Similar in spirit, Allen et al. (2006) develop an intertemporal asset pricing model with heterogeneous expectations where higher-order beliefs enter into the aggregate market demand function, without an explicit coordination motive. The fact that public information enters in all traders' demand function renders public information a good predictor for aggregate demand and gives rise to the overweighting phenomenon.

Considering such effect, Morris and Shin (2005), Amato and Shin (2006) or Vives (2014), among others, call attention to a sort of paradox of public information in markets where prices are the main suppliers of endogenous public information. In those markets, the release of more precise public information might reduce the informativeness of prices (as endogenous public signals). The literature refers to the presence of a crowding out[18] of exogenous public information on endogenous public information. The release of public information induces traders to rely less on their private information or, conversely, overrelay on public information.

[18] A cautionary note is in order here. When we refer to crowding out, we consider the reduction in the demand for private information due to the presence of an additional free signal (public or common). The theoretical and experimental literature refers also to the crowding out of an exogenous public signal on the informativeness of endogenous signals, prices or other statistics (see, e.g., Amador and Weill, 2010; Vives, 2014). In our paper, we refer to this effect as overweighting of public information in order to clearly distinguish between the two effects.

Our experimental setting exhibits the key elements suggested by the theoretical literature to observe traders' overweighting on public information: (i) The access to private and public information and (ii) heterogeneous expectations due to the endogenous acquisition of noisy private information. Even though an explicit coordination motive is missing, we rely on conjecture of Allen et al., 2006: if traders take into account the beliefs of other traders in the market when deciding their trading strategies, we expect to observe the overweighting phenomenon.

Alternative Hypothesis 4. *In presence of a public signal, prices overweight public information.*

In order to quantify the overweighting phenomenon (see Section 1.3.2), let us define here the public information benchmark as the expected price conditional just on the public signal:

$$PB = 10 \cdot Pr(D = 10|I_0, S) + 0 \cdot Pr(D = 0|I_0, S) = 10 \left[1 + \left(\frac{Q}{P}\right)^S\right]^{-1} . \qquad (1.7)$$

Note that both the fully revealing benchmark of eq. (1.6) and the public information benchmark of eq. (1.7) take into account the presence of public signal. The main difference is that, while in the fully revealing benchmark all pieces of information are weighted according to their respective precisions, the public information benchmark depends exclusively on the precision of public signal. In other words, it assigns a zero weight to the private information in aggregating all available information. Therefore, if the public information benchmark turns out to be a better predictor for actual prices than the fully revealing benchmark, we are able to prove the existence of overweighting phenomenon, since private information is not a determinant of the market prices.

1.3 Results

Figures from 1.8 through 1.21, included in the Appendix, display the trading activity in all markets for all treatments. Each panel of those figures refers to one particular market. A simple inspection of the market activity shows that the "do nothing" equilibrium is not a meaningful description of the subjects' trading behavior in any of the implemented treatments in both the asset market and the information market. This empirical finding is in line with many experiments on laboratory financial markets characterized by "no-trade equilibrium". Several recent papers study under which conditions subjects do trade in the laboratory despite the theoretical incentives not to do so (Angrisani et al., 2008; Carrillo and Palfrey, 2011). They essentially show that subjects fail to consider the strategic implications of trading within an asymmetric information environment. The failure of "do nothing" equilibrium speaks in favor of a certain degree of bounded rationality of the subjects.

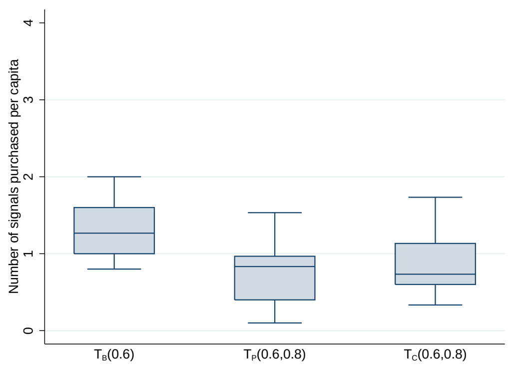
In the following, we present our results focusing on how the access to public information impacts the information and the asset market.

1.3.1 Information demand and market informativeness

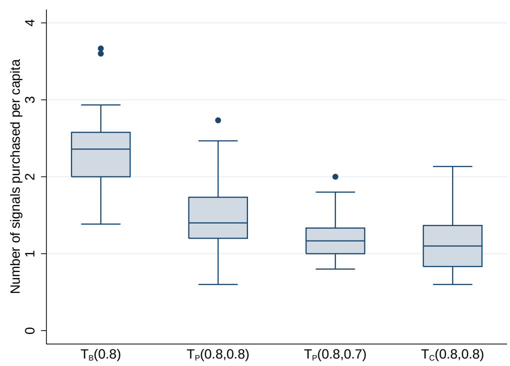
A crucial aspect of our experimental design is that the demand for private information is endogenous in a market. Therefore, in order to characterize the information market, it is sufficient to analyze the demand for private information, which we define as the number of signals purchased by the traders[19] in a given market.

Crowding out effect of public information on the demand for private information

Figure 1.1 and Table 1.2 show that the release of a free signal, whether public or common, *crowds out* the demand for private information. Traders substitute part of their private information with the information provided by the public signal. It is a robust effect, since it can be observed in treatments with low as well as high precision of private information. A Mann-Whitney test shows that the introduction of a free signal *significantly* reduces the traders' investment in private information. To the best of our knowledge, this is the first paper in the empirical as well as experimental literature that proves the existence of the *crowding out* effect of public information on the demand for private information, demonstrating that such effect is measurable and empirically relevant.



(a) Private signals' precision $p = 0.6$



(b) Private signals' precision $p = 0.8$

Figure 1.1 Per capita demand for private information per market and treatment.

When evaluating the effect of releasing public information into a financial market it is not only important to evaluate the impact on the demand for private information,

[19] Hereafter we will refer to the experimental subjects as *traders*.

Treatments	statistic	p-value
$T_B(0.6)$ vs. $T_P(0.6,0.8)$	3.797	0.000
$T_B(0.6)$ vs. $T_C(0.6,0.8)$	3.523	0.000
$T_B(0.8)$ vs. $T_P(0.8,0.8)$	3.315	0.000
$T_B(0.8)$ vs. $T_P(0.8,0.7)$	5.063	0.000
$T_B(0.8)$ vs. $T_C(0.8,0.8)$	5.061	0.000
$T_P(0.6,0.8)$ vs. $T_C(0.6,0.8)$	-0.474	0.635
$T_P(0.8,0.8)$ vs. $T_C(0.8,0.8)$	2.420	0.016
$T_P(0.8,0.8)$ vs. $T_P(0.8,0.7)$	-2.211	0.027

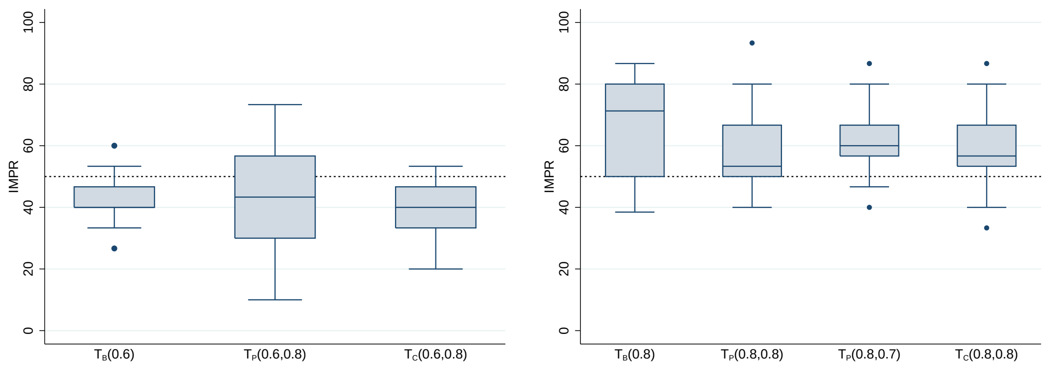
Table 1.2 Mann-Whitney test for the crowding out effect of public and common signal in the information market.

but also to determine its impact on the traders' participation in the information market. In our experiment, we observe a high degree of heterogeneity in the participation of traders in the information market. In particular, the role of uninformed traders, i.e. traders who do not purchase information, can be relevant for the dynamics of the asset market (Section 1.3.2). Bloomfield et al. (2009), for example, show experimentally that uninformed traders provide liquidity to the market, increasing market volume, as well as reducing price informativeness.[20] In order to characterize how the access to public information affects the traders' participation in the information market, we define the information market participation rate (henceforth IMPR), as the proportion of traders who purchase at least one signal during the trading activity in a given market (active traders). Considering the IMPR, the crowding out effect in the per capita demand for private information can be decomposed into the combination of two adjustments: (i) a reduction in the IMPR and/or (ii) a reduction in the demand for private information of active traders. In order to disentangle the two possible adjustments, Figure 1.2 and Table 1.3 illustrate that the release of a free signal does not significantly affect the IMPR. Therefore, the crowding out is largely caused by the reduction of the private information demand of the active traders.

Result 1. *The release of a free signal crowds out per capita demand for private information. However, the proportion of traders that purchase costly private information remains unaffected.*

According to the Result 1, we cannot reject Hypothesis 1 of crowding out of private information. Such results are compatible with a sort of intrinsic attitude of a fraction of traders to be informed, which is affected marginally by the presence of the free signal. Instead of not participating in the information market, they adjust their demand purchasing, on average, fewer signals. Conversely, the other group of traders

[20]In Bloomfield et al. (2009) the information is exogenously distributed among the market participants.



(a) Private signals' precision $p = 0.6$

(b) Private signals' precision $p = 0.8$

Figure 1.2 IMPR per market and treatment.

Treatments	statistic	p-value
$T_B(0.6)$ vs. $T_P(0.6{,}0.8)$	0.068	0.945
$T_B(0.6)$ vs. $T_C(0.6{,}0.8)$	0.789	0.430
$T_B(0.8)$ vs. $T_P(0.8{,}0.8)$	1.552	0.121
$T_B(0.8)$ vs. $T_P(0.8{,}0.7)$	1.107	0.268
$T_B(0.8)$ vs. $T_C(0.8{,}0.8)$	1.361	0.174
$T_P(0.6{,}0.8)$ vs. $T_C(0.6{,}0.8)$	0.560	0.576
$T_P(0.8{,}0.8)$ vs. $T_C(0.8{,}0.8)$	-0.539	0.590
$T_P(0.8{,}0.8)$ vs. $T_P(0.8{,}0.7)$	1.436	0.151

Table 1.3 Mann-Whitney test comparing the effect of public information on the IMPR.

does not purchase private signals, relying on the price chart or other market signals (e.g. bid/ask spread). This categorization of traders resembles the dichotomy fundamentalists/chartists introduced by Beja and Goldman (1980), afterwards developed in the literature of economic agents with heterogeneous expectations (see for instance Lux and Alfarano, 2016; Dieci and He, 2018).

Effect of common knowledge of the free signal An additional feature that we can test with our experiment is whether the magnitude of the crowding out is mainly due to the informational role of the public signal, or instead the commonality component contributes to the crowding out. Comparing public and common information treatments in Figure 1.2, one can see that the IMPR is not affected by the commonality of the free signal. When the precision of private signals is the same in public and common information treatments, there are not significant differences between treatments. Nevertheless, the per capita demand for information is differently affected depending on the precision of the private signals. When the private information has low precision ($p = 0.6$), there is no difference between treatments. Differently, when private information is of high precision ($p = 0.8$), the magnitude of the crowding out is significantly higher in T_C(0.8,0.8) than in the T_P(0.8,0.8). It seems that the crowding out effect also depends on the commonality role of the public signal and, additionally, on its relative precision with respect to the private signal. This is evidence against the Hypothesis 2, which attributes the crowding out effect solely to the information about fundamentals.

How can we interpret these findings? Following Hellwig and Veldkamp (2009), under strategic substitutability of actions in a coordinating setting state "*agents want to know what others do not*". Interestingly, Page and Siemroth (2017) come to the same conclusion from their laboratory asset market. They find that traders are more likely to purchase signals when their initial information is public rather than private. This result suggests that traders purchase more information in order to gain an advantage over the other traders. If our interpretation is correct, "*knowing what the others do not*" seems, in fact, a very reasonable behavior in a financial market. Following this reasoning, our conjecture can also account for the significant difference in T_C(0.8,0.8) and T_P(0.8,0.8). In the common information treatment, in fact, an active trader believes to have access to a free private signal. We, therefore, clearly reject Hypothesis 2.

Result 2. *The magnitude of the crowding out effect depends on the commonality of the released signal.*

Effect of relative precision of information sources We observe a significantly lower magnitude of the crowding out in T_P(0.8,0.8) with respect to T_P(0.8,0.7). It seems that when private and public signals have the same precision, i.e. T_P(0.8,0.8), an active trader has a higher incentive to purchase private information to be more informed than the privately uninformed traders. On the contrary, the relatively high precision of the private information in T_P(0.8,0.7) gives to active traders a lower incentive to purchase private information, as compared to T_P(0.8,0.8). Our experimental findings indicate that the demand for information is sensitive to the relative precision of public information. Our result is in line with finding of Page and Siemroth (2017).

Result 3. *The information demand of active traders is significantly affected by the relative precision of public information with respect to private information.*

This might be an important feature to take into account when designing communication policies. Before deciding the transparency of the communication policy by the regulator, it would be desirable having a proxy of the average precision of the information available to the traders, in order to evaluate its impact on traders' information demand.

Market informativeness

After having analyzed how the release of public information affects the demand for private information, it remains the question whether the public signal compensates for the reduction in private information due to the crowding out effect. Stated differently, is the introduction of a public signal neutral, beneficial or detrimental for the overall market informativeness? Does the potential of the market to discover the true state of the world in the presence of public information remain unaffected, enhanced or reduced?

Let us introduce as an indicator of market informativeness the mean absolute deviation between the fully revealing benchmark and the dividend value averaged during the last minute of the market:[21]

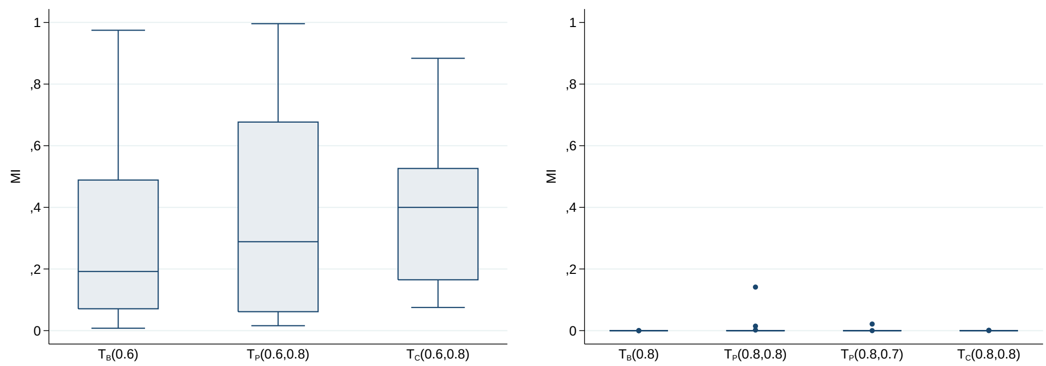
$$MI = \frac{1}{60}\sum_{t=120}^{180}\frac{|FR_t - D|}{10}\ . \tag{1.8}$$

Recall that the definition of FR_t is based on the efficient market hypothesis. The EMH rests on the idea that the traders make an optimal use of all the available information, without explicitly modeling the traders' incentives to gather such information. Relying on the EMH to compute the market informativeness, it might probably be a strong (behavioral) assumption; however, it allows us not to include *ad hoc* behavioral rules in describing the traders' activity. Moreover, the indicator MI can be thought as the upper bound for the efficiency in the aggregation of available information into prices. The higher the value of MI, the lower is the market informativeness. Instead, a value of MI close to zero indicates that the information present in the market is sufficient to discover the dividend value.

Figure 1.3 shows how the market informativeness is strongly affected by the precision of the private information. When we consider a low precision of the private signal, market informativeness is sufficient to discover the dividend value only in a few markets.[22] In the majority of markets, the aggregate information provides an imprecise indication of the true state of the world. Conversely, in treatments with high precision of the private signal, the indicator MI is very close to zero in almost all markets, signaling that the information present in the market is always sufficient to

[21] In principle, we should introduce an index indicating the particular market and treatment, but we omit such index for notational convenience. The choice of averaging over the last trading minute is a compromise between having a good statistics for market informativeness indicator and low activity in the information market. In the last minute, in fact, either zero or few signals are purchased 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 to the fully revealing benchmark its "best shot" as Plott and Sunder (1988) state. We divided by 10 in order to normalize all distances to be between 0 and 1.

[22] We can arbitrarily state that market informativeness is sufficient to discover the true state of the world when $MI < 0.05$. Different values of this threshold do not change the essential message that the information is sufficient to discover the dividend value in just a few markets.



(a) Private signals' precision $p = 0.6$ (b) Private signals' precision $p = 0.8$

Figure 1.3 Market informativeness per markets across treatments.

discover the dividend value.[23]

Despite the crowding out effect on the demand for private information, we cannot reject the Hypothesis 3 that the market informativeness is not significantly affected by the release of a free signal.[24] This means that within the framework of the EMH, the additional information provided by the exogenous public signal is sufficient to counterbalance the effect of the crowding out on private information.

Result 4. *The crowding out effect due to a free signal leaves invariant market informativeness.*

Our experimental analysis on the information market, summarized by Results 1 and 4, confirms the theoretical conjectures of many authors (for instance, Colombo et al., 2014) on the role of public information in competitive markets. The implications of our findings are important for regulators: the release of public information might not increase the overall market informativeness. The intervention of the public institutions reduces traders' effort to gather private information at a level that the loss in private information is not compensated by the presence of public information. When introducing a new source of public information in a market, in fact, the regulator should pay particular attention to its complex interaction with other sources of information already at the disposal of market participants.

1.3.2 Asset market and price informativeness

Until now, we have presented our experimental findings that releasing public information has on the information market. Result 4 shows that the public signal compensates for the crowding out effect on the demand for private information, leaving invariant

[23] Except for one market in T_P(0.8,0.8), market informativeness always satisfies the condition $MI < 0.05$.

[24] A Mann-Whitney test cannot reject the null hypothesis of equal market informativeness if we compare the baseline treatments with all other treatments.

market informativeness. However, how does the release of public information effectively impact the aggregation of available information into prices? Can we observe the overweighting phenomenon of public information as predicted by the theoretical literature? Can we preserve the beneficial effect of releasing public information, while minimizing its adverse effects?

Overweighting of public information

In this subsection, we analyze how the information disseminated among traders (market informativeness) is aggregated into prices (price informativeness). According to the EMH in its strong form, we should observe that the market price reflects all available information. Thus, our measure of price informativeness should be a mere reflection of the behavior of our measure of market informativeness from eq. (1.8). Taking into account Figure 1.3 and Result 4, therefore, the price informativeness should not be affected by the release of a free signal, neither public nor common.

As a measure of price informativeness, we consider the difference between *what traders have actually done* in a given market and *what they could have done* in aggregating information into prices. In order to do so, we evaluate how the fully revealing benchmark FR_t, introduced in Section 1.2, accounts for market prices PR_t, averaging the absolute distance between FR_t and PR_t in the last minute of trading activity in a given market:[25]

$$PI = \frac{1}{60} \sum_{t=120}^{180} \frac{|FR_t - PR_t|}{10} \, , \tag{1.9}$$

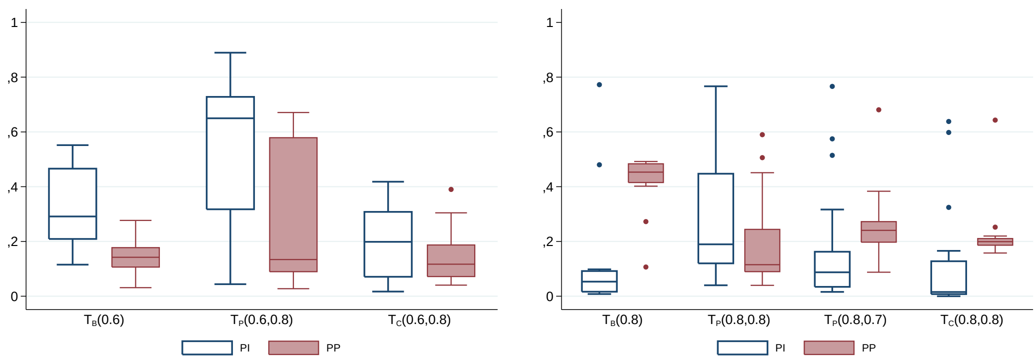
where the index t denotes seconds. The maximum level of price informativeness is reached when $PI = 0$, i.e. when market prices reflect correctly all available information ($PR_t \approx FR_t$). Significant deviations from this lower bound, instead, indicate a reduction in price informativeness. Recall that in the fully revealing benchmark all information is weighted according to its precision. In order to study how private and public information are weighted when actually aggregated into market prices, we introduce a further indicator to measure the goodness of fit of the public benchmark. The indicator is the averaged distance of market prices from the public information benchmark:

$$PP = \frac{1}{60} \sum_{t=120}^{180} \frac{|PB - PR_t|}{10} \, , \tag{1.10}$$

[25]We consider only the last minute for the same reasons explained in Footnote 21. We have normalized the distance PI in eq. (1.9) to be bounded to 1. We omit the market index for notational convenience.

where PB is defined in eq. (1.7).[26] A PP value of zero indicates that prices fluctuate around the public information benchmark.

The comparison of the relative performance of the indicators PI and PP in describing market prices can help us to evaluate whether deviations from fully informative prices are systematically favoring public information, as suggested by several theoretical models in the literature (e.g. Allen et al., 2006). A PP value significantly lower than the PI indicator means that the public information benchmark accounts better for prices than the fully revealing benchmark. Given that public information does not have a significantly impact on market informativeness (see Figure 1.3), this condition indicates that the market weights public information well beyond its informational content, being the main determinant of the price level.[27]



(a) Private signals' precision $p = 0.6$ (b) Private signals' precision $p = 0.8$

Figure 1.4 Performance of price informativeness indicator (PI) and public information indicator (PP) per market and treatment.

Figure 1.4 (a) and Table 1.4 show that in those markets where traders have access to private information with low precision, releasing a more precise public signal strongly reduces price informativeness with respect to the baseline treatment, i.e. $T_B(0.6)$ vs. $T_P(0.6{,}0.8)$. A similar effect on price informativeness is observed when traders have access to more precise private information (Figure 1.4 (b) and Table 1.4). If we compare $T_P(0.8, 0.7)$ with the baseline treatment, the deterioration of price informativeness is weaker but still present, at least at 10% confidence level. Our results are robust under different relative precision of both private and public signals. Hence, we reject the null hypothesis of Hypothesis 4 that prices directly aggregate the dispersed information.

[26] As for the indicator in eq. (1.9), we omit the market index for notational convenience. The indicator PP is also normalized to 1.

[27] Note that such condition is a sufficient but not a necessary condition for detecting the overweighting phenomenon. In principle, we cannot exclude the presence of overweighting of public information even in the case of PI lower than PP.

Effect	Treatments	PI	
		MW statistic	p-value
Releasing public information	$T_B(0.6)$ vs. $T_P(0.6,0.8)$	-2.597	0.009
	$T_B(0.8)$ vs. $T_P(0.8,0.8)$	-3.949	0.000
	$T_B(0.8)$ vs. $T_P(0.8,0.7)$	-1.731	0.083
	$T_P(0.8,0.7)$ vs. $T_P(0.8,0.8)$	-2.732	0.006
Releasing common information	$T_B(0.6)$ vs. $T_C(0.6,0.8)$	2.597	0.009
	$T_B(0.8)$ vs. $T_C(0.8,0.8)$	1.082	0.279
Public vs. common information	$T_P(0.6,0.8)$ vs. $T_C(0.6,0.8)$	3.760	0.000
	$T_P(0.8,0.8)$ vs. $T_C(0.8,0.8)$	3.544	0.000

Table 1.4 Mann-Whitney test to compare values of PI indicator among treatments.

	Treatments	$PI\ vs.\ PP$ p-value
Baseline treatments	$T_B(0.6)$	**0.041**
	$T_B(0.8)$	0.000
Public information	$T_P(0.6,0.8)$	**0.000**
	$T_P(0.8,0.8)$	**0.041**
	$T_P(0.8,0.7)$	0.012
Common information	$T_C(0.6,0.8)$	0.332
	$T_C(0.8,0.8)$	0.003

Table 1.5 Sign-test to compare PI and PP indicators. The numbers in bold signal that the PP indicator is significantly lower than the PI indicator.

Result 5. *Releasing public information in a market where traders have access to costly private information worsens price informativeness.*

Our result suggests that price informativeness is not a mere reflection of market informativeness. Contrary to what the EMH states, the aggregation of information into prices depends on the nature of the information present in the market (private or public) and the spectrum of information sources at the disposal of the traders. Why do we observe a deterioration of price informativeness when a public signal is released? We can interpret our experimental results relying on the theoretical literature on overweighting of public information in asset-pricing contests (Allen et al., 2006). In those models, the reduction in price informativeness is consequence of the overreliance of traders on public information because of its common knowledge property. Individual actions systematically overweight public information more than justified by its informational content. We expect that market prices in our experiment overweight the public signal (Alternative Hypothesis 4). We should observe, therefore, that the PP indicator is significantly lower than the PI indicator in our data.

Figure 1.4 and Table 1.5 confirm our conjecture when the public signal is at least as precise as a single private signal, i.e. in $T_P(0.6,0.8)$ and $T_P(0.8,0.8)$. In those treatments, the public signal is unambiguously overweighted since it constitutes the main determinant of the price level. When traders have access to less precise public information than a single private signal, i.e. in $T_P(0.8,0.7)$, we cannot exclude that public information is overweighted. However, it is not anymore the main determinant of the price level. It is the fully revealing benchmark, in fact, that better accounts for market prices. Both, private and public information, contribute to the determination of the price level.

The magnitude of the overweighting effect is strongly influenced by the relative precision of the public signal with respect to the precision of a single private signal. Interpreting the relative precision of the public signal as its transparency, our results speak in favor of the possibility of acting on the relative precision of the public signal to reduce the overweighting effect. Figure 1.4 and Table 1.5 illustrate how lowering the level of transparency, i.e. moving from $T_P(0.6,0.8)$ to $T_P(0.8,0.8)$ and, then, to $T_P(0.8,0.7)$, the magnitude of the overweighting effect is significantly reduced. Interestingly, in $T_P(0.8,0.7)$, the public signal is not anymore the main driver of market prices.

Result 6. *Depending on its relative precision, i.e. its transparency, public information is overweighted when incorporated into the price. Lowering transparency reduces overweighting of public information.*

To the best of our knowledge, this is the first contribution in the literature in observing and measuring qualitatively the overweighting of public information in a non-coordination setting. Our results provide a robust back up to the conjecture that acting on the transparency of public information constitutes an effective control instrument at disposal of regulators.

The double-edged nature of public information

In order to interpret the overweighting phenomenon in light of the existing theoretical literature, we rest on the idea that traders double count on public information when deciding their strategy. Implicitly, we assume that traders' beliefs about the information possessed by other traders play a role when deciding at what price to trade. In particular, Allen et al. (2006) show that such condition necessarily leads to overweight public information when information is aggregated into prices.

We implement the common information treatment, where the free signal provides the same information on the fundamentals without influencing the higher-order beliefs of traders. It should lose its role as coordination device, and, being informative, should favor price convergence towards the fully revealing benchmark. Thus, with the introduction of the common information treatment, we can disentangle how the *commonality* and the *informative* features of the public signal impact on the aggregation of information into prices. If traders base their trading strategy on second-order beliefs, we expect to observe that the overweighting effect disappears or, alternatively, it is strongly attenuated when comparing the common information with the public information treatments.

Looking again at Figure 1.4 and Table 1.4, the release of a free signal in $\mathrm{T}_C(0.6{,}0.8)$ and $\mathrm{T}_C(0.8{,}0.8)$ significantly improves price informativeness compared to the markets where public information is released, i.e. in $\mathrm{T}_P(0.6{,}0.8)$ and $\mathrm{T}_P(0.8{,}0.8)$, respectively. Indeed, the common signal improves price informativeness even with respect to $\mathrm{T}_B(0.6)$. In the case of the private information with high precision, $\mathrm{T}_B(0.8)$ and $\mathrm{T}_C(0.8{,}0.8)$, price informativeness does not improve, being already at its (almost) maximum level. Therefore, we do not observe a distorting effect of the common signal on price informativeness.

The most striking result concerns the overweighting effect. In common information treatments, the overweighting effect is strongly attenuated. Contrary to the public information treatment, prices turn out to be more informative since the fully revealing benchmark performs by far better than the public information benchmark in describing market prices. Even more, in $\mathrm{T}_C(0.8{,}0.8)$, the overweighting effect disappears since prices converge, in most markets, to the fully revealing benchmark. Once the commonality feature is eliminated, the common signal does not constitute the main driver of market prices. Contrary to the public signal, the common signal cumulates to the private information when aggregated into the prices, without distorting the aggregation process.

Result 7. *The overweighting effect is limited to the public information treatment. There is not evidence of overweighting in common information treatments*

Intuition about traders' reasoning Let us introduce a simple qualitative idea on how our financial market could give the incentive to forecast the other traders' expectations inspired by Allen et al. (2006). More specifically, if a trader purchases private information that tells him that with some probability the asset dividend is 10, he would be willing to buy assets at any price equal or lower than his expected dividend.[28] He will make higher profits from trade the lower the asset purchasing price. If this trader thinks that the market is populated by a non-marginal fraction of uninformed traders,[29] he has an incentive to bid at a price around what he expects it would be the expectation of the group of uninformed traders, that is, the public

[28]His expected dividend is higher than the public information benchmark, independently of the realization of the public signal.

[29]In this context, we define uninformed traders as those traders who do not purchase any signal.

information benchmark. Uninformed traders could be willing to buy and sell their assets around their expected dividend, determined solely by the public signal.

If the proportion of uninformed traders willing to trade is high enough to provide sufficient liquidity and/or assets, market prices fluctuate around the expected dividend conditional on the public signal. In this case, the public information benchmark better predicts the market price than the fully revealing benchmark. As a consequence, prices do not reflect the traders' private information, but mostly the expectations of uninformed traders' expectations that are biased towards public information. This could be a simple mechanism behind the overweighting of public information, based on the impact of public information on the traders' second-order beliefs. Further research will be necessary to investigate the microstructure details of this process.

It is evident that our simple idea relies heavily on the bounded rationality of the traders. The overweighting effect has been introduced as an equilibrium outcome of coordination models with full rational agents, as in Morris and Shin (2002). Cornand and Heinemann (2014) is the only contribution in the literature that analyses 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 is the level of boundness in rationality, which is measured as a reduction in the degree of inductive reasoning, the lower is the overweighting phenomenon. Instead, we observe, in a certain sense, the opposite relationship between the level of rationality and the overweighting of public information.

In our setting, fully rationality implies either no-trade equilibrium or, if such equilibrium is broken, a noisy rational expectation equilibrium, following the reasoning of Sunder (1992). In both cases, we should not observe the overweighting effect, since either we have no trade or the price reflects the information according to its precision. Therefore, detecting this effect as a relevant experimental result seems to be connected to the bounded rationality of the traders. Our findings on the role of bounded rationality in the emergence of the overweighting effect as a non-equilibrium outcome confirm again the empirical relevance of such distorting effect of public information on prices. At the aggregate level, traders in our experimental markets (might) overrely on public information with respect to private information. Since we do not explicitly introduce a coordination setting, our experimental results generalize their main conclusions, showing that they can be also applied to a more general financial market setting. It would be interesting, then, to investigate which are the minimal conditions for the emergence of such complex interplay between private and public information in financial markets along the line sketched in our simple example. We leave this as an issue for our future research agenda.

In Chapter 2 of this thesis, we will sketch a simple belief theoretical model along the line of our intuition. In the literature, there are several elegant frameworks to account for deviations from fully rationality, like the cognitive hierarchy model of Camerer et al. (2004) and the coursed equilibrium of Eyster and Rabin (2005). In particular, Eyster et al. (2015) apply the cursed equilibrium to a financial market, showing that public information is overweighted when aggregated into market prices. Our experimental results can be cast into those theoretical frameworks, providing an alternative explanation to the phenomenon of overweighting of public information in financial markets within bounded rationality of traders. The differences between our results and the existing literature deserve, therefore, further theoretical as well as experimental research.

Other important contributions are find in the literature on noise traders (De Long et al., 1990). The interaction between a group of informed traders with limited horizons and uninformed traders could give rise to an equilibrium price where deviates from fundamentals. In their paper, it is exogenously imposed a correlation among the noise traders. Without being too rigorous, this correlation can be a convergence of a noisy public signal in our reasoning.

1.4 Discussion and conclusions

The main purpose of this paper is to study experimentally the aggregation of information in financial markets as a function of the access of traders to different sources of information, namely costless public and costly private information. Such informational setting has been extensively used 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 overweighting of public information and crowding out of private information.

We show that the crowding out effect of public information and traders overreliance on public information do exist. Those two effects are measurable and empirically relevant, heavily affecting the market performance. Moreover, in our experimental setting, those effects emerge 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 can infer, therefore, that the crowding out and overreliance are more general phenomena than conjectured by the literature. By investigating the dual role of public information, i.e. providing information on the fundamentals and information on the other traders' beliefs, we find that the latter characteristic is the main responsible for the overweighting phenomenon. Introducing public information negatively affects the aggregation of information into prices since prices are biased towards the public signal. Conversely, providing an identical free signal to all traders without being common knowledge improves the aggregation of information.

Some general warnings for regulators can be derived out of our simple set of experiments. Policymakers should be aware that the release of public information might have distorting effects on the traders' effort to find alternative sources of information and on the aggregation of information into prices. Those effects might be extremely significant as demonstrated by the role that credit rating agencies had on the spreading of the 2008 financial crisis. Far from being against 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 the market performance.

As a policy advise we recommend that ongoing reforms on the regulation of financial institutions (for instance, the credit rating agencies) should account for such complex interplay, that we have identified in our experiments. In particular, they should provide incentives for the investors (institutional and/or private) to actively search for alternative sources of information. In order to take stock of the regulatory advantages of releasing public information and smooth its potential adverse effects, we give some guidelines for the design of public communication and disclosure strategies: (i) More precise public information does not necessarily help the market to align to the fundamentals, since public information does not cumulate but substitutes private information due to the crowding out and overweighting effects. (ii) It is not always optimal to reveal all the information possessed by public institutions. It might be better to release an informative signal that it is not perceived as too precise by the investors to avoid overreliance. In this respect it is of great importance to know the characteristics of the private information. The level of transparency of public information, in fact, should be tuned considering the precision of the private information at the disposal of traders. Therefore, it is advisable to use econometric techniques to develop some proxies for the precision of the traders' private information, based, for instance, on surveys data. Interestingly, if we interpret the common information setting as a disclosure strategy, the most effective measure that we have identified to enhance market efficiency and, at the same time, reducing the cost of gathering private information, is whispering in the ears of investors, i.e. to spread a common information among investors without being common knowledge. However, we understand that this measure is unrealistic to be implemented in real financial markets.

Finally, we strongly believe that our 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. So that, our conclusions are far more robust than ones based on experimental settings currently employed. Several other measures can be also tested, like a sequential release of public information, reducing the level of publicity, or increasing the number of institutions releasing public information. The study of the effects of those measures is the focus of ongoing research.

Appendix

1.A Instructions of the experiment

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

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 purchase or sale offer 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:

- **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.[30]
- **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.

[30] The values of the different probabilities are changed in accordance to the different treatments.

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 your same market.

1.A.1 Screenshots

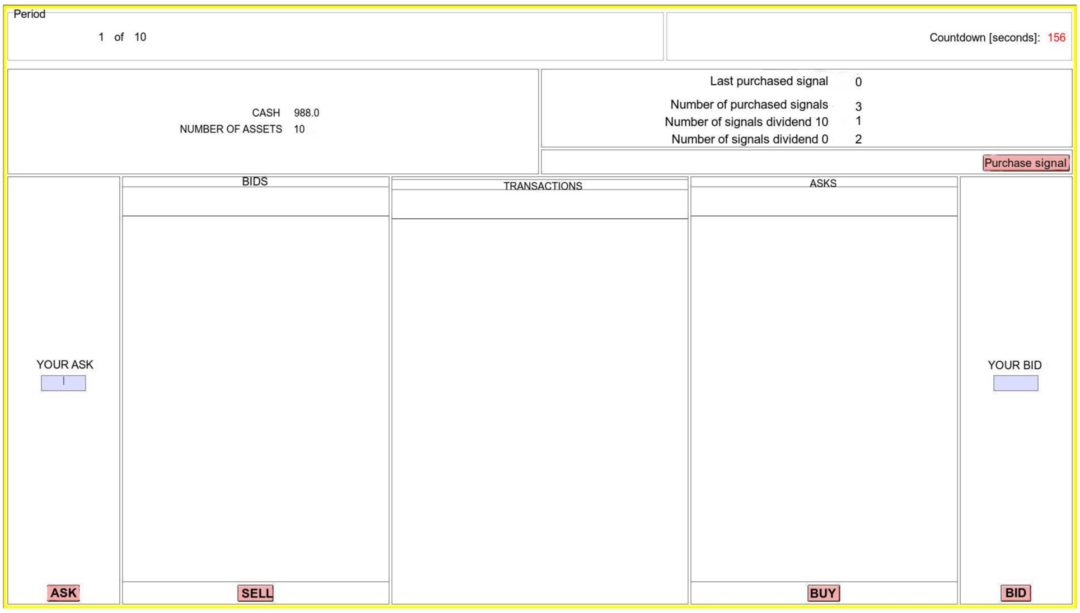


Figure 1.5 Screenshot of baseline treatments, $\mathrm{T}_B(\cdot)$

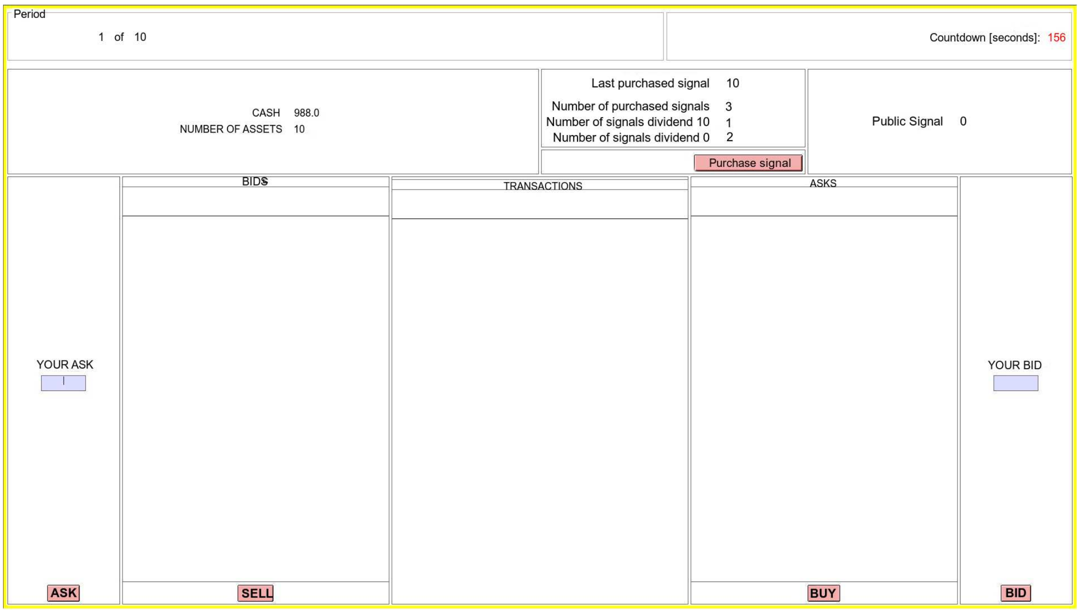


Figure 1.6 Screenshot of public information treatments, $\mathrm{T}_P(\cdot,\cdot)$

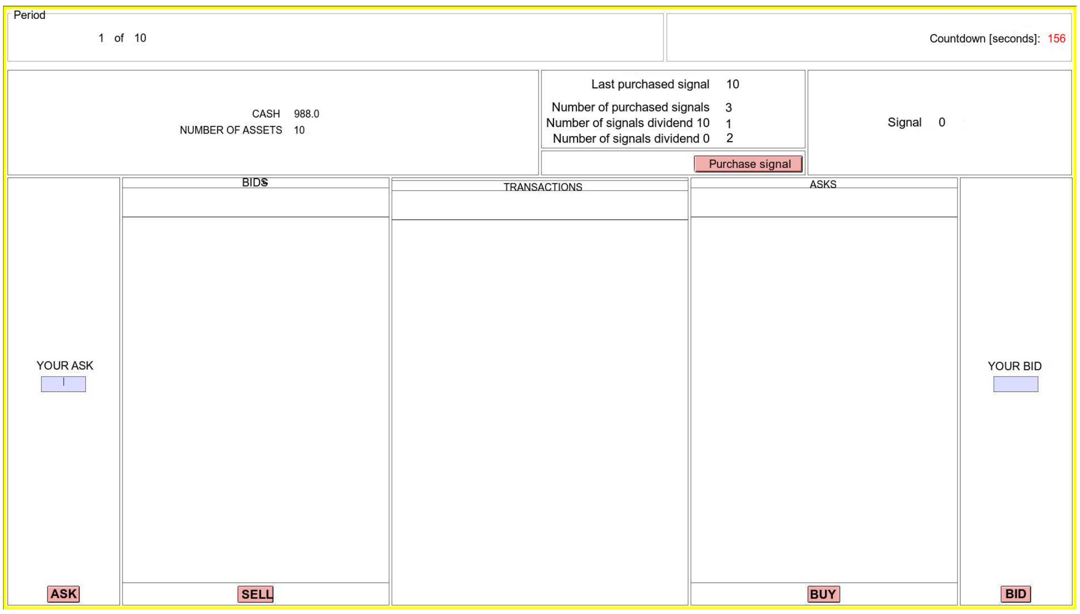


Figure 1.7 Screenshot of common information treatments, $\mathrm{T}_C(\cdot,\cdot)$

1.B Trading activity per treatment

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, while the dashed line indicates the public information benchmark.

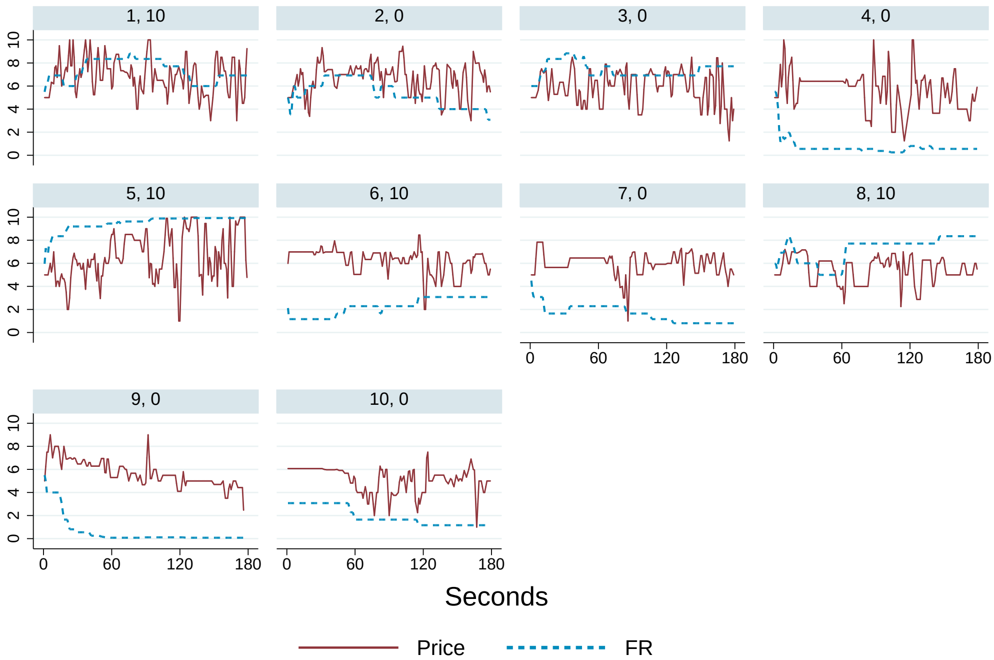


Figure 1.8 Markets Treatment $T_B(0.6)$ (Group 1).

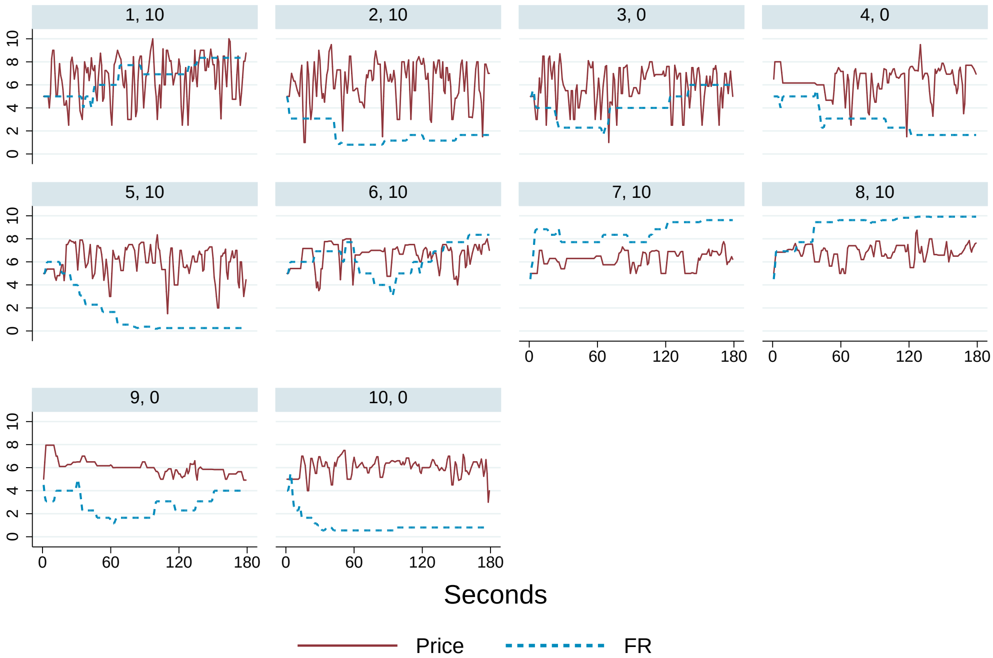


Figure 1.9 Markets Treatment $T_B(0.6)$ (Group 2).

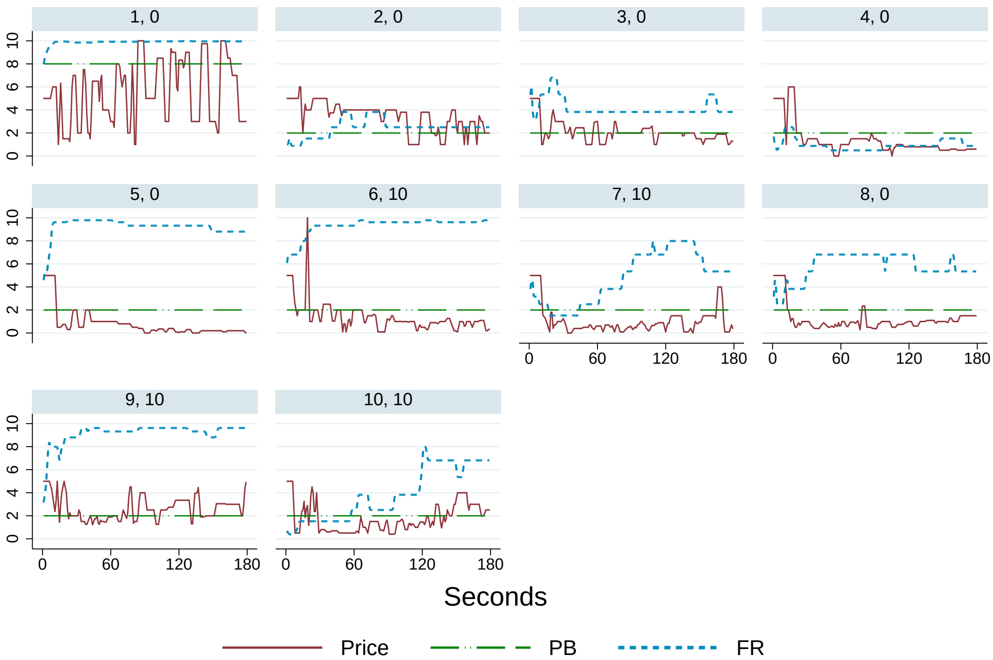


Figure 1.10 Markets Treatment $T_P(0.6,0.8)$ (Group 1).

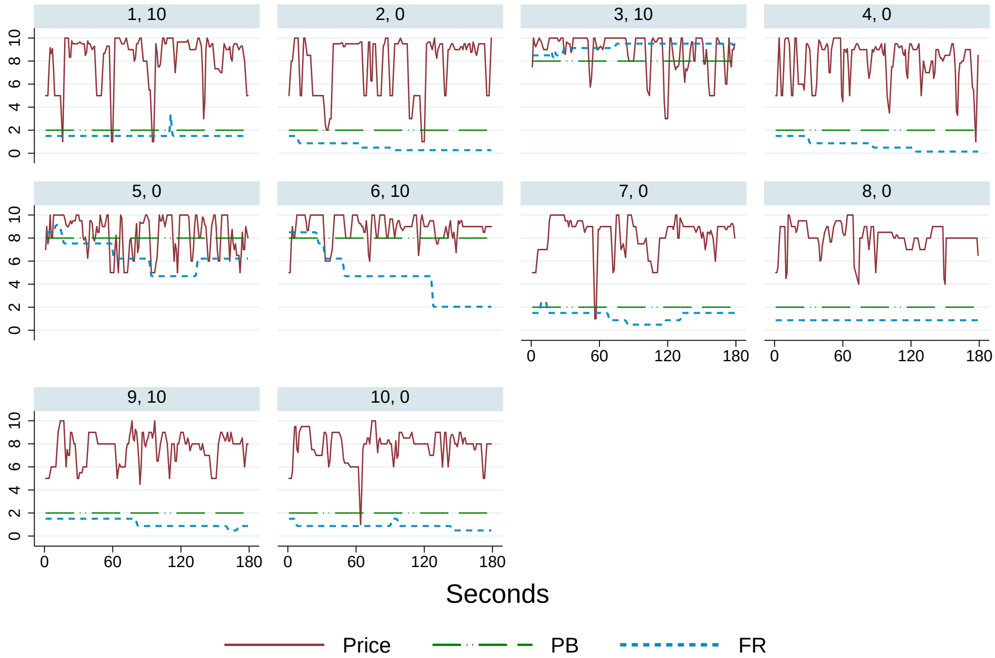


Figure 1.11 Markets Treatment $T_P(0.6,0.8)$ (Group 2).

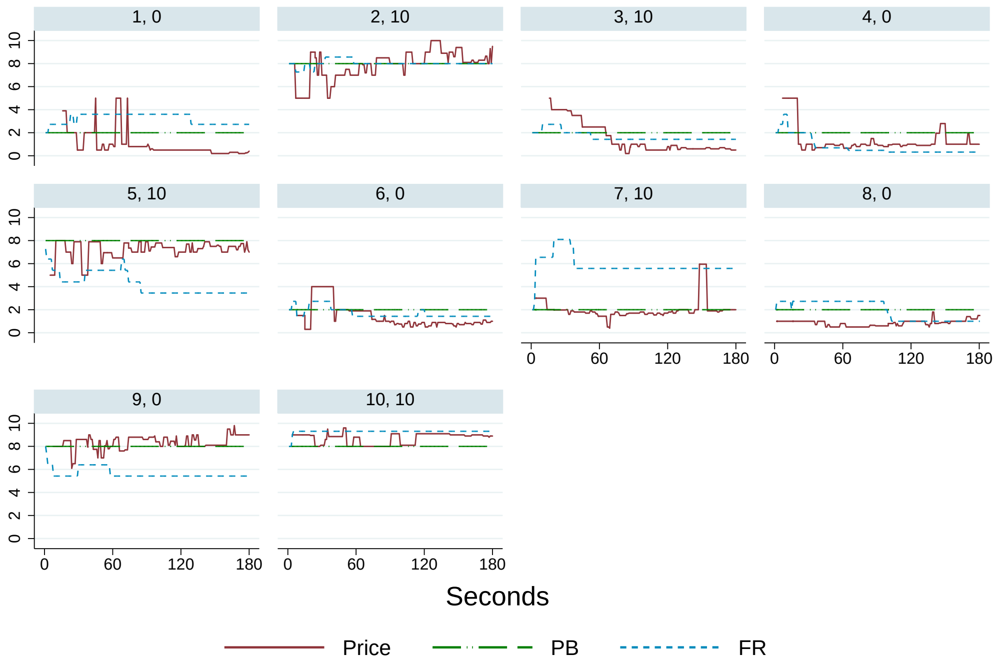


Figure 1.12 Markets Treatment $T_C(0.6,0.8)$ (Group 1).

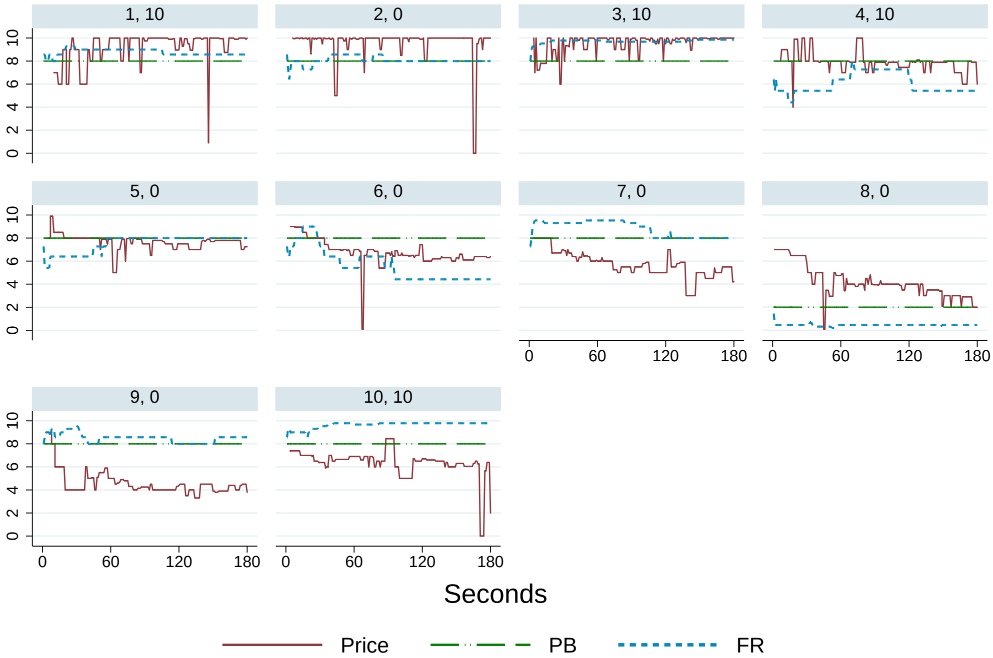


Figure 1.13 Markets Treatment $T_C(0.6,0.8)$ (Group 2).

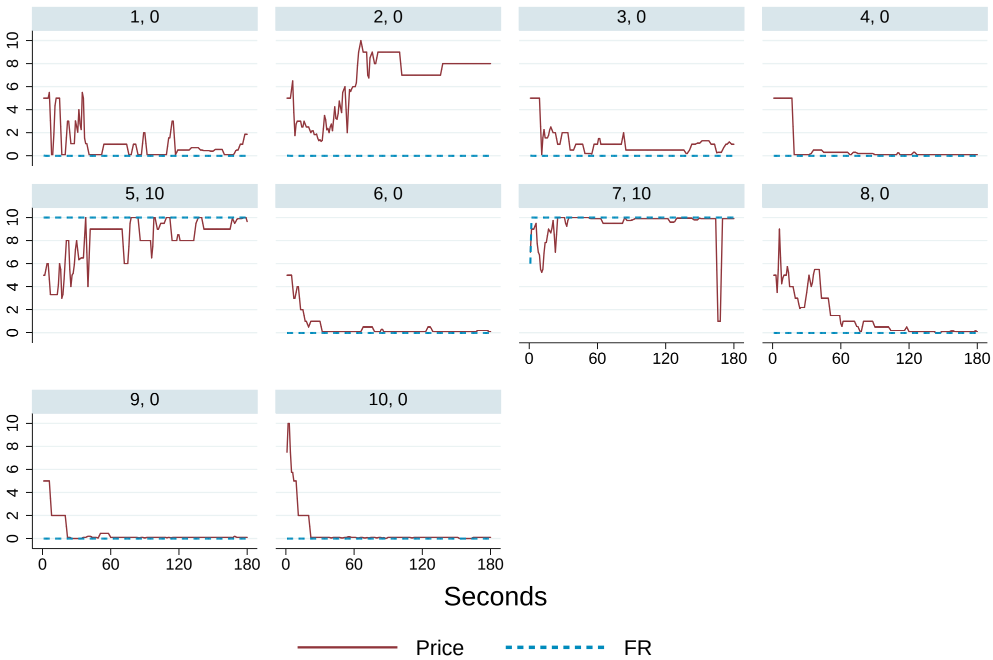


Figure 1.14 Markets Treatment $T_B(0.8)$ (Group 1).

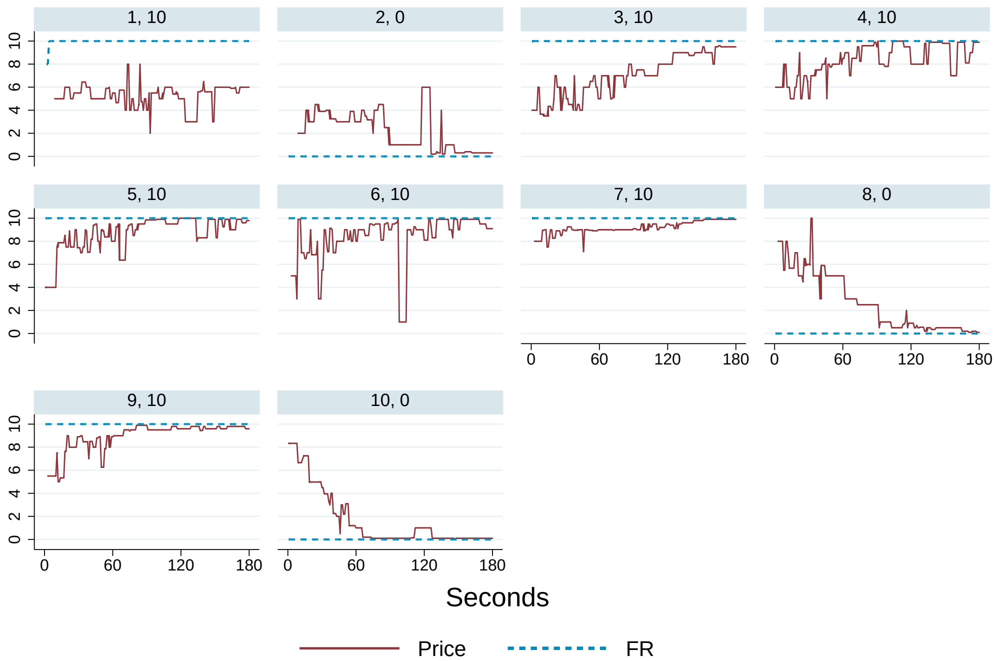


Figure 1.15 Markets Treatment $T_B(0.8)$ (Group 2).

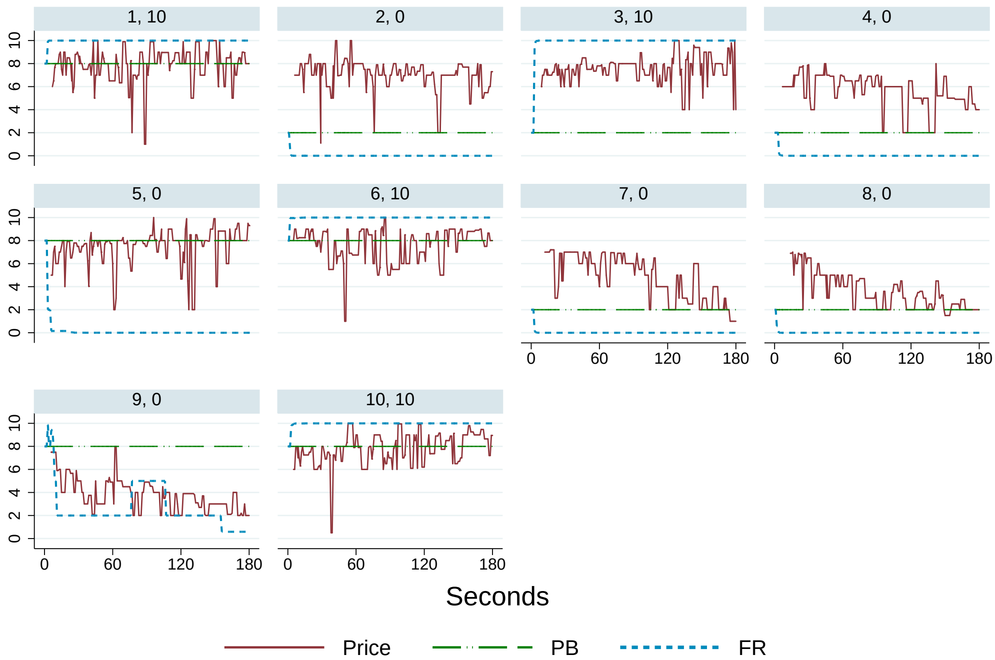


Figure 1.16 Markets Treatment $T_P(0.8,0.8)$ (Group 1).

Figure 1.17 Markets Treatment $T_P(0.8,0.8)$ (Group 2).

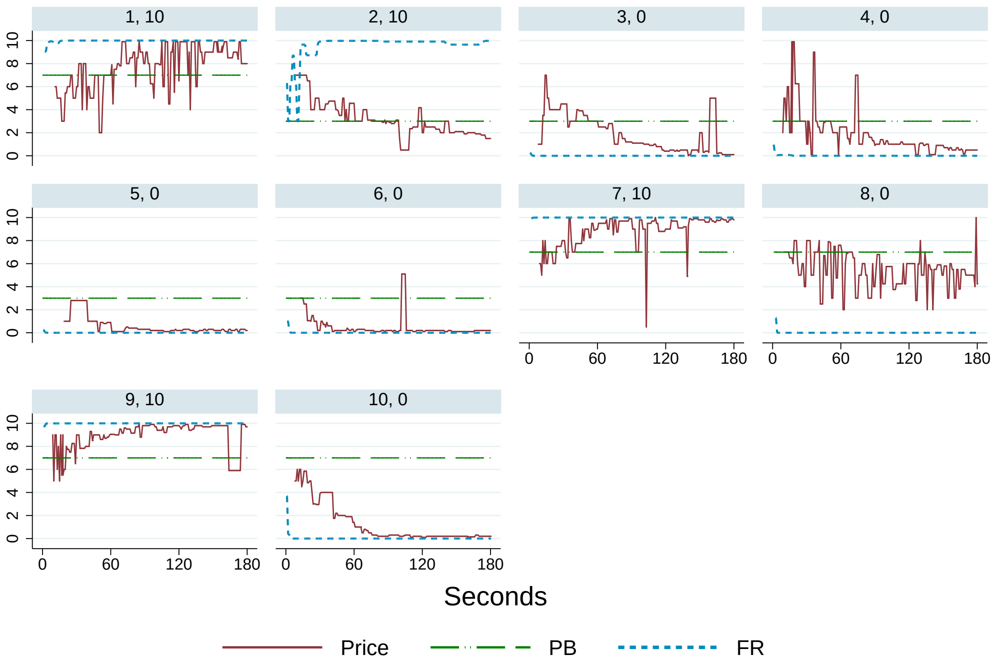


Figure 1.18 Markets Treatment $T_P(0.8,0.7)$ (Group 1).

Figure 1.19 Markets Treatment $T_P(0.8,0.7)$ (Group 2).

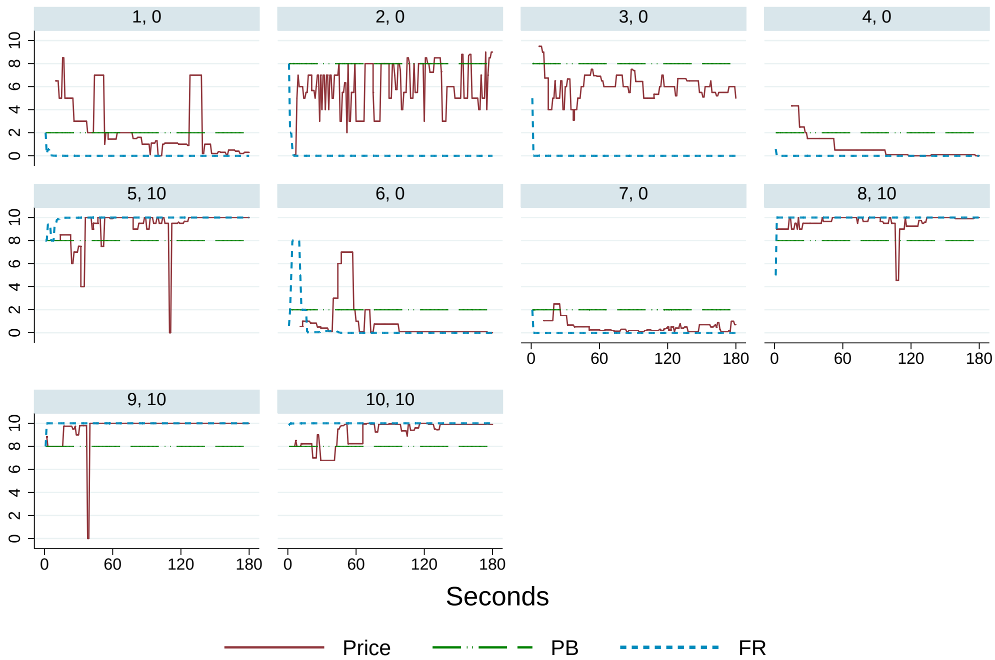


Figure 1.20 Markets Treatment $T_C(0.8,0.8)$ (Group 1).

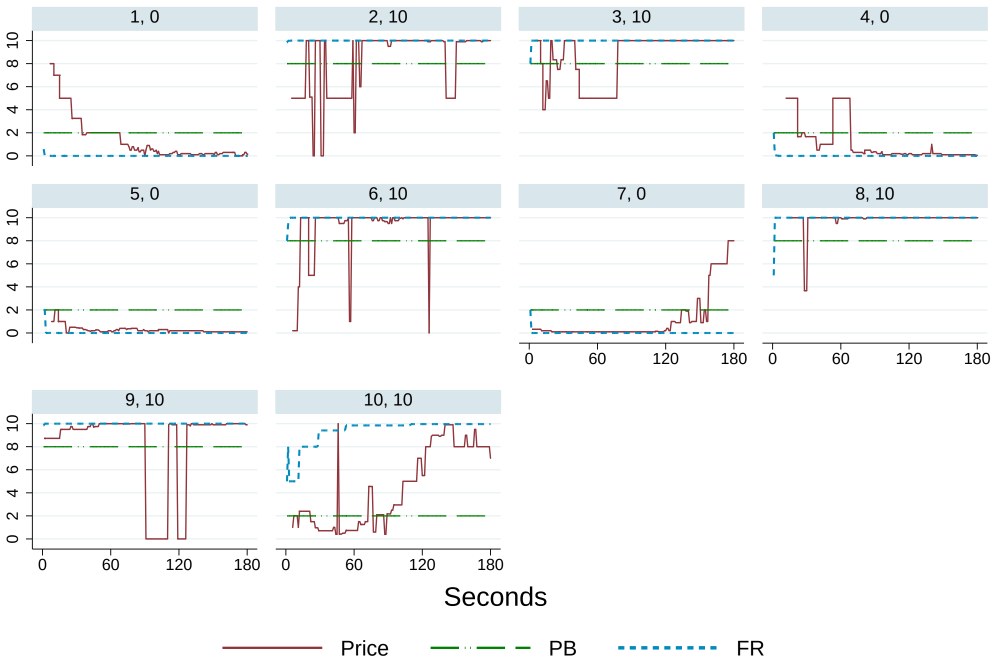


Figure 1.21 Markets Treatment $T_C(0.8,0.8)$ (Group 2).

Chapter 2

Higher-order beliefs and overweighting of public information in a laboratory financial market

Economists have largely studied whether and to what degree prices are able to aggregate the information held by economic agents. The efficient market hypothesis has been the cornerstone of asset-pricing literature, stating that markets are efficiently informational if prices "fully reflect" available information (Fama, 1970). However, the difficulty that prices incorporate all information dispersed in the market has been proven in laboratory experiments (Plott and Sunder, 1988). The aggregation and dissemination of imperfect information depends crucially on market features, such as information distribution or subjects' experience (Sunder, 1995; Plott, 2000).

What could institutions do to create more informational efficient markets? Public announcements from institutions as central banks may help prices to more efficiently incorporate and transmit information and eventually stabilize market behavior. For example, the European Central Bank gives forward guidance providing information about the expected future path of interest rates and about its asset purchase program. However, several authors have casted doubt that more public information is always beneficial.[1] If we focus on financial markets behavior, for example, they are not just affected by agents' beliefs about future asset values, but also by their beliefs about other agents' expectations. Thus public announcements may lead to adverse and unexpected consequences if they are not properly design.

Among the theoretical models devoted to analyze the impact of public information, we should highlight the conclusion of Morris and Shin (2002). In their seminal paper, they model the agents' overreliance on public information in coordination games, inspired by Keynes' beauty contest metaphor. They show that public information has a dual role: it provides information on fundamentals and, at the same time, allows to second guess the other agents' beliefs. Their model poses the problem of managing the release of public information, minimizing its possible adverse effects while preserving

[1] For example Amato et al. (2002), Morris and Shin (2002), Morris and Shin (2005), and Allen et al. (2006) and Kool et al. (2011).

the obvious benefits.

In a broader perspective, Angeletos and Pavan (2007) analyze the *efficient use of information* and *social value of information* in a range of economies with dispersed information, modeling games with strategic complementarity or substitutability. Allen et al. (2006) investigate the overreliance of traders without introducing an explicit coordination motive. Their model provides evidence for the role of higher-order beliefs in an asset-pricing environment. They claim that the beauty contest metaphor is a suitable framework to understand financial markets. Overall, the theoretical literature indicates essentially two main problems when dealing with the social value of public information: (i) the crowding out effect on costly private information[2] and (ii) the overweighting of public information with the corresponding underweighting of private information.

The experimental literature clearly finds the existence of an overweighting effect, at least when the subjects' profit function explicitly includes a coordination incentive within a beauty contest framework (Dale and Morgan, 2012; Baeriswyl and Cornand, 2014; Cornand and Heinemann, 2014; Baeriswyl and Cornand, 2016). Following this line of research, recent studies analyze the reasons behind this phenomenon and methods of relieving this effect. These studies suggest the existence of a detrimental effect of public information on welfare, unless the public signal is sufficiently more precise than private signals. For instance, Baeriswyl and Cornand (2016) conclude that the impact of public information depends more on the signal's precision rather than overreaction to common knowledge. Baeriswyl and Cornand (2014) study two strategies to reduce overweighting: partial publicity and partial transparency and prove that both strategies are equivalent since they introduce the same equal degree of common knowledge in the experiment. However, their efficacy is lower than the theory predicts.

Nevertheless, the experimental literature on financial markets has not been paid much attention to the interplay between private and public information and its potential adverse effect on market performance. The acquisition of private information in markets has been widely studied, analyzing how it affects the benefits of the subjects and the aggregation of information in prices.[3] How public information impacts on prices and other market outcomes is still a controversial issue. In particular, whether there is a distortive impact on market price as a consequence of the agents' overreliance on public information. To the best of our knowledge, we are the first in analyzing the overweighting phenomenon of public information in a laboratory financial market. In

[2]See Colombo and Femminis (2008), Kool et al. (2011), and Colombo et al. (2014) for models with endogenous information acquisition. For example, Colombo et al. (2014) show that public information might partially crowd out the demand for private information and exacerbate overreliance on public announcements.

[3]See, for example, Huber et al. (2011) and Page and Siemroth (2017) and Asparouhova et al. (2017).

the previous chapter, we implement a market with Arrow-Debreu assets and traders have access to costly imperfect private signals about that state. We show that both crowding out effect and overweighting of public information emerge *without necessarily* introducing an explicit coordination motive to the traders, like in the legacy of the papers based on Morris and Shin (2002). Therefore, the overweighting of public information can be found beyond the beauty contest framework.

The present chapter simplifies the design of Chapter 1 by implementing exogenous allocation of the (private and public) information to the subjects. This feature allows us to observe more clearly the impact of public information in the asset market, removing the noise of information acquisition. Moreover, subjects are aware of the distribution of private signals and, therefore, they are aware of the existence of uninformed subjects, and also of an upper and lower bound in the private information possessed by other traders. Essentially, they know the degree of information asymmetry they face in the market. Our simplified setting allows us to study the impact of the market configuration, specifically the proportion of uninformed traders, on the aggregate market behavior.

Our results show that, under some circumstances, the release of a public signal distorts the aggregation of information into prices in such a way that rational expectation equilibrium is not a good predictor for market prices. In particular, the presence of misleading public information might impede the dissemination of private information in the market instead of promoting it. The main contribution of this chapter is to show that: (i) the overweighting phenomenon introduced in the literature can be observed in a more realistic and general setting, (ii) such phenomenon is more empirically relevant than suggested in the literature, (iii) the overweighting of public information is related to its role in shaping the higher-order beliefs of traders as conjectured by Allen et al. (2006).

The reminder chapter is organized as follows. Section 2.1 describes the experimental design. Section 2.2 briefly discusses the theoretical background and a set of hypothesis which are tested in Section 2.3. Section 2.4 presents a qualitative analysis of traders' activity and Section 2.5 explains theoretically the impact of public information on traders' beliefs. Finally, concluding remarks are given in Section 2.6.

2.1 The experimental design

We implement a single-unit double-auction trading mechanism where subjects are allowed to submit bids and asks or directly accept any other subject's offer as long as they have cash or assets (no short sale is allowed). Every bid, ask or transaction concerns only one unit of the asset. The market is open for a known amount of time (3 minutes). Each market is populated by 15 subjects who are endowed with 1000 units of experimental currency (ECU)[4] and 10 single-period life risky assets. Prior to the beginning of each market, the dividend is randomly determined by the experimenter, taking the values $D \in \{0, 10\}$. At the end of the market, the dividend is announced. Subjects are paid the value D for each asset held at the end of the market plus the cash held minus a fixed amount of 1000 ECU, which is the loan for the initial endowment.

Subjects receive imperfect signals about D at the beginning of each market. There are three kinds of signals that can be observed by the subjects:[5] i) *private signals* that are independent realizations conditional on the dividend value, ii) a *public signal* that is identical for all subjects and common knowledge, and iii) a *common signal* that is identical for all subjects but no common knowledge. The precision of every private signal is $p = 0.8$ and $P = 0.8$ in case of the public and common signal. The quality of signals, p and P, as well as the number of signals observed by each subject, are common knowledge. Each subject receives always two private signals that might take the value 10 or 0 and they are positively correlated with the dividend. Thus, if a subject observes a private signal equal to 10 (0), she can infer that the dividend is expected to be 10 (0) with probability $p = 0.8$ and 0 (10) with probability $q = 0.2$. Additionally, an identical (public or common) signal might be released to all subjects depending on the treatment. Analogously to the private signals, if this signal is equal to 10 (0), subjects can infer that the dividend at the end of the market will be 10 (0) with probability $P = 0.8$ and 0 (10) with probability $Q = 0.2$.

Signals		Characteristics
private signals		randomly generated for every subject
an identical signal	public	identical for all subjects and common knowledge
	common	identical for all subjects and non-common knowledge

Table 2.1 Characteristics of signals.

According to the characteristics of the information possessed by the subjects, we implement three treatments (Table 2.2): (i) TB where each subject observes only two private signals.[6] (ii) TP where each subject observes two private signals and an identical public signal. (iii) TC where each subject observes two private signals and an identical common signal. Hereafter we will refer to public and common signal as *released signal* when it is not relevant the particular nature of the signal.

[4]Earnings, as well as prices and dividends, during the experimental sessions are expressed in experimental currency units (ECU) and converted into Euro at the end of the session. One experimental currency unit is equivalent to 2 cents of Euro.

[5]See Table 2.1 for a description of the characteristics of the signals.

[6]In this treatment, it is present unbiased public information since all subjects are informed that the two states of the world are equally likely.

We can classify subjects according their private information from the beginning. Subjects are classified as: (i) *informed traders* (inf), who receive two correct private signals; (ii) *uninformed traders* (uninf), who receive two opposed signals; and (iii) *misinformed traders* (misinf), who receive two incorrect private signals.[7]

Treatment	Released signal	Groups	Markets
TB	-	1	10
TP	public	2	20
TC	common	2	20

Table 2.2 Experimental design.

The implementation of such an information structure allows us to disentangle the dual role of the public information in the determination of the subjects' expectations. Following Allen et al. (2006), public information may have an excess impact on prices when higher-order beliefs play a role in the determination of prices. A public signal provides information on the dividend and information on the other subjects' beliefs. Therefore, a public signal has an impact on the formation of, at least, second-order expectations of subjects. Conversely, a common signal is just informative on the value of the dividend without providing information on the other subjects' beliefs. Note that the first-order beliefs of subjects are the same independently of whether the signal is public or common. The second-order beliefs are, instead, different depending on the nature of the signal.

The comparison between treatments TP and TC allows us to evaluate the additional impact of the common knowledge on the aggregation of information into prices. Namely, we can test whether the common knowledge of the public signal is the main responsible for the distortion effect of public information as conjectured by theoretical literature (Allen et al., 2006; Morris and Shin, 2008). To keep both treatments as similar as possible, we implement the same realizations of dividend, private signals and released signal in treatments TP and TC.[8]

The experimental sessions are conducted in the LEE (*Laboratori d'Economia Experimental*) at University Jaume I of Castellón. The experiment is programmed using the Z-Tree software (Fischbacher, 2007). A total of 75 undergraduate students in Economics, Finance and Business Administration in at least their second year of study are recruited. Each subject can only participate in one session that consists of 10 markets. When subjects arrive at the laboratory the instructions were distributed

[7] One needs to bear in mind that there are not actually privately uninformed traders in TC treatment.

[8] This experimental condition has been used in other studies like Huber et al. (2008). Figures 2.19 and 2.20 show the market configuration given the private signals allocation in treatments TP and TC.

and explained aloud. This was followed by one practice auction period for subjects to get familiar with the software and the trading mechanism. Subject's final payoffs is computed as the accumulated profit in all markets and paid cash at the end of the session. The average payoff was about 15 Euro and each session last around 60 minutes.[9]

2.2 Theoretical background and working hypotheses

2.2.1 Theoretical background

Grossman (1976) postulates that rational agents do not trade when they face the same state of the world and information is immediately incorporated into the market price. To resolve this paradox, Grossman and Stiglitz (1980) introduce an exogenous noise, so that market price cannot be fully informative. Thus, an equilibrium might be possible in both the asset and the information market. Milgrom and Stokey (1982) argue that no-trade equilibrium occurs when the motivation for trading is only information-related.

Under risk neutrality, there are two equilibria in our experimental setting: the no-trade equilibrium and the fully revealing equilibrium (FRE). Applied to our experimental setting, the no-trade theorem implies that uninformed traders are better doing nothing rather than trading with informed traders. Likewise, informed traders should also not trade if they have the perception of even a tiny cost related to their trading activity, such as the effort of managing offers or the time involved in record keeping. To characterize the other equilibrium, we can rest on the notion of the fully revealing equilibrium, which implies that prices convey all private information available in the market. Some experiments have shown that the FRE might be a reasonable predictor to describe price behavior in laboratory asset markets (Sunder, 1992). The expected price conditional on all information available in the market can be computed as:[10]

$$FR = 10 \cdot Pr(D = 10|I, S) + 0 \cdot Pr(D = 0|I, S) = 10 \left[1 + \left(\frac{Q}{P}\right)^S \left(\frac{q}{p}\right)^H\right]^{-1}, \quad (2.1)$$

where I denotes the market private information set, being $I = \{s_1, s_2..., s_j, ...s_{30}\}$.[11] The variable s_j takes value -1 when a signal predicts a dividend 0 and 1 when it predicts dividend 10. Finally, $H = \sum_{j=1}^{30} s_j$ represents the quantity of net private signals suggesting that the asset will pay a dividend 10. Likewise, S corresponds to the public or common signal, taking value 1 or -1 depending on whether the

[9] Note that subjects can make losses. To avoid some of the problems associated with subjects making real losses in experiments, we endow all subjects with a participation show-up fee of 3 Euro, which could be used to offset losses.

[10] See Chapter 1 for the details of the calculation of the eq. (2.1).

[11] s_j refers to the signal number j. The total number of private signals in each market is 30 since there are 15 traders and each trader gets two private signals.

signal predicts a dividend 10 or 0, respectively. We assign the value $S = 0$ in the baseline treatment. At the price level FR, a risk-neutral trader is indifferent between holding an asset or trading it. The empirical relevant question is under which conditions the market acts as an efficient device in disseminating the dispersed information and, therefore, if the FRE represents a good description of the market outcome.

Analogously to eq. (2.1), let us define the public information benchmark (PB) as the expected price conditional just on the value of the public signal:

$$PB = 10 \cdot Pr(D = 10|\hat{S}) + 0 \cdot Pr(D = 0|\hat{S}) = 10 \left[1 + \left(\frac{Q}{P} \right)^{\hat{S}} \right]^{-1}, \qquad (2.2)$$

where $\hat{S}$ denotes the realization of the public signal in TP. $\hat{S} = 0$ for the other treatments, so that $PB = 5$. It should be noticed that the PB, contrary to the FR, is not an equilibrium. We use PB as a reference level to evaluate how biased are market prices with respect to the public signal.

Note that the two benchmarks described in eqs. (2.1) and (2.2) take into account the presence of the public signal. The main difference is that, while all signals are weighted according to their respective precision in the FRE, the PB considers only the public information. In other words, it assigns a zero weight to the private information. If PB turns out to be a better description of the prices than the FR, it means that public information is overweighted with respect to its relative precision. Thus, evaluating the distance between prices and the two proposed benchmarks allow us to study how information is aggregated into market prices and measure the extent of the overweighting of public information. Contrary to coordination models where the overweighting is a rational expectation equilibrium, the overweighting phenomenon in our framework is an out-of-equilibrium phenomenon.

2.2.2 Working hypotheses

We design the experiment to study the impact of public information in market outcomes. The theoretical literature predicts that prices are able to aggregate dispersed information in the market. Therefore, if the information available in the market allows to discover the state of the world and prices efficiently aggregate that information, prices should converge to the dividend D.

We define the potential of the market to discover the dividend value as *market informativeness* (MI). This is computed as the normalized absolute difference between the prediction of the FRE and the dividend value for each one of the markets:[12]

$$MI = \frac{|FR - D|}{10} \ . \tag{2.3}$$

Using the FR as a reference level to evaluate market informativeness implies that traders correctly account for all available information. Although it might be a strong behavioral assumption, MI can be thought as an upper limit for market informativeness. It is noteworthy that, at the level of precision of the private signals and considering the total number of signals, the information present in our laboratory markets is always sufficient to identify the value of the dividend at any reasonable confidence level in all markets. Indeed, the MI averaged over markets is almost zero ($MI < 0.0001$) in all treatments, even when the released signal points to the incorrect value of the dividend. Note that the released signal has just a marginal impact on market informativeness independently of its realization.[13]

Thus, in our experiment, differences in price convergence to the dividend cannot be due to differences in the quantity of information present in the market. Instead, they should be related to how traders' behavior changes depending on the nature of the information at their disposal. According to the Efficient Market Hypothesis in its strong form and considering the level of market informativeness, we should not observe any significant difference in the price informativeness across treatments. Even more, we should observe that traders always identify the true state of the world independently of the particular realization of the public or common signal.

Hypothesis 1. *Prices aggregate dispersed information in the market. Prices converge to the dividend value independently of the realization of the released signal.*

The following two hypotheses describe the relation between information and traders' behavior. The fully revealing equilibrium provides no allocation prediction for assets holdings, since all traders have the same reservation price (Copeland and Friedman, 1992). Under FRE, we expect to observe no systematical differences in the assets held by the different types of traders at the end of the market.

Hypothesis 2. *Assets are not systematically held by one type of traders.*

According to the fully revealing equilibrium, prices reveal all information available in the market and differences in profits are absent. Some experimental studies have found evidence of supporting the FRE predictions when asset prices correctly reveal

[12]We omit the index to indicate the particular market for notational convenience. The index MI is normalized to be bounded to 1.

[13]Using eq. (2.1), it is easy to show theoretically that, at the chosen level of precision of a private signal, the contribution to FRE of introducing an additional signal is negligible regardless of its realization.

information in a competitive market equilibrium (Sunder, 1992; Plott and Sunder, 1988). However, other contributions find that informed traders make higher profits than uninformed traders when information is not fully disseminated and prices are not fully informative since less informed traders are not able to extract information from trading activity (Copeland and Friedman, 1992; Ackert et al., 2002).

Hypothesis 3. *Profits of informed traders are indistinguishable from other traders.*

In contrast to the Hypothesis 1, there is a growing strand of the literature concerned on the excess the impact of public information in pricing assets (Morris and Shin, 2002; Allen et al., 2006). The release of a public signal might prevent the efficient aggregation of information. Several experimental contributions have found that traders have an excess of reliance on public information in a coordination environment.[14] We therefore introduce an alternative hypothesis:

Alternative Hypothesis 1. *Prices overweight public information and converge to the public signal independently of its realization.*

2.3 Results

Figures from 2.13 through 2.17 included in the Appendix display the time series of prices for each market and treatment. It is apparent that the no-trade equilibrium and its prediction of absence of market activity does not constitute a good description of our experiment. Traders fail to infer the implications of asymmetric information and, therefore, they trade when informational incentives for exchanging assets are absent.

In the following, we analyze the effects of releasing a public signal on market performance, comparing them with the common information treatment. In particular, we consider the following measures: price informativeness, stock allocation and profit distribution.

2.3.1 Price informativeness

This subsection presents the results of the impact of releasing a public signal on the market performance in aggregating the information into prices. Essentially, we analyze how the information disseminated among traders (market informativeness) is aggregated into prices (price informativeness). Thus price informativeness measures *what traders have done* with the information at their disposal with respect to *what they could have done.* As a simple proxy for price informativeness, we compute the

[14] Dale and Morgan (2012), Baeriswyl and Cornand (2014), and Cornand and Heinemann (2014).

absolute distance of prices (PR_t) from FR averaged across transactions recorded in the last minute of the market:[15]

$$PI = \frac{1}{T} \sum_{t=1}^{A} \frac{|FR - PR_t|}{10} \,, \tag{2.4}$$

where the subscript t denotes every single transaction and T is the number of transactions during the last minute of a given market.[16] Considering only the last minute gives the FRE its "best shot" (Plott and Sunder, 1988), making sure that traders have been able to aggregate all information present in the market.

In order to disentangle the effect of the public signal on the aggregation of information into prices, we consider also the public information benchmark. We test whether prices converge to the PB instead of converging to FR. Thus, similarly to PI, we introduce an indicator to measure how market prices are solely described by the public information:[17]

$$PP = \frac{1}{T} \sum_{t=1}^{T} \frac{|PB - PR_t|}{10} \,. \tag{2.5}$$

The indicators PI and PP allow us to easily assess how informative are market prices. In Table 2.3, one can find the summary of the predicted values of the indicators according to the FRE and the experimental data. If market prices are fully informative and they reflect correctly all available information, the PI indicator is close to zero in all treatments since $PR_t \approx FR \equiv D$. On the other hand, the PP indicator is close to 0.2 or 0.8 in TP depending on whether the public signal ends up being correct or incorrect, respectively. Differently, the PP indicator is close to 0.5 in TB and TC.

Let us focus first on the aggregate data (in bold), where all markets of every treatment are considered together. The median values of the PI and PP indicators for TP and TC follow closely the prediction of the FRE, which is also clearly visible in Figure 2.1. Indeed, the median values of PI are close to zero in the case of releasing a public signal whereas the median values of PP centered in 0.2. By contrast, outcomes are not in line with the predictions in treatment TB, where prices exhibit a much lower level of informativeness than predicted by FRE.

Our results allow to precisely quantify the magnitude of the increase in price informativeness. In particular, we can answer to the questions: how good is the prediction of fully informative prices? Can we observe systematic deviations from FRE? The

[15] We have normalized the distance PI in eq. (2.4) to be bounded to 1. Note that, in principle, we should introduce an index indicating the particular market and treatment. However, we omit it for notational convenience. The same holds for eq. (2.5).

[16] Recall that the information is exogenously allocated at the beginning of each market; so that, FR is constant overtime.

[17] In eq. (2.5), the transactions are those recorded in the last minute of the market. Likewise to the FR, the value of the PB is constant in a given market.

		PI indicator			PP indicator		
Treatment	Signal	Prediction	Median	SD	Prediction	Median	SD
TB		**0**	**0.14**	**0.17**	**0.50**	**0.36**	**0.10**
TP		**0**	**0.01**	**0.28**	**0.20**	**0.19**	**0.14**
	correct	0	0.01	0.07	0.20	0.19	0.30
	incorrect	0	0.64	0.32	0.80	0.16	0.30
TC		**0**	**0.02**	**0.15**	**0.50**	**0.48**	**0.13**
	correct	0	0.01	0.04	0.50	0.49	0.02
	incorrect	0	0.36	0.14	0.50	0.14	0.12

Table 2.3 Theoretical predictions and summary statistics of the observed values for PI and PP indicators across markets for each treatment.

comparison of the relative performance of the two indicators in describing the market prices can help us to evaluate whether deviations from full informative prices are *systematically favoring public information*, as suggested by several theoretical models in the literature (e.g. Allen et al., 2006). In particular, when the PP is significantly lower than the PI means that the public information benchmark better accounts for price behavior than the FRE. Considering that a public signal alone contributes just marginally to the market informativeness, such scenario would indicate that prices weight public information beyond its informational content. Therefore, comparing how FR and PB account for market prices allows to precisely measure whether and under which conditions we can observe the phenomenon of overweighting of public information in our laboratory financial market. Figure 2.1 and Table 2.4 present and compare the values of the PI and PP indicators across markets per treatment. One can see that releasing an identical signal significantly increases price informativeness with respect to the TB. This improvement does not depend on the nature of the released signal, public or common, since there is not a significant difference when comparing TP and TC treatments. Hypothesis 1 cannot be rejected when we carry out the aggregate analysis of markets. The presence of the public signal converts the limited informative prices of the TB into fully informative prices, in aggregate terms.

Treatments	Signal	PI p-value	$Var[PI]$ p-value
TB vs. TP		0.02	0.03
TB vs. TC		0.02	0.40
TP vs. TC		0.68	0.02

Table 2.4 Mann-Whitney test to compare values of PI indicator and Levene's test to compare its dispersion among treatments.

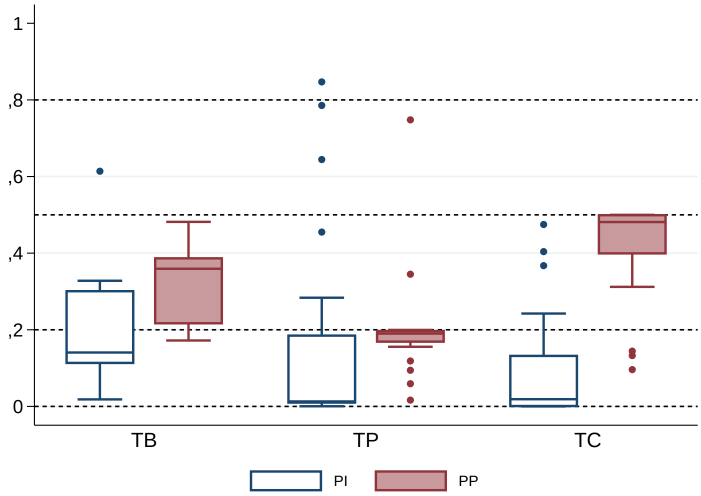


Figure 2.1 Values of the PI indicator (empty boxes) and the PP indicator (filled boxes) across markets for each treatment. Theoretical predictions of $PI = 0$, $PP = \{0.2, 0.8\}$ for treatment TP and $PP = 0.5$ for treatments TB and TC are represented by dashed lines.

Result 1. *Price informativeness significantly increases when a public (or common) signal is released into the market, even though the released signal just marginally contributes to the market informativeness.*

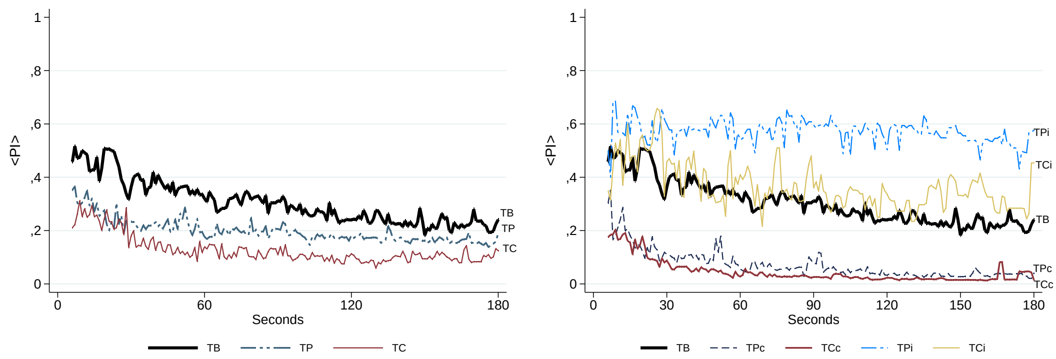
Although price informativeness significantly improves when releasing a public signal at an aggregate level, we observe various markets where the price informativeness is markedly lower than the median value of the treatment TB (Figure 2.1). It is apparent a much wider level of fluctuations in the values of PI when we introduce a public signal. A simple non-parametric variance-ratio test indicates that the dispersion of PI in treatment TP is significantly higher than in the treatment TB (see Table 2.4).

Our results point out that releasing a public signal improves price informativeness, but it also increases its dispersion. Why do we observe such higher level of dispersion? A close inspection to desaggregated information in Table 2.3 shows that median PI and PP indicators are very close to the theoretical prediction when the signal is correct. This result contrasts sharply with markets where the signal is incorrect. In those cases, deviations from the theoretical prediction are much larger than the deviation of TB.

Some insight into the information-aggregation process can be gain by analyzing the price informativeness dynamics. Instead of averaging across transactions in the last minute of the market, we consider the evolution of price informativeness as the absolute distance between the market price and FR in every second.

Figure 2.2(a) plots the time evolution of mean price informativeness $< PI >$ across markets for every treatment.[18] One can see that prices show a tendency towards the equilibrium, although on the aggregate level it is never reached. Consistently with

[18]Note that $< PI >$ does not depend on the realization of the dividend.



(a) (b)

Figure 2.2 Mean price informativeness across markets: Baseline treatment (TB), treatment with public signal (TP), treatment with common signal (TC). Additionally, Figure (b) differentiates between markets with a correct public signal (TPc), an incorrect public signal (TPi), a correct common signal (TCc) and an incorrect common signal (TCi).

Figure 2.1, prices do not always fully reveal all information present in the market. Figure 2.2(b) presents a more detailed analysis, differentiating by the realization of the signal whether the prediction of the public or common signal is correct (TPc and TCc) or incorrect (TPi and TCi). Looking again at Hypothesis 1, we can reject it in the market in favor of the alternative when the released signal is incorrect. We observe that prices converge to the equilibrium when a correct signal is released in the market independent of whether the released signal is public or common. On the contrary, an incorrect signal can lead to a failure of the aggregation of information into prices, since prices do not converge to the FR. Moreover, the price distortion of an incorrect public signal is clearly more severe than an incorrect common signal. Whereas the mean price informativeness in treatments TB and TCi are almost equal, price informativeness is lower in TPi than TB. These findings speak in favor of the Alternative Hypothesis 1 that prices overweight public information, at least then the public signal is incorrect.

In view of those differences and considering the fact that the information distribution in markets of both treatments is exactly the same, we came to believe that the common knowledge of the public signal is a relevant factor responsible for price distortion. The market follows two different regimes of information aggregation depending on the realization of the public signal:

i) When the released signal is correct, the aggregation of information into prices can be meaningfully described by the FRE: the correct public signal triggers a more efficient aggregation of private information into prices, turning them into a system of fully informative prices.

ii) The second regime is characterized by the incorrect public signal, which almost entirely determines the price level.

In the first regime, public information accumulates "over" private information in coordinating prices. In the second regime, instead, the disclosure of an incorrect public signal drives market prices far from the dividend in most of the cases; even when private information is sufficient, if correctly aggregated, to offset an incorrect public signal. Our markets, which should not be affected by the public signal according to the EMH, turn out to be highly sensitive to the public information, magnifying its noise to such an extent that is determinant in the behavior of market prices.

Result 2. *Public information improves price convergence to the fully revealing equilibrium when it is correct. However, an incorrect public signal (might) pushes prices away from fundamental values. The common knowledge is determinant feature for the emergence of the overweighting phenomenon.*

Our findings are consistent with the conclusions obtained in Chapter 1, identifying the dual role of public information in a laboratory financial market. Nevertheless, we do not find overweighting of public information on aggregate. These differences in results are in line with Sunder (1992)'s proposition about the effect of knowing the distribution of information upon market performance. It is well established in the experimental finance literature that the knowledge of the distribution of information among traders facilitates the aggregation of information into prices. We will see that this general principle holds also for our experiment. Whereas in our experimental design the distribution of information and then the proportion of informed traders is known, this is not the case in the framework of previous chapter.

2.3.2 Stock allocation

Thus far, we have observed that prices might be distorted by the presence of an incorrect public signal. Bearing in mind that the fully revealing equilibrium makes no prediction about the allocation of assets among traders, what about stock allocation in the laboratory? Can we find different patterns depending on the released information to the market?

We compute the ratio of the total number of assets (a_i) held by each type of trader $i \in \{inf, uninf, misinf\}$ and the proportion of that type of traders in the population (λ_i).[19]

$$z_i = \frac{a_i}{\lambda_i} \ . \tag{2.6}$$

From eq. (2.6), three cases may arise: (i) $z_i > 1$ if traders of type i hold more than the endowed assets at the end of the market, i.e. they systematically buy assets,

[19] We omit the market index for notational convenience. $\sum \lambda_i = 1$ for $i \in \{inf, uninf, misinf\}$. For example, λ_{inf} is computed as the number of informed traders in a given market divided by market population (15 traders).

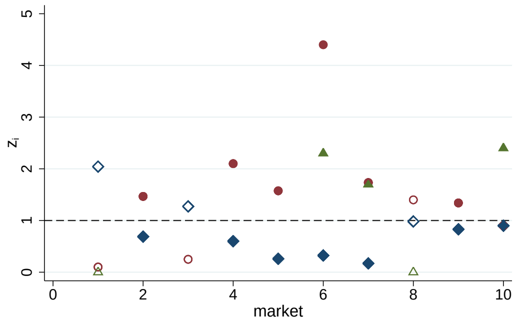
(ii) $z_i < 1$ if traders of type i hold less assets than their initial endowment, i.e. traders i systematically sell their assets[20] and (iii) $z_i = 1$ if traders of type i do not exhibit a systematic trading pattern.

Figure 2.3 reports the ratio in eq. (2.6) providing evidence that informed traders tend to sell assets when the dividend is 0 (filled circles) and buy when dividend is 10 (empty circles). Whereas uninformed and misinformed traders exhibit the opposite behavior. Therefore, we can reject Hypothesis 2 that there is no systematically stock allocation among traders. For the sake of clarity, we look at markets where that signal is incorrect (highlighted by vertical lines). The fact that markets with an incorrect released signal are indistinguishable from those where the released signal is correct suggests that an incorrect public signal has no impact on stock allocation.

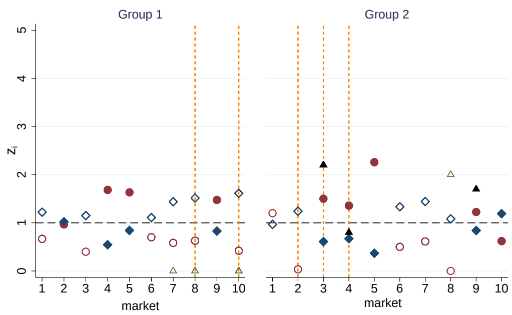
Table 2.5 yields more insights into the influence of public information on stock allocation. It shows a Spearman's correlation between traders' expected dividend[21] and the number of assets held at the end of the market. The results suggest that those traders with the highest expected dividend tend to hold more stocks. This tendency is stronger in markets with an incorrect public or common signal. We can conclude that releasing an identical signal might increase the differences between types of traders. The basic intuition behind this result is the fact that a correct public signal contributes to the aggregation of information into prices, so differences in traders expectations become less relevant and they hold a similar number of assets. When the public signal is incorrect, traders with the highest expected dividend systematically hold more assets the other traders.

[20] More specifically, $z_i = 0$ when traders of type i sell all of their assets.

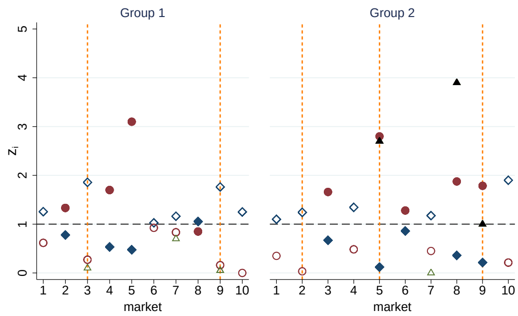
[21] Traders' expected dividend is computed by Bayesian inference like eq.(2.1). However, x_i denotes the net number of private signals predicting dividend 10 assigned to the trader i type: $D_{x_i,S} = 10\left[1 + \left(\frac{q}{p}\right)^{x_i} \left(\frac{Q}{P}\right)^{S}\right]^{-1}$.



(a) TB



(b) TP



(c) TC

Figure 2.3 Ratio of the stock held by each type of trader from eq. (2.6): informed traders (diamonds), uninformed traders (circles) and misinformed traders (triangles). Filled markers represent markets where dividend is 0 whereas empty markers represent markets with dividend 10. Vertical lines point out markets where the public or common signal is incorrect.

Treatment	TB	TP		TC	
Signal released	-	correct	incorrect	correct	incorrect
Correlation	0.33	0.21	0.43	0.17	0.71

Table 2.5 Spearman's correlation coefficient between traders' expected dividend and number of assets held at the end of the trading period.

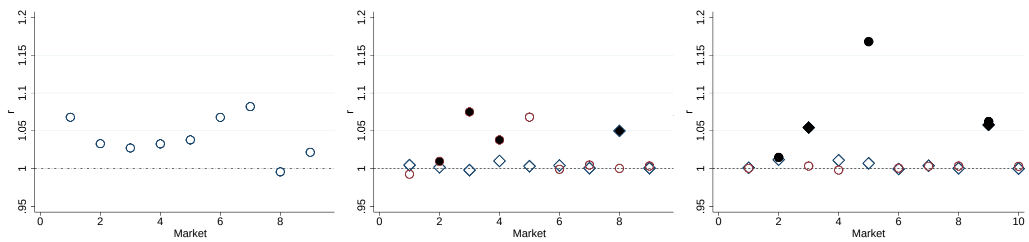
Result 3. *The release of a public signal, when correct, slightly affect stock allocation. However, an incorrect signal increases correlation between expectations and the number of stocks held at the end of the market.*

2.3.3 Profits

How does the release of a public signal affect the profit distribution among traders? Figure 2.4 shows the ratio of average profits of informed over uninformed traders,[22] $r = \frac{<\pi_{inf}>}{<\pi_{uninf}>}$. We observe that informed traders obtain greater profits than uninformed traders in most markets in treatment TB. Markets with larger profit asymmetries are

[22]Due to the few number of traders with two incorrect private signals, we prefer to avoid the detailed analysis of the relative profit of those traders. The number of observations is too few to compute a reliable statistics.

those with a lower proportion of informed traders (markets 1 and 7 in Figure 2.18). One can see that releasing a public signal reduces these differences if the prediction is correct. The reason lies in a reduction of the advantage of informed traders when a correct public signal is revealed and, then, information asymmetry is reduced. Conversely, when the public signal is incorrect, prices do not disseminate information. As a consequence, the information asymmetry persists or even is amplified and mirrors into an asymmetry in the distribution of profit at advantage of informed traders.[23] In those markets where the released signal is incorrect, profits differences are similar to the treatment TB.



(a) TB (b) TP (c) TC

Figure 2.4 Average profits of informed over uninformed traders by markets and treatments. The two groups are represented separately and markets with an incorrect public (common) signal are indicated in black.

To delve deeper into the consequences of the presence of an incorrect released signal for traders' profits, Table 2.6 reports the results of an OLS regression with robust errors by treatment. Our baseline treatment is reported in the first column followed by three additional specifications for treatments TP and TC. The first specification (TPc and TCc) considers only those markets where the released signal is correct. The second specification (TPi and TCi) considers those markets where the released signal is incorrect. Last specification represents all markets although controlling between correct and incorrect signal, including an interaction among dummy variables: the signal released and the type of traders. The variable *Signal* takes value 1 when the released signal's prediction is incorrect (*ISignal*) and 0 when correct (*CSignal*) and variables that identify the net information of traders (*Uninformed* and *Misinformed*).

As expected, traders always make more profits when the dividend is 10 and that impact is similar in the three treatments.[24] Moreover, both *Uninformed* and *Misinformed* traders make less profits than informed traders independently of the treatment. When comparing markets with a correct public signal (TPc) and treatment TB, uninformed and misinformed traders still make less profits than informed traders, although with reduced coefficients and significance values. By contrast, an incorrect

[23]The above results are also link to the distribution of information across traders in the market. When the common or public signal is incorrect and the proportion of informed traders is nearly 80% (Figures 2.19 and 2.20 in Appendix), informed traders do not outperform uninformed traders since prices reveal their information.

[24]*Dividend* is a dummy variable that takes value 1 if dividend is 10 and 0, otherwise.

public signal (TPi) accentuates those differences. The profits of uninformed traders and misinformed traders significantly fall in comparison with informed traders' profits. The third specification (PS and CS) shows that informed traders make significantly more profits in markets where the released signal is incorrect than when it correctly predicts the dividend. Uninformed and misinformed traders make significantly less profits when the public signal is incorrect than when it is correct.[25]

Overall, a correct released signal improves predictability of the fully revealing equilibrium whereas an incorrect released signal diverts experimental outcomes from the theoretical predictions. In particular, profit differences among informed and other traders are reduced when the released signal predicts the dividend, but they rise when the released signal ends up being incorrect independently of the nature of the released signal. Therefore, consequences of overweighting of misleading public information go beyond of market price efficiency; the overweighting of misleading public information entails emphasizing profits asymmetry. We can safely reject the strong prediction of fully revealing equilibrium for the three treatments (Hypothesis 3).

Result 4. *Informed traders make higher profits than uninformed traders. Profits asymmetry is more pronounced in presence of an incorrect released signal, while a correct released signal reduces profit asymmetries.*

It is interesting to think about the link between profit asymmetry and price distortions. We have seen in section 2.3.1 that the impact of an incorrect released signal differs depending on its nature. An incorrect public signal has a larger impact on price informativeness than an incorrect common signal. Nevertheless, this difference is not reflected in the profits distribution, which is not affected by the nature of the released signal. Indeed, we have just seen that the impact of a correct and an incorrect released signal is very similar in both treatments.

2.4 Empirical analysis of the aggregation of information into prices

From the previous empirical analysis, it is clear that, when correct, a public signal helps traders to discover the dividend value. Conversely, an incorrect public signal distorts the price aggregation process. In order to identify the root cause of the price distortion, this section provides a detailed description of traders' behavior in markets where the public signal is incorrect. The analysis of traders' activity, namely offers and transactions, might shed some light on how the presence of a public signal distorts the price formation process towards the public signal itself.

[25]Interaction variables *CSignal*Uninformed* and *ISignal*Uninformed* or *CSignal*Misinformed* and *ISignal*Misinformed* are not equal at a 10% and 5% level of significance, respectively.

	Dependent variable: Profits						
	TB		**TP**			**TC**	
		TPc	TPi	PS	TCc	TCi	CS
Constant	13.301***	2.096	25.507**	2.515	1.092	28.235***	1.414
	(3.15)	(1.64)	(10.05)	(2.25)	(0.85)	(6.59)	(1.39)
Dividend	100.704***	100.019***	96.781***	99.233***	100.069***	97.576***	99.464***
	(7.94)	(2.42)	(13.93)	(3.80)	(0.98)	(9.28)	(2.34)
Trader							
Uninformed	−36.043***	−6.424*	−47.552***		−3.216***	−62.893***	
	(10.02)	(3.32)	(14.85)		(1.20)	(9.99)	
Misinformed	−67.302***	−8.042*	−96.564***		−10.238**	−72.706***	
	(18.14)	(4.74)	(33.43)		(5.06)	(16.78)	
Signal * trader							
CSignal * Uninformed				−6.428*			−3.218***
				(3.33)			(1.21)
CSignal * Misinformed				−7.937			−10.157*
				(4.98)			(5.23)
ISignal * Informed				21.488**			25.662***
				(9.47)			(4.86)
ISignal * Uninformed				−26.030**			−37.205***
				(11.18)			(8.70)
ISignal * Misinformed				−74.798**			−46.830***
				(32.26)			(16.04)
N	150	225	75	300	225	75	300
R^2	0.565	0.895	0.469	0.699	0.981	0.721	0.882

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 2.6 OLS regression results with robust errors for profits of each type of trader (informed, uninformed and missinformed) and the realization of the released signal (correct and incorrect).

Our empirical analysis of the trading activity points towards a simple behavioral rule: traders act on their own information to maximize their profits and adjust their offers to the market conditions. In order to account for what our analysis suggests, we have first to assume a certain degree of bounded rationality of traders to avoid the consequence of no activity in the market due to the "no trade" theorem. By bounded rationality, we mean that traders just partially consider the consequences of the asymmetric informational environment and the strategic implications of their actions.

A trader try to maximize his expected profit submitting bids or asks *in accordance with* his expected dividend, i.e. buying at a "low" price or selling at a "high" price depending on his information. Inspired by Plott and Sunder (1988), an offer in accordance with proposer's information is a bid when his signals indicate dividend

10 or an ask when his signals indicate dividend 0.[26] Besides the high expected profit that they provide to the proposer, those offers carry low informational content since they just partially reveal to the market the information possessed by the proposer. If those offers are accepted, the proposer continues to submit offers at a similar price. In case those offers are not accepted, the proposer adjusts his offers towards his expected dividend. He increases the chances of acceptance while reduces his expected profit and contemporaneously reveals information on his private signals to the other traders through his trading activity (bids and asks). The crucial point of this adjustment process is at what "market price" converges. We will see that the public signal is the main determinant of the market price, i.e. the price level toward the adjustment process settles down. In this section, we empirically show that our explanation for the market dynamics is plausible, illustrating the empirical facts that lead us to formulate this simple and intuitive behavioral characterization of the activity of traders. In Section 2.5, we formalize our arguments within a belief theoretical model.

In order to classify the offers, we fix a threshold τ as a reference for differentiating "low" and "high" prices and expected dividends. Given that our aim is to identify differences in traders behavior, we fix τ equal to the middle of the range of prices $PR \in [0, 10]$, i.e. $\tau = 5$. Therefore, the value of prices, offers and dividends is "high" when they are above τ, and "low" when they are below tau. Furthermore, according to the informational content, we define two categories of offers:

(i) *Lowly informative* offers (LI) are asks above τ or bids below τ. Those offers reveal a relatively low informational content on the signals of the proposer.

(ii) *Highly informative* offers (HI) are asks below τ or bids above τ. Those offers reveal a relatively high informational content on the signals of the proposer.

In the following, experimental outcomes are reviewed by treatment. We start analyzing offers in accordance with informed and uninformed traders' information.[27] Afterwards, we analyze the common information treatment. Comparing both treatments allows us to disentangle the effect of the common knowledge nature of the public signal on the trading behavior of the traders. Finally, we examine the offers that are not in accordance with proposers' information.

[26]Bearing in mind that the asset dividend can only take two values, we find reasonable to assume that a trader with a high expected dividend can infer that the dividend is 10, whereas a low expected dividend indicates dividend 0.

[27]Misinformed traders are excluded from the analysis. Since they are too few and even absent in some markets, their trading activity does not have a significant impact on the determination of the prices. In median terms across markets, they submit the 3.4% of total offers and they account for 4.6% of total transactions in treatment TP. Similarly, they submit 4.1% and 4.2% of offers and transactions, respectively, in treatment TC. Nevertheless, their existence is a consequence of the fact that signals are noisy.

2.4.1 Public information treatment (TP)

The median number of offers and transactions in accordance with proposers' expected dividend across markets are shown in Figure 2.5 (left y-axis). The right y-axis represents the mean absolute distance between the public signal and prices.[28] Thus diamonds indicate how biased is every category of offers and transactions towards public information. As we observe in Figure 2.5, informed traders essentially submit LI offers, which provide high expected profits and 50% are accepted.[29] They can buy cheap or sell dear depending on the value of the dividend. So, informed traders do not further adjust their offers and we observe fewer HI offers. Note that a double auction design constraints subsequent asks to be lower and subsequent bids to be higher with respect to the current offers. The flow of information in a double auction does seem to make the presence of LI and HI bids or asks at the same time unfeasible. For example, if the first asks and transactions have occurred at a high price (LI), then the next asks will be at high price too. No trader will submit asks at a low price (HI) when there are traders willing to accept more expensive offers.

In our simple behavioral framework, uninformed traders have the incentive to sell when informed traders want to buy, and vice versa. Looking at the case of uninformed traders in Figure 2.5,[30] uninformed traders submit a number of LI offers of similar magnitude as the informed traders. This supports our starting intuition that traders tend to make use of their information selling dear and buying cheap in order to maximize their profit based on their private information, independently of their type. Contrary to LI offers of informed traders, only the 23% of the LI offers are accepted. Uninformed traders have to adjust their strategy by submitting offers closer to their expected dividend, which coincides with the public benchmark, reducing their expected profits and increasing the probability of acceptance. The HI offers are, in fact, much more numerous and they are accepted at a rate of 59%. Doing so, the uninformed traders do not reveal their information; it is, in fact, already publicly available. All traders already know the information available to the uninformed traders, which is the public signal. Moreover, the uninformed traders do not incur in the hidden cost of revealing information. Note that, the mean absolute distance between HI offers of uninformed traders and the incorrect public signal (3.2) is smaller than LI offers and that signal (7.9). Thus, the activity of both type of traders, informed and uninformed, pushes prices towards the incorrect public signal instead of the dividend. At the end of this adjustment process, public information is overweighted when aggregated into

[28]Since we study markets where the public or common signal predicts the incorrect state of the world, a lower distance between prices and that signal directly implies a larger distance between prices and the dividend value.

[29]The acceptance rate is computed as the median number of transactions over the median number of offers.

[30]Note that when the public signal is incorrect, the expected dividend of uninformed traders' offers is "opposite" to the one of the informed traders. If the expected dividend of informed traders is high ($D_{inf} > \tau$), the expected dividend of uninformed traders is low ($D_{uninf} < \tau$).

market prices.

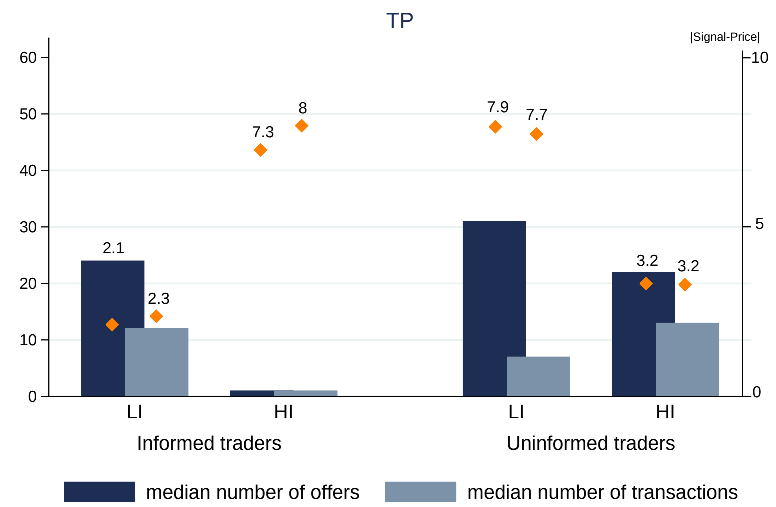


Figure 2.5 Median number of offers and transactions in accordance with the expected dividend of the proposer in treatment TP (left-axis): carrying low informational content (LI) and high informational content (HI). Diamonds represent the mean absolute distance between prices and the public signal (right-axis).

	Proposers			
	Informed		Uninformed	
Receivers	LI	HI	LI	HI
Informed	32%	13%	100%	72%
Uninformed	48%	88%	0%	22%
Misinformed	23%	0%	0%	17%

Notes: We computed first the proportion of offers accepted by each type of trader in each market. After that, we compute the median of those values. So, the values in the rows do not have to sum 100%.

Table 2.7 Median percentage of offers acceptance rate according to the type of receiver in treatment TP.

Table 2.7 describes the median percentage of transactions accepted by every type of trader. Transactions are classified according to the type of proposer (informed, uninformed) and their informational content (LI, HI). The majority of the offers submitted by informed traders are accepted by uninformed traders (48%) and most of the offers of uninformed traders are accepted by informed traders (72%). Two additional comments are worth mentioning: i) 100% of LI transactions submitted by uninformed traders are closed by informed traders. But, since transactions are very few and the mean absolute distance between prices and the public signal is large (7.7), they have no impact on the price distortion. ii) The 32% of LI transactions submitted by informed traders are accepted by other informed traders. We define them as herd behavior and we will comment on it later in this section. Herding is an original phenomenon that we have identified in our experiment, which decisively contributes to the overweighting of public information.

There is an evident asymmetry in the willingness to accept of the two types of traders. The acceptance rate of LI offers submitted by uninformed traders is much lower as compared to the informed traders' LI offers. Why uninformed traders are willing to accept LI offers from the informed traders? And, on the contrary, which is the reason for informed traders not to accept the LI offers of the uninformed traders? What would happen if we eliminate the common knowledge of the public signal? The elimination of the common knowledge of the released signal helps us to answer to those questions.

2.4.2 Common information treatment (TC)

We focus now on the analysis of trading in TC treatment where the identical released signal is not common knowledge among traders. Note that we continue to use the terminology of informed and uninformed traders. However, in the TC treatment, traders are not aware of being "uninformed" regarding the other traders. Figure 2.6 plots the median number of offers and transactions in accordance with proposers' expected dividend in treatment TC (left y-axis). The right y-axis describes the mean absolute distance between prices and the common signal. One can see that the informed traders submit LI offers in a similar magnitude to the TP treatment, signaling once again the consistency of that behavioral rule among treatments and type of traders. However, only the 11% of their LI offers are accepted. They adjust their offers reducing their expected profits and revealing their private information. Eventually, they submit HI offers, 34% of which are accepted, at prices biased towards the dividend value. The right side of the figure presents an even starker result: the uninformed traders submit numerous LI offers and 49% of them are accepted, but they do not submit HI offers.

As a consequence of the traders' behavior, prices turn out to be biased towards the dividend value. The mean absolute distance between prices and the incorrect common signal is 5.8 and 7.7 for the informed and uninformed traders, respectively. Similarly to treatment TP, Table 2.8 shows that most of the offers of informed traders are accepted by uninformed traders and vice versa. Figure 2.6 and Table 2.8 reveal that, contrary to markets with a public signal, uninformed traders do not accept offers close to their expected dividend. They mainly accept HI offers of informed traders. Informed traders, on the other hand, accept LI offers of uninformed traders. In this treatment, uninformed traders pay the cost of revealing their information to the market.

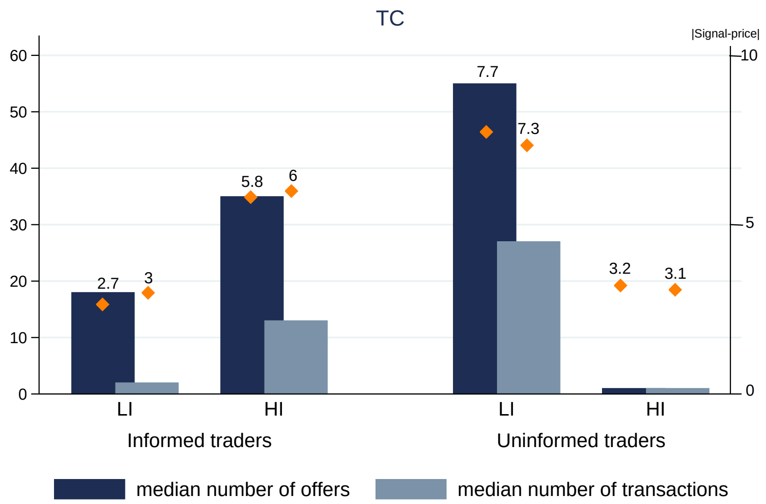


Figure 2.6 Median number of offers and transactions in accordance with the expected dividend of the proposer in treatment TC (left-axis): carrying low informational content (LI) and high informational content (HI). Diamonds represent the mean absolute distance between prices and the common signal (right-axis).

	Proposers			
	Informed		Uninformed	
Receivers	LI	HI	LI	HI
Informed	0%	23%	95%	97%
Uninformed	76 %	50 %	4%	3%
Misinformed	24%	0%	3%	0%

Notes: We computed first the proportion of offers accepted by each type of trader in each market. After that, we compute the median of those values. So, the values in the rows do not have to sum 100%.

Table 2.8 Median percentage of offers acceptance rate according to the type of receiver in treatment TC.

2.4.3 Comparing public and common information treatments

Which are the consequences of the observed asymmetries between both treatments? Experimental outcomes in treatment TP and TC lead to a market by different aggregated price tendency. While in treatment TP prices are biased toward the public signal, this is not the case in treatment TC. In TP, transactions mainly occur at prices close to the public signal. The mean absolute distance is 2.3 and 3.2 for transactions proposed by informed and uninformed traders, respectively. On the contrary, the mean absolute distance between prices and the common signal is 6 and 7.3.

Our experimental results point towards the direction that the asymmetric behavior between treatments is due to the impact of common knowledge of the public signal on the traders' beliefs[31] about other traders' expectations. Although the first-order beliefs

[31] We did not elicit traders' beliefs in our experiment to avoid disrupting their normal trading behavior. Literature has proved that eliciting beliefs may provoke hedging behavior (Schotter and Trevino, 2014), which could interfere with the purpose of our experiment.

about the dividend of each trader remains unchanged in the TP and TC treatments, what traders believe about others' expectations is markedly different. In the case of TP, uninformed traders are aware that they are privately uninformed and that the other traders know it. Informed traders are aware that a non-marginal group of uninformed traders exists. Conversely, in TC, traders with two opposite private signals are not aware that they are privately uninformed nor that the informed traders are aware that a group of uninformed traders exists. Our experiment indicates that such asymmetry in second-order beliefs of traders affects the willingness to accept offers, favoring informed traders when the public signal is incorrect. Second and higher-order beliefs of uninformed traders are not affected by the presence of the public signal (see section 2.5). Thus, the public signal is effective in coordinating transactions because the common knowledge of that signal affects second (and higher) order beliefs and makes evident the presence of uninformed traders. Moreover, the public signal makes uninformed traders willing to accept offers closer to their expected dividend, which coincides with the public benchmark (PB).

In section 2.5, we will formalize such reasoning with a simple model, showing how public information affects second and higher-order beliefs of all traders. The biased of prices toward the public signal arises because of the heterogeneity of beliefs and bounded rationality. The common knowledge of the presence of a non-marginal fraction of uninformed traders willing to provide liquidity and/or assets is a crucial ingredient in the aggregation of information around the public signal.

2.4.4 Informed traders: herd behavior

We have seen previously that many HI offers of informed traders are closed by other informed traders in the TP treatment. We conjecture that some informed traders might be induced to discard their private information and follow the misleading information carried by an incorrect public signal and uninformative market prices. Thus public information may generate herd behavior. By herd behavior, we mean that (i) informed traders submit offers non-accordant with their private information and (ii) those offers carry high informational content. This action might be induced by the misleading public signal and previous transactions biased towards that public signal. For example, consider a trader whose private signals predict dividend 10. He follows a herd behavior if he submits asks at prices below τ since he tries to sell cheap, contrary to what his private information indicates.

Looking again at Table 2.7, one can observe that 32% of LI transactions submitted by informed traders are accepted by other informed traders. We have interpreted this result as an imprint of herd behavior. Interestingly, this herd behavior is completely absent in the TC since none of the LI offers submitted by informed traders is accepted by other informed traders (see Table 2.8). Once again, we observe an asymmetry between the two treatments.

We evaluate now whether the herd behavior of informed traders is also present in their strategy as proposers. Figure 2.7 plots the median number of offers and transactions of informed traders that are not in accordance with their private information. Again, diamonds indicate the mean absolute distance between prices and the released signal for every category of offers and transactions. On the left side, one can see that informed traders submit HI offers and the 76% of them are accepted. Since the mean absolute distance between those prices and the public signal is 2.9, those transactions reinforce the misleading public signal. The important consequence of their high acceptance rate is that price informativeness is significantly reduced. Interestingly, there is almost no HI offers in treatment TC, on the right side of Figure 2.7.[32] An important conclusion emerges, the common knowledge of the public signal induces some traders to give up their information and herd on the information carried by the market price.

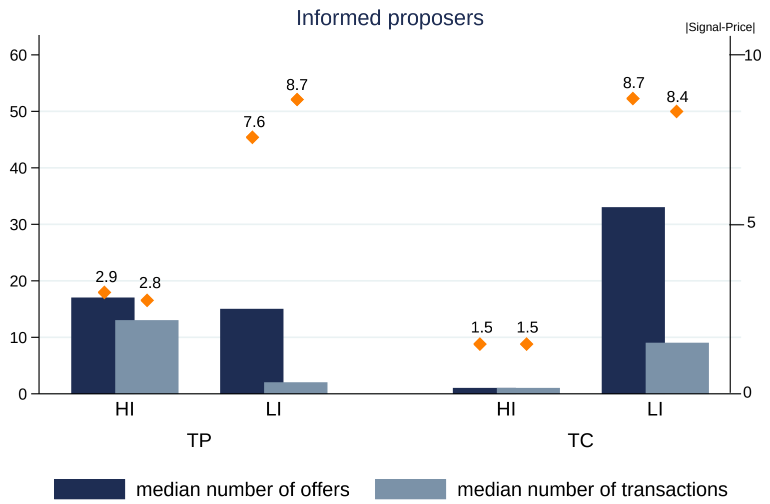


Figure 2.7 Median number of offers and transactions non-accordant with the expected dividend of the informed trader (left-axis): carrying low informational content (LI) and high informational content (HI). Diamonds represent the mean absolute distance between prices and the released signal (right-axis).

The emergence of herd behavior is a further adverse effect of releasing public information in the market. To the best of our knowledge, it is the first time that herd behavior induced by a public signal is observed.[33] The herding phenomenon generated by the presence of public information, therefore, reinforces the distortive effect of the public signal on prices. Prices are endogenous public signals that might disseminate misleading information and further contribute to the reduction of the

[32]In both treatments, informed traders submit LI offers, which are not in accordance with their private information, although they are hardly accepted. These transactions do not entail a reduction of price informativeness since prices do not carry misleading high informative content.

[33]Note that such effect is not theorize in the theoretical literature of coordination games à la Morris and Shin.

informativeness of the market.[34] The identification of herd behavior as a possible cause of overweighting of public information can be added to the typical cause described in the literature of overreliance of rational traders in coordination environment. Our experimental finding opens new and interesting issues to be explored.

2.4.5 Uninformed traders: asset/liquidity providers

The last piece of the picture is provided by the offers of uninformed traders that are non-in-accordance with their expected dividend. Figure 2.8 plots the median number of those offers and corresponding transactions per market. In the left side of the figure, one can see that uninformed traders submit LI offers, which mean absolute distance between the price and the public signal is 1.8. Those offers and especially transactions are around the public signal, reinforcing its coordination role as the main determinants of the market price. Together with Figure 2.5, we can observe that uninformed traders submit in accordance and not in accordance offers biased towards the public signal. Thus, their trading activity provides liquidity and/or assets to the market at the PB level. If the fraction of uninformed traders is sufficiently high, the market price "gets stacked" around the PB as long as they can provide liquidity and/or assets.

Regarding the TC treatment, the right side of Figure 2.8 shows that uninformed traders submit a similar number of LI and HI offers. The amount of offers, however, is very limited and not sufficient to affect the market price, comparing to offers in Figure 2.6.

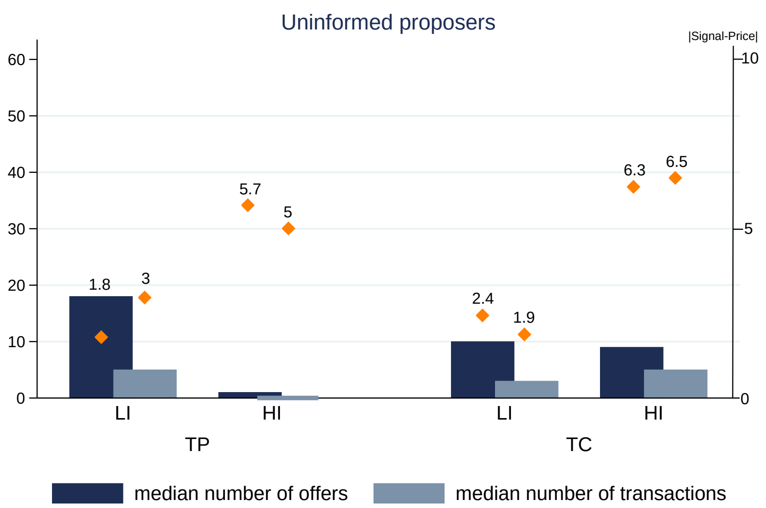


Figure 2.8 Median number of offers and transactions submitted by uninformed traders that are non-accordant with the expected dividend (left-axis): carrying low informational content (LI) and high informational content (HI). Diamonds represent the mean absolute distance between prices and the released signal (right-axis).

[34]Morris and Shin (2002), Amato and Shin (2006) and Vives (2014) analyze the role of prices as suppliers of endogenous public information.

2.5 Modeling higher-order beliefs with public information

Inspired by the findings of our experiment, we introduce a simple belief-theoretic approach that explains the asymmetric behavior of traders between common and public information treatments, which we have detailed in Section 2.4. Our model provides a rationale for the role that the public signal plays on traders higher-order beliefs and the impact on the reservation price of traders. A complete theoretical model of a double auction in continuous time is well beyond the scope of this chapter. Moreover, it is important to emphasize that this section is an ex-post formalization of the results that we observe in our experiment.

Let us focus our attention on the causes of the strong distortion of market prices in the case of an incorrect public signal. The intuition behind the model is that the public signal allows traders to better characterize other traders' beliefs in the market and, therefore, the aggregate demand. This assumption is similar in spirit to Allen et al. (2006), who argue that a public signal is a good predictor of average expectations because traders know that every trader in the market observe that signal. They assert that prices overweight the public signal beyond its information role when "individuals' willingness to pay for an asset is related to their expectations of average opinion". They claim that "any model where higher-order beliefs play a role in pricing assets will deliver the conclusion that there is an excess reliance on public information" (Allen et al., 2006). Indeed, we consider particularly appropriate the intuition of Allen et al. (2006) to interpret the results of our experiment, since their model exhibits the overweighting phenomenon without an explicit coordination incentive to the traders. Following their idea, the main assumption of our model is that the reservation price of each trader is proportional to her beliefs about the average opinion about the dividend among the entire market population. Such information is systematically influenced by the presence of the public signal, as pointed out in Allen et al. (2006).

To understand the influence of the public signal on traders' beliefs, we present the following example based on our experimental setting. Suppose that the trader A observes two private signals predicting dividend 0 while the public signal predicts dividend 10. In order to decide her reservation price for selling an asset or accepting an offer, she assesses the weighted average expectation of traders in the market being aware of: (i) the presence of a non-marginal fraction of uninformed traders and (ii) most of the traders have two correct private signals, although she cannot know with certainty the true state of the world. Given her beliefs about the distribution of traders in the market, she computes her expectation about the average expected dividend among the market population. Next, she can estimate the average expectation of traders' average expectation in the market weighted by the distribution of traders that she had assumed in the first iteration. Thus, her new reservation price is higher than in the previous iteration. By iterating this process, we obtain that higher-order beliefs about the average opinion of expected dividend converge to the common prior, i.e. the public benchmark. An uninformed trader has an expected dividend that coincides with the public benchmark in TP. So, he cannot refine his reservation price and must rely just on public information. In the following, we relate such asymmetry between informed and uninformed traders average expectations to their asymmetric trading behavior.

2.5.1 Formalization of the model

Let us formalize the Allen et al. (2006)'s conjecture within our setting. The dividend value[35] is $D \in \{0, 1\}$ and n is the number of non-public signals that a trader receives, that is, the two private signals and, when available, the common signal. Thus, $n = 2$ in treatment TP, while $n = 3$ in treatment TC. Let us define then $\eta = \sum_{i=0}^{n} s_i$, where $s_i \in \{-1, 1\}$ $\forall i$ refers to the prediction of each non-public signal; $s_i = 1$ if a non-public signal predicts dividend 1, while $s_i = -1$ if it predicts dividend 0. So, the variable η can take the values $\{-2, 0, 2\}$ in treatment TP and $\{-3, -1, 1, 3\}$ in treatment TC. Note that there is a biunivocal correspondence between the value of the variable η and the type of trader in a particular treatment. For instance, $\eta = 2$ means that we are considering a trader with two private signals pointing towards $D = 1$ in TP. The public signal is denoted by the variable $\hat{S} \in \{-1, 1\}$, where $\hat{S} = -1$ means that the public signal indicates $D = 0$, conversely $\hat{S} = 1$ means $D = 1$.[36] We indicate with $D^k_{\eta,\hat{S}}(n)$ the k^{th} iteration of trader's expected average dividend. For $k = 0$, we define $D^0_{\eta,\hat{S}}(n)$ as:

$$D^0_{\eta,\hat{S}}(n) = \left[1 + \left(\frac{q}{p}\right)^{\eta} \left(\frac{Q}{P}\right)^{\hat{S}}\right], \tag{2.7}$$

which is the expected dividend of a trader given her information set $\{\eta, \hat{S}\}$. We define the $D^0_{\eta,\hat{S}}(n) = D_{\eta,\hat{S}}$ for notational convenience.

We now compute the expected value of the average expectation of the dividend in the market for the iteration $k \geq 1$ for traders characterized by η. A trader with an expected dividend $D_{\eta,\hat{S}}$ computes the average expectation of the dividend as the weighted average of each possible expected dividend of all types of traders. The first term to be computed is the average expectation conditional to $D = 1$:

$$\textstyle\sum_{h=0}^{n} \begin{pmatrix} n \\ h \end{pmatrix} p^h \, q^{n-h} \, D^{k-1}_{2h-n,\hat{S}} \, .$$

[35]We redefine two states of the world as $D \in \{0, 1\}$ instead of $D \in \{0, 10\}$.

[36]In the TC, the variable $\hat{S} = 0$, so that it does not have an impact on the eqs. (2.7) and (2.8).

The sum runs over the variable h, which refers to the number of non-public signals indicating $D = 1$. The second term is the average expectation conditional to $D = 0$:

$$\sum_{l=0}^{n} \begin{pmatrix} n \\ l \end{pmatrix} p^l \, q^{n-l} \, D^{k-1}_{n-2l,\hat{S}} \, .$$

This second sum runs over the number of non-public signals indicating $D = 0$, which are denoted by l. Plugging the two terms together, the average expected dividend at iteration k of a type of trader η can be expressed as a linear combination of the average expected dividend of all other types at the iteration $(k-1)$ weighted by the probability of observing $D = 1$ and $D = 0$ according to his information set $\{\eta, \hat{S}\}$:

$$\begin{aligned} D^k_{\eta,\hat{S}}(n) &= \left[\sum_{h=0}^{n} \begin{pmatrix} n \\ h \end{pmatrix} p^h \, q^{n-h} \, D^{k-1}_{2h-n,\hat{S}} \right] D_{\eta,\hat{S}} + \\ &+ \left[\sum_{l=0}^{n} \begin{pmatrix} n \\ l \end{pmatrix} p^l \, q^{n-l} \, D^{k-1}_{n-2l,\hat{S}} \right] (1 - D_{\eta,\hat{S}}) \ \text{ if } \ k \geq 1 \, . \end{aligned} \tag{2.8}$$

The previous iterative formula can be expressed as a Markov chain. We define a matrix $\mathbf{\Lambda}(p, \hat{S}) \in \mathbf{M}_{(n+1)\times(n+1)}$ as a matrix specified in Appendix 2.C, which depends on p and $\hat{S}$. The vector $\mathbf{d}^k_{\eta,s}(n) \in \mathbf{V}_{n+1}$ is defined as a vector whose elements are the k^{th} iteration of the average opinion across the different types of traders. It is easily to show that:

$$\mathbf{d}^k_{\eta,\hat{S}}(n) = \mathbf{\Lambda}(p, \hat{S}) \;\; \mathbf{d}^{k-1}_{\eta,\hat{S}}(n) \, . \tag{2.9}$$

Iterating this operation for any type of trader, the expected average opinion in the market converges to the public benchmark:

$$\mathbf{d}^{\infty}_{\eta,\hat{S}}(n) = \lim_{k\to\infty} \mathbf{d}^k_{\eta,\hat{S}}(n) = \lim_{k\to\infty} [\mathbf{\Lambda}(p, \hat{S})]^k \; \mathbf{d}^0_{\eta,\hat{S}}(n) = \mathbf{d}_{0,\hat{S}}(n) \, . \tag{2.10}$$

Note that the asymptotic value of the components of the vector does not depend on the private information of the traders. It is the same value across all types of traders and it coincides with their prior information. Such result does not come as a surprise. Indeed, it is derived by Allen et al. (2006) and, in a more general framework, by Samet (1998). Thus, the public benchmark, defined in eq. (2.2), can be thought as the limit of the hierarchical iterations of traders in updating their average expectations of the dividend. Figure 2.9 plots the evolution of the expected average opinion over iterations for each type of trader in the TP and TC treatments according to eq. (2.9).

2.5.2 The model and experimental data

We use now our framework to explain the results of the experiment, with particular attention to the empirical evidence of Section 2.4. Let us assume a specific scenario in the TP treatment: $D = 0$ and the presence of a misleading public signal $\hat{S} = 1$.[37] We assume that the reservation price of traders is proportional to $D^k_{\eta,1}$ for some k, so that the reservation price of an informed trader is $D^k_{-2,1}$. In particular, when $k = 1$, her reservation price is $D^1_{-2,1} \approx 0.5$, therefore she only accepts bids or submit asks above this value. If $k = 2$, her reservation price further increases up to $D^2_{-2,1} \approx 0.7$. Thus, she only accepts bids or submits asks above this value. Examining now the other side of the market, an uninformed trader with a $k = 0$ level of reasoning has a reservation price $D^0_{0,1} = 0.8$. Thus, he accepts asks or submits bids below that value. If $k = 1$, one can easily see that his reservation price has not changed. In fact, his reservation price remains invariant across iterations. It clearly emerges an asymmetry: the reservation price of the informed traders increases with the number of iterations towards the public benchmark, while the reservation price of the uninformed traders remains invariant. Therefore, the range between reservation prices of informed and uninformed traders gets narrower as k increases, approaching zero when k tends to infinity. Note, however, that already after a few iterations, this difference becomes negligible (see Figure 2.9).

Comparing Figure 2.9 and the findings of Section 2.4, a level of reasoning $k = 1$ or $k = 2$ is sufficient to identify consistent patterns between our model and the experimental data in TP. In the considered scenario, we have observed that informed traders try to sell at a high price submitting LI offers that are accepted mainly by uninformed traders (Figure 2.5). The left panel of Figure 2.9 shows that the reservation price of uninformed traders is 0.8, so they are in principle willing to accept the LI offers of informed traders. In our experiment, uninformed traders submit LI offers in a similar order of magnitude of informed traders, but they are not accepted (or only in a marginal fraction) since they are well below the reservation price of informed traders. So, uninformed traders asymmetrically adjust their offers to match the offers of their counterpart, submitting necessarily HI offers. Conversely, informed traders do not adjust their LI offers and they are willing to accept offers significantly above their expected dividend $D^0_{-2,1}$ since they are aware of the presence of a non-marginal fraction of uninformed traders. The discrepancy between $D^0_{-2,1}$ and $D^k_{-2,1}$ for $k \geq 1$ reflects this reasoning of the informed traders. Accounting for the distribution of the signals across traders does not provide any new information to the uninformed traders, which is formalized in our framework by their invariant reservation price.

Why does informed traders do not accept offers between $D^0_{-2,1}$ and $D^k_{-2,1}$ (i.e. between 0.2 and 0.7 for $k = 2$)? The mechanism of the double auction allows for

[37] Mutatis mutandis, we can describe the opposite framework $D = 1$ and $\hat{S} = -1$.

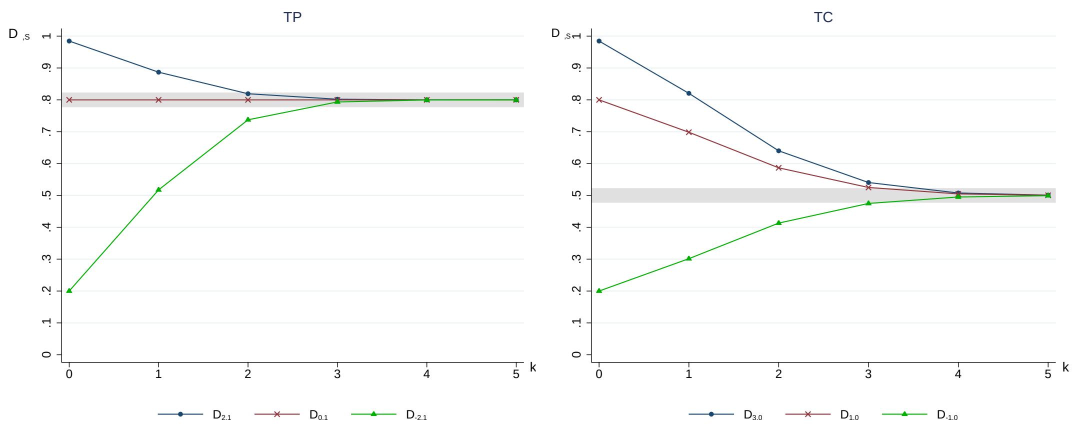


Figure 2.9 Expected average opinion over iterations (k) for each type of trader when the dividend is 0 and the public or common signal is 1. The lines represent the different types of traders and thick-gray line indicates the public benchmark.

the option of waiting for higher expected profits in the future. So, we conjecture that informed traders exploit such option, waiting for higher profits, i.e. for the adjustment of the uninformed traders' offers. The informed traders are aware of the presence of uninformed traders, which, in turn, are conscious that they have no informational advantage. The specific details of the adjustment process of the offers and the microstructure of the market mechanism might play an important role in the determination of the market price. It seems that the double-auction trading protocol favors the overweighting phenomenon. The comparison of different market mechanisms and trading protocols on the emergence of the overweighting phenomenon is an interesting issue that we cannot answer in this chapter and we leave for future research.

Our simple framework allows to define the reservation price of the informed and uninformed traders, which are compatible with the empirical findings. As a consequence, an incorrect public signal becomes a focal point when the proportion of uninformed traders in the market is large enough that they submit or accept sufficient offers, providing liquidity/assets. By keeping transactions close to the PB and preventing the adjustment of prices towards the dividend, the activity of uninformed traders prevents the dissemination of information throughout the price mechanism. Additionally, this may lead some informed traders to ignore their private information, following the suggestion of the incorrect public signal and market prices. Hence, the trading activity around the public benchmark can be further reinforced by the presence of herd behavior, so that prices are uninformative and reflect just public information. When the public signal is instead correct, following the logic of our model, prices fluctuate around the public information in the beginning of the trading period (see Figure 2.2(b) of this chapter). Being prices informative, they trigger the "correct" dissemination of information, reinforcing the learning process of uninformed (and when present) misinformed traders. Therefore, the correct public signal promotes the aggregation of information.

Can we interpret the empirical findings observed in TC using our framework? In treatment TC there is not a biased public signal to characterize the aggregate demand of the market population as well as there are not privately uninformed traders. Traders are not aware of the existence of a common signal available to all of them since they consider that the three allocated signals are private. According to eq. (2.9), in this scenario the reservation price of uninformed traders[38] is close to 0.7 if $k = 1$ and to 0.6 if $k = 2$. Conversely, the reservation price of informed traders in TC is close to 0.3 when $k = 1$ and to 0.4 for $k = 2$. Figure 2.9 captures the difference among traders and treatments (TP and TC). The contemporaneous symmetric convergence of reservation prices towards the $PB = 0.5$ of informed and uninformed traders can explain the empirical observations of Figure 2.6. Both types of traders submit LI offers, but uninformed traders do not accept them given their much lower reservation price with respect to the TP. So that the informed traders are forced to adjust their offers and eventually submit HI offers, while accepting the LI offers of uninformed traders. Unlike treatment TP, prices exhibit wider fluctuation showing a slight tendency towards the dividend value (see the right panel of Figure 2.2). Both informed and uninformed traders perceive the same informational advantage over the other market participants. The symmetric situation depicted in Figure 2.9 is broken by the large number of informed traders and, therefore, the price should tend to the dividend, transmitting information. In the case of the incorrect common signal, our model predicts a less distorting market prices compare to TP, compatible with the empirical evidence (see Figure 2.2(b)).

All in all, a incorrect public signal prevents the dissemination of information; even more, it strongly reduces price informativeness, inducing herd behavior. Conversely, a correct public signal enhances the dissemination of information, promoting the learning process of traders.

2.6 Conclusions

This chapter is inspired by the concern of regulatory institutions about public information overreliance in financial markets. Until now, models and experiments have proved the overweighting of public information phenomenon on a simple game-theoretical framework with explicit incentive to coordinate, like a beauty contest framework. We have studied this phenomenon in a laboratory financial market, which is a more realistic environment that is characterized by the absence of an explicit coordination incentive for the subjects. We provide evidence that public information is overweighted. In order to prove it, we have tested the effect of introducing a noisy public signal

[38]Note that, for notational convenience we continue to define those traders as "uninformed traders" although they are not privately uninformed as in TP. They are not aware that a common signal exists; so that they believe to be privately informed relative to other traders.

in markets where asymmetrically informed subjects trade risky assets. Overall, the level of information present in the market is always sufficient, if efficiently aggregated, to discover the true state of the world. The introduction of a public signal helps the aggregation of information into prices when it is correct. By contrast, an incorrect public signal may drive prices far from fundamentals. Furthermore, we have shown that the effectiveness of public information in distorting prices is caused by the common knowledge about that information. In order to show it, we have removed the common knowledge of the public signal. The incorrect common signal still distorts market price, but the effect is greatly attenuated with respect to the public signal.

Digging into the markets where the public signal fails in predicting the dividend, we find evidence that higher-order beliefs are key elements in the overweighting mechanism. Our public information serves as a focal point when traders' willingness to accept an offer depends on the expected average opinion of the market (Allen et al., 2006). An incorrect public signal favors informed traders to trade around the value predicted only by such signal. Thus, they make high expected profits while they do not reveal their private information. On the other side of the coin, uninformed traders make transactions close to their expected dividend, which provides them with low expected profits. Those transactions become misleading endogenous public signals that reduce price informativeness. As a consequence, some traders discard their own private information and follow the public signal. For the first time, we have shown that an incorrect public signal might cause herd behavior.

Overall, our results provide insight into the potentially adverse effects of public announcements on the economy. Full transparency of institutions or central banks may affect too much economic agents' expectations.

Appendix

2.A Instructions of the experiment

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

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 purchase or sale offer 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%.

[*Only in the baseline and public information treatment:*] Moreover, you will receive Two **private information signals** about the value of the dividend at the end of the period in the form of signals. If you look:

- **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.
- **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.

This will be your private information and therefore you will be the only one able to see it.

[*Only in the public information treatment:*] 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 treatment:*] Moreover, you will receive 3 information signals about the value of the dividend at the end of the period in the form of signals. If you look:

- **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 your same market.

2.A.1 Screenshots

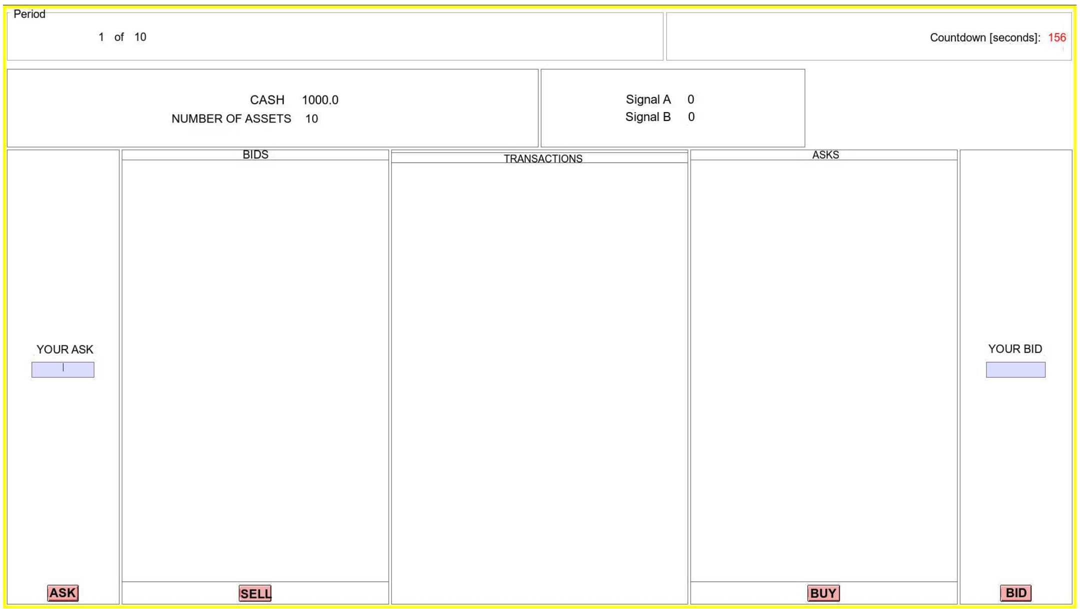


Figure 2.10 Screenshot of baseline treatment, TB

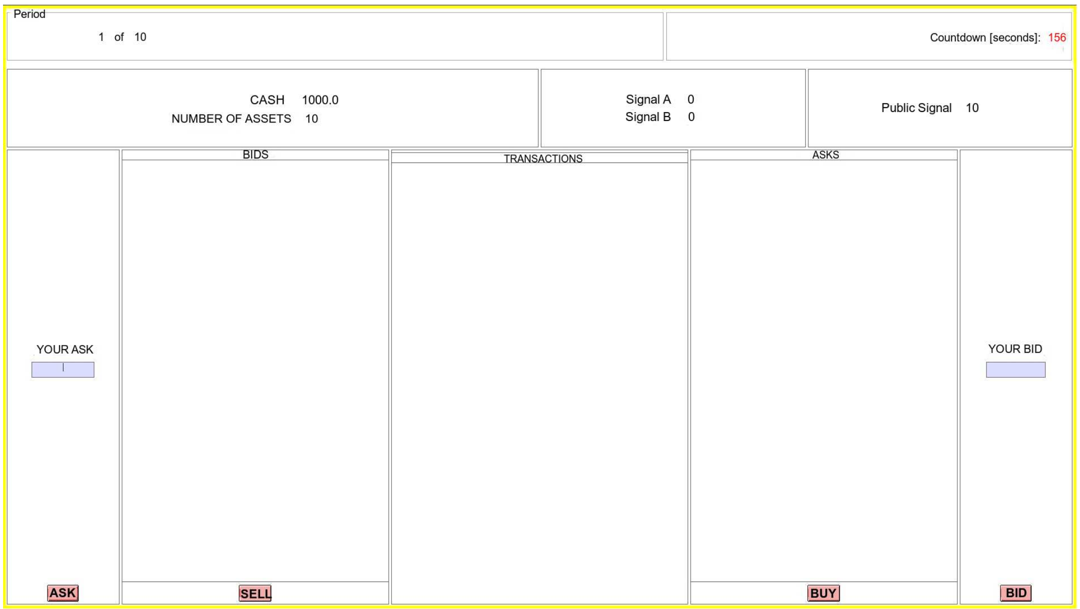


Figure 2.11 Screenshot of public information treatment, TP

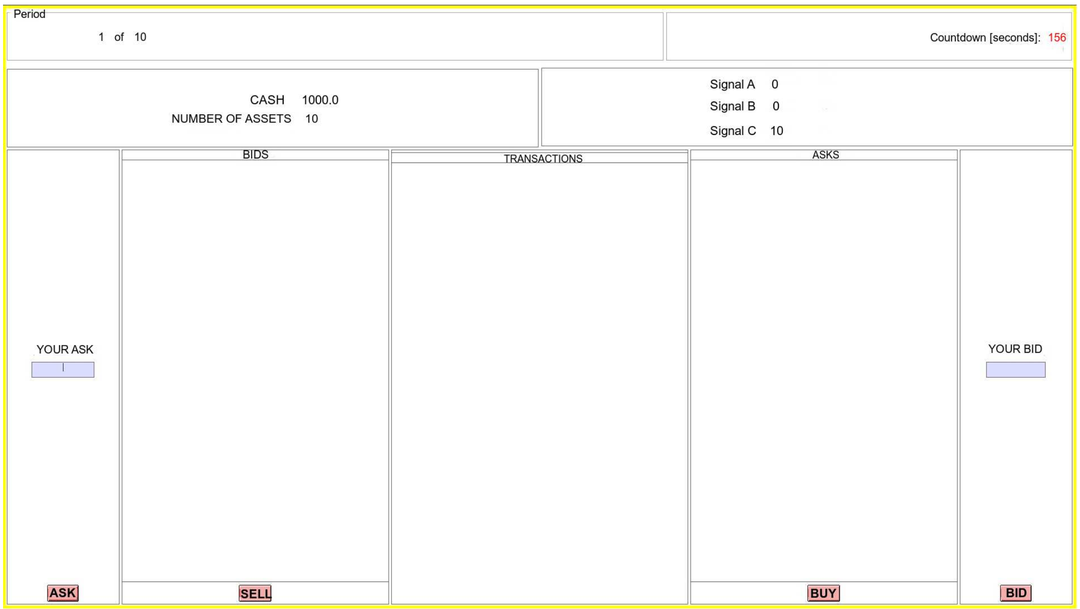


Figure 2.12 Screenshot of common information treatment, TC

2.B Experimental results

2.B.1 Trading activity per treatment

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, while the dashed line indicates the public information benchmark.

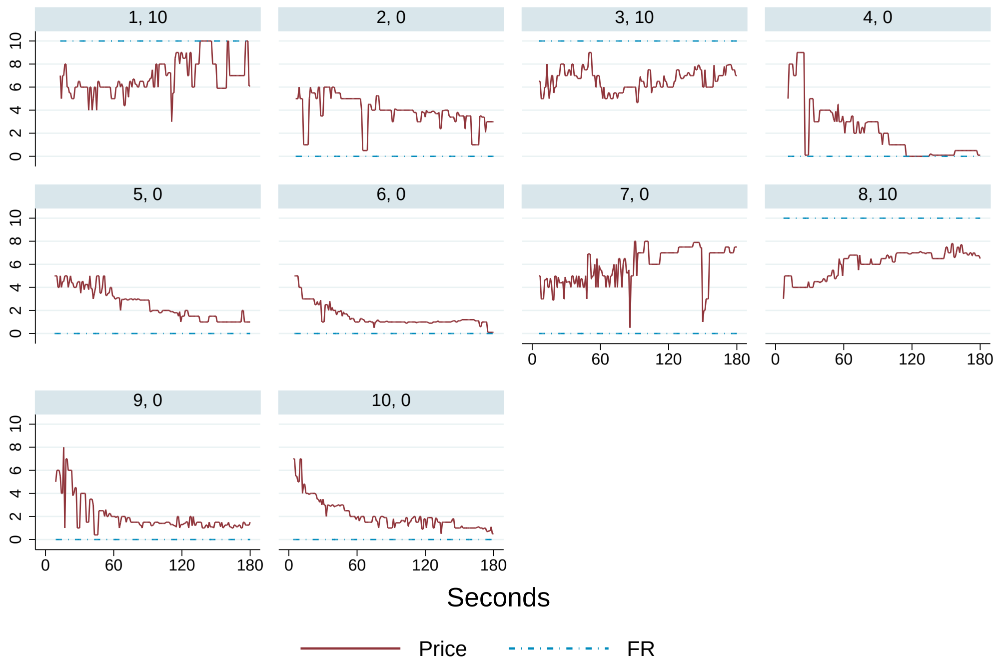


Figure 2.13 Markets in Treatment TB.

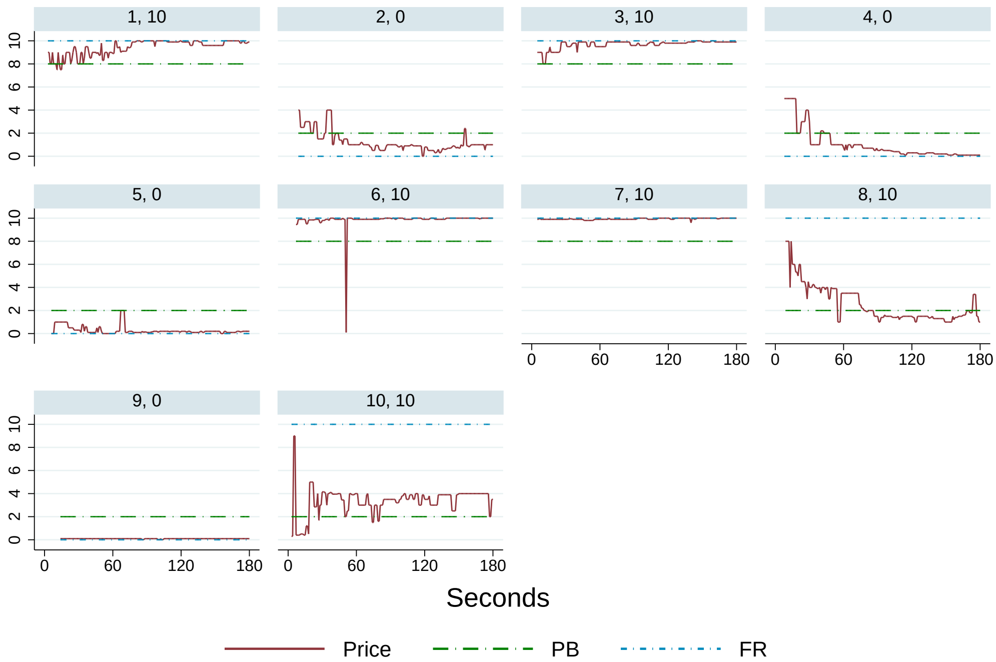


Figure 2.14 Markets in Treatment TP (Group 1).

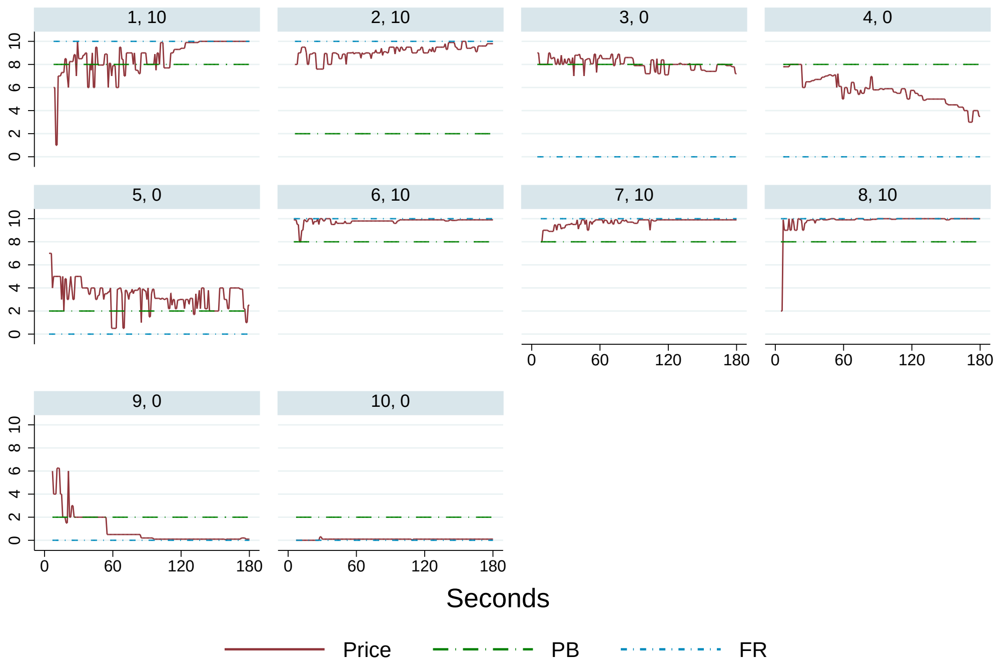


Figure 2.15 Markets in Treatment TP (Group 2).

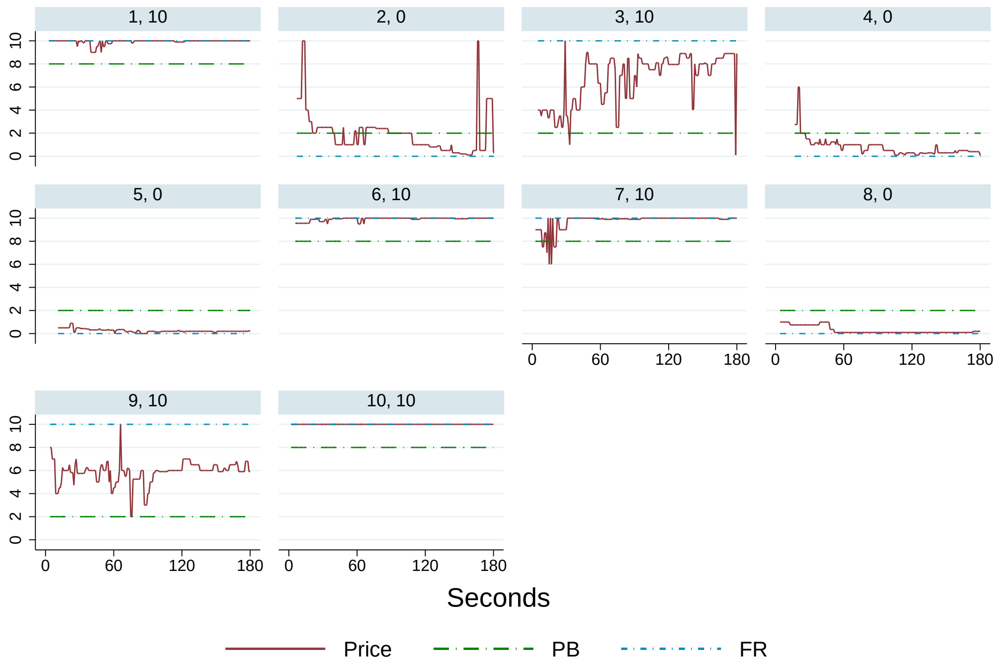


Figure 2.16 Markets in Treatment TC (Group 1).

Figure 2.17 Markets in Treatment TC (Group 2).

2.B.2 Distribution of information across traders

The following figures plot the distribution of traders according their private information. The horizontal axis denotes markets and vertical axis indicates the number of uninformed and misinformed traders.

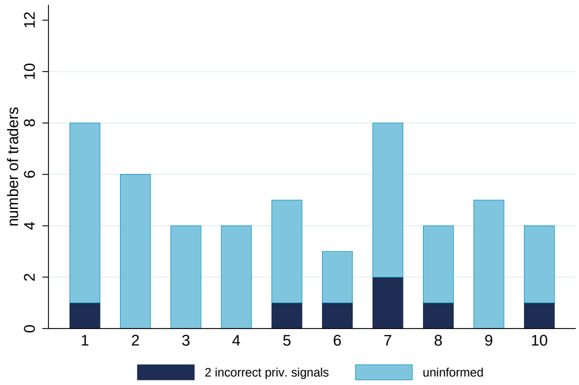


Figure 2.18 Treatment TB: Number of non-informed subjects: $avg = 5.1$, $min = 3$ and $max = 8$.

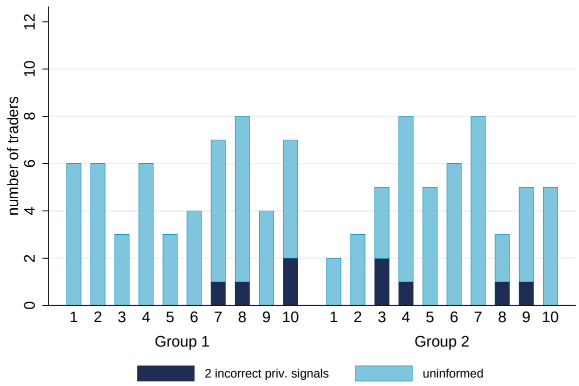


Figure 2.19 Treatment TP: Number of non-informed subjects: $avg = 5.2$, $min = 2$ and $max = 9$.

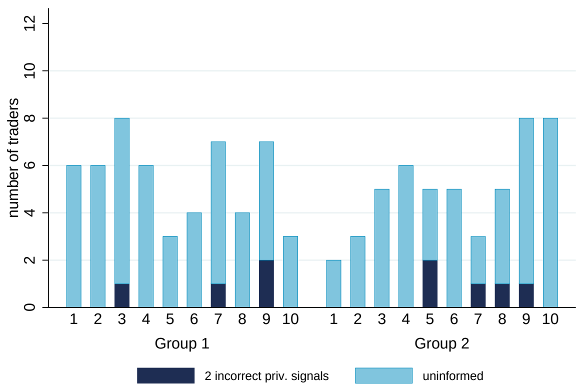


Figure 2.20 Treatment TC: number of non-informed subjects: $avg = 5.2$, $min = 2$ and $max = 8$.

2.C Iterating expectations

In this Appendix, we explicitly specify the matrices $\mathbf{\Lambda}(p, \hat{S})$ from eq. (2.9) for treatment TP and TC. Note that it does not depend on the value of the dividend.

Markets with a public signal (Treatment TP)

In the following, matrix $\mathbf{\Lambda}(p, 1)$ in treatment TP when the public signal predicts dividend 1 ($\hat{S} = 1$):

$$\mathbf{\Lambda}(p,1) = \begin{bmatrix} \frac{p^5+q^5}{p^3+q^3} & 2pq & \frac{p^2q^2}{p^3+q^3} \\ 1-3pq & 2pq & pq \\ pq & 2pq & 1-3pq \end{bmatrix}$$

In case the public signal predicts dividend 0 ($\hat{S} = -1$), the matrix $\mathbf{\Lambda}(p, -1)$ is:

$$\mathbf{\Lambda}(p,-1) = \begin{bmatrix} 1-3pq & 2pq & pq \\ pq & 2pq & 1-3pq \\ \frac{p^2q^2}{p^3+q^3} & 2pq & \frac{p^5+q^5}{p^3+q^3} \end{bmatrix}$$

Markets with a common signal (Treatment TC)

In order to specify the matrix $\mathbf{\Lambda}(p, 0)$ for markets with a common signal, we compute the four possible expected dividends for all four types of traders' average expectations ($\eta \in \{-3, -1, 1, 3\}$). In the following, matrix $\mathbf{\Lambda}(p, 0)$ in treatment TC:

$$\mathbf{\Lambda}(p,0) = \begin{bmatrix} \frac{p^6+q^6}{p^3+q^3} & \frac{3pq(p^4+q^4)}{p^3+q^3} & \frac{3p^2q^2(p^2+q^2)}{p^3+q^3} & \frac{2p^3q^3}{p^3+q^3} \\ p^4+q^4 & 3pq(p^2+q^2) & 6p^2q^2 & pq(p^2+q^2) \\ pq(p^2+q^2) & 6p^2q^2 & 3pq(p^2+q^2) & p^4+q^4 \\ \frac{2p^3q^3}{p^3+q^3} & \frac{3p^2q^2(p^2+q^2)}{p^3+q^3} & \frac{3pq(p^4+q^4)}{p^3+q^3} & \frac{p^6+q^6}{p^3+q^3} \end{bmatrix}$$

In the common information treatment, we do not have to distinguish between a common signal predicting a high or low value of the dividend. In fact, all types of traders consider the four possible combinations of the three signals, which are allocated among traders, to compute their average expected dividend, namely $\eta = -3, -1, 1.3$. However, one of the expected dividends is associated with a type of traders that does not exist. $\eta = -3$ or $\eta = 3$ depending on the value of the common signal. If the common signal predicts dividend 1, we consider the expectations of traders $D^k_{3,0}$, $D^k_{1,0}$ and $D^k_{-1,0}$. If the common signal, on the other hand, predicts dividend 0, we account the expectations of traders $D^k_{1,0}$, $D^k_{-1,0}$ and $D^k_{-3,0}$.

Chapter 3

Price distortions and public information: theory, experiments and simulations

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 about 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 microstructure. Grossman and Stiglitz (1980) demonstrate that a paradox exists when in a competitive and efficient market, the production of information is costly. Nobody has the incentive to buy information if there is no compensation for the cost under perfect efficiency of prices in reflecting information, and, if nobody buys information, prices cannot reflect it. Informed traders have no incentive to reveal their private information into the market if not properly compensated for the costs of producing information, and therefore it does not exists an equilibrium. This problem is solved when prices only partially reveal the information (Grossman and Stiglitz, 1980).

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). This literature proves that prices do not reveal all available information when only one asset is traded. For example, Camerer and Weigelt (1991) document evidence that prices might behave as if they reveal information that is not actually held by any traders. More recently, Corgnet et al. (2015) find that traders fail to use market prices to infer other traders' information. While theoretical models focus on transaction prices as a vehicle for information transmission in markets, experiments reveal the presence and importance of other parallel channels of communication such as bids and asks, identification of traders and timing.

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). Asparouhova and Bossaerts (2017) find that prices manage to aggregate dispersed information in a laboratory decentralized market.

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. Instead of leaving the market operating alone in aggregating information, one might think that releasing public information can facilitate the aggregation process. 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 *forward guidance* to manage the expectation 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. The announcements of the central bank can 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. As Morris and Shin (2005) argue, there is a trade-off between managing market expectations and learning from market expectations. "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.

In this chapter, 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 included in the previous chapter, we establish two conjectures.[2] Our first conjecture

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

[2]Controlled laboratory experiments and computer simulations share the possibility of monitoring and recording every variable of interest, such as the information possessed by each trader and their activity at every moment.

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.

Our model reproduces qualitatively the main patterns observed in the laboratory experiment. Despite the fact that we do not consider herding and learning behavior, the similarity between the experimental and simulated data is noticeable for a wide range of model parameters. 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 observe by all traders, is not common knowledge.

The rest of the chapter is organized as follows. Section 3.1 introduces the behavioral trading model and its results. Section 3.2 illustrates the model calibration and the finite sample properties of the model, implementing Monte Carlo simulations. Section 3.3 describes the laboratory experiment and compare the observed data with the computational data. Finally, Section 3.5 concludes.

3.1 The model

3.1.1 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 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

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

$$E[D = 1|x_i, y] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{x_i} \left(\frac{1-q}{q}\right)^{y}} \,. \tag{3.1}$$

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.

3.1.2 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, using their information. Naive traders only consider the information they have on 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 $D_i \equiv E[D = 1|x_i, y]$.

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 [5] 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:

$$s_i = \operatorname*{argsup}_{s\in\{a,b,nt\}} \pi^N(s|D_i) \ , \tag{3.2}$$

where a, b and nt refers 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 about the 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.

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

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

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:

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

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]

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

[7]See Appendix 3.A.1 for the extended functions.

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:

$$s_i^* = \operatorname*{argsup}_{s\in\{a,b,nt\}} \pi^S(s|D_i) \ , \tag{3.3}$$

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. (3.3), 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, selling at the highest possible price or buying at the lowest possible price that a trader is willing to accept is her optimal choice.

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

[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.

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 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 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.

3.1.3 Endogenous order flow

Having defined the optimal strategy for each type of trader, we now compute the optimal number of offers submitted by each type of trader. 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

$$\Pi^\tau(s|D_i) = [\pi^\tau(s|D_i) - c\, z_i^\tau - D_i] \; z_i^\tau \;, \tag{3.4}$$

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. (3.4) with respect to z_i^τ:

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

[9] Table 3.4 in Appendix 3.A.2 describes the information revealed in every offer. Moreover, it provides illustrative examples to explain the computing process of the expected payoffs.

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

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

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 $c = \frac{\varepsilon}{2}$.

3.1.4 Transactions

What we have characterized so far is the traders' behavior given their level of reasoning and information. In general, 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 3.1 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 trader accept the offer.

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 represents traders' expected dividend. The other two columns of the table show the offers and their corresponding prices.

Table 3.1 Transactions.

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 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

$$t(\tau_i) = \omega_i^\tau \sum_{\tau' j} f(\tau_i, \tau'_j) \ , \tag{3.5}$$

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

Table 3.2 shows the expected number of transactions per unit of time for each trader of type τ_i listed in Table 3.2. Note that it is already included the corresponding order flow.[13] 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:

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

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 3.2 Probability of transaction per unit of time.

[12] In order to compute it, we refer to Table 3.1. Note that $f(\tau_i, \tau'_i) = 0 \quad \forall i$.

[13] Table 3.5 in Appendix 3.A.3 shows in more detail every transaction probability per unit of time between two specific traders. The sum of columns of Table 3.5 is listed in Table 3.2.

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 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 3.1.[14] 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

$$\overline{P} = \frac{\mathbf{T}'}{F}\mathbf{P} \ . \tag{3.6}$$

3.2 Model calibration

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

The literature claims that public information is a double-edged instrument that simultaneously provides information about the fundamentals and information about other traders' beliefs.[15] 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 reports information about the fundamentals but do 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 claim that it is the public nature of information the main determinant of traders' overreliance. Stated differently, we will 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 not be biased toward the common signal when it predicts the incorrect dividend. Onward, we will refer to the following scenarios: markets with a public signal are labeled as scenario PS, and markets with an identical signal that is no common knowledge (common signal) as scenario CS.[16] Additionally, we introduce a baseline scenario (B) where there is no identical signal released to the

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

[15] Morris and Shin, 2002; Allen et al., 2006; Cornand and Heinemann, 2008 and Baeriswyl and Cornand, 2016 among others.

[16] In the case of a common signal, the procedure for the resolution of the theoretical model is explained in Appendix 3.B.

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:

$$E[D=1|\hat{y}] = \frac{1}{1+\left(\frac{1-q}{q}\right)^{\hat{y}}}\ , \tag{3.7}$$

where $\hat{y}$ takes values 1 or -1 if the signal is public and $\hat{y}=0$ if the signal is common.[17] $PB=0.8$ 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 frequencies in the population implies that we neglect the fluctuations in the configuration of the population due to a finite number of traders.[18] Just like the experimental design, we fix the quality of every private, public and common signal at $p=q=0.8$.

3.2.1 Results

Without loss of generality, Figure 3.1 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] We denote now the released signal by $\hat{y}$ instead of y like in eq. (3.1) to unify the three scenarios (benchmark, public signal, and common signal) into a single equation.

[18] 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 in our model is quite a robust outcome. The distance between mean prices and the public signal is 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, 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 3.1 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 cases with respect to the scenario 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 cases with a public and a common signal. The mean price takes similar values in both cases.[19] In both cases, 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.

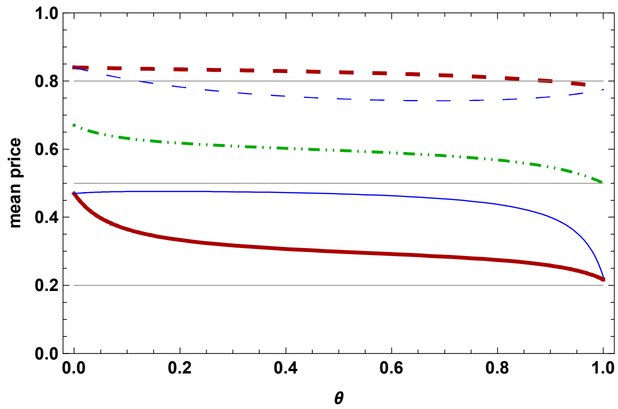


Figure 3.1 X-axis represents the proportion of sophisticated traders and Y-axis denotes the mean price when $\varepsilon = 0.025$. Horizontal lines represent the PB in every case. Dashed-dotted line denotes the mean price of scenario B, thick-dashed line refers to the scenario PS when the signal is 1 whereas the thick-solid line refers to the public signal is -1. For the scenario CS, the thin-dashed line represent the mean price when the signal is 1 and the thin-solid line represents the mean price when the common signal is -1.

[19]In the case of correct public or common signal, mean price evolution does not depend on the heterogeneous order flow. Figure 3.6 in Appendix 3.C.1 compares the theoretical results assuming heterogeneous and homogeneous order flow among traders.

We can deduce from our model that public information is beneficial *per se* when it is correct. Both information about fundamentals and information about 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 excess of relying on the public signal by traders turns into price overweighting of 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 how the released signal has different impacts on the mean price in aggregate terms. Figure 3.2 plots the mean price for every case 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 cases are closer to the dividend than the mean price in the baseline case. Figure 3.2 shows that the impact of the common knowledge about the identical released signal is almost indistinguishable in aggregate terms.

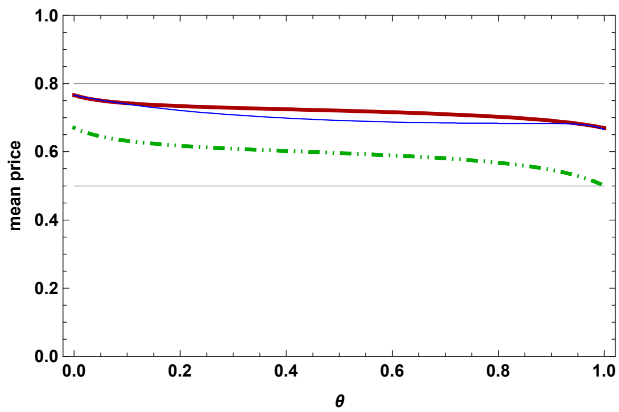


Figure 3.2 X-axis represents the proportion of sophisticated traders and Y-axis denotes the mean price when $\varepsilon = 0.025$ in aggregate terms. Horizontal lines represent the PB in every case. Thick-dashed line denotes the mean price of B case, thick-solid lines refer to the PS scenario whereas thin-solid lines refer to the CS case.

3.2.2 Monte Carlo simulations

Eq. (3.6) 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 by $\theta = 0$ and 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.

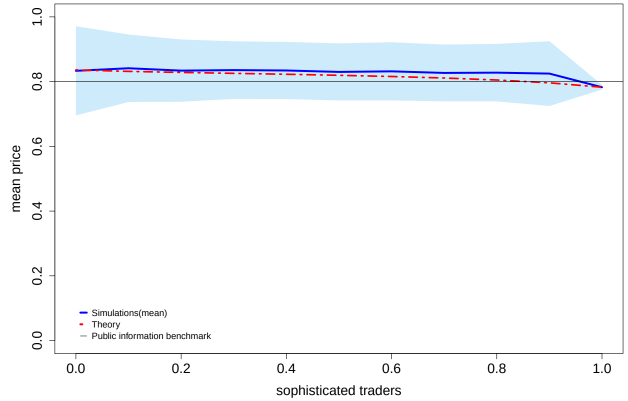
Figure 3.3 shows the mean price obtained in Monte Carlo simulations for PS cases on the panels (a,c) and CS cases on the panels (b,d). We also differentiate between markets where the released signal is correct ($y = 1$) on the panels (a,b) and those where it is incorrect ($y = -1$) on the panels (c,d). One can see that mean price of simulations closely follow the theoretical predictions in all cases. We note further that CS cases appear to have larger price dispersion than those with a public signal. This finding indicates that the price is more sensitive to the distribution of signals in CS cases than PS cases.

3.3 Laboratory experiment

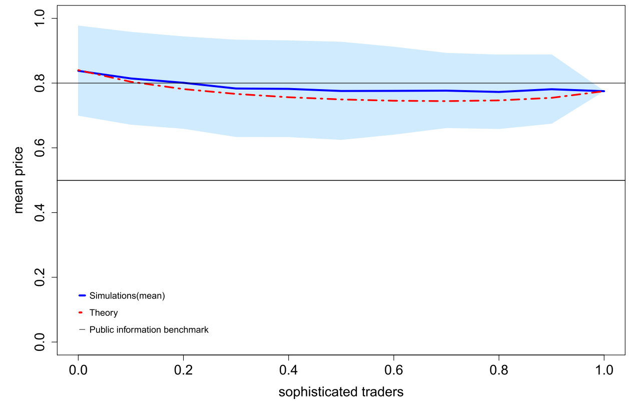
In this section we sketch the experimental design of Chapter 2. The experiment took place in the LEE (*Laboratori d'Economia Experimental*) at University Jaume I in Castellón.[20] All subjects are undergraduate students from Economics, Finance and Business Administration in at least their second year of study. At the beginning of the session, the instructions are distributed and explained aloud. This is followed by one practice auction period for subjects to get familiar with the software and the trading mechanism.

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 for assets or directly accept any other trader's outstanding bid or ask. Every bid or ask concerns only one unit of the asset, but subjects can handle so much as desired as long as they have enough cash or assets (no short sale is allowed).

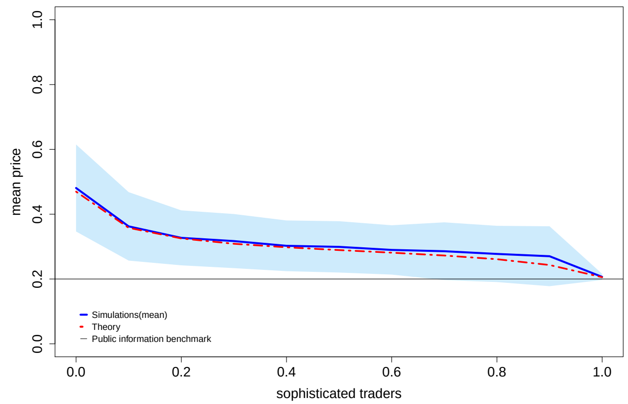
[20]The experiment is programmed using the Z-Tree software (Fischbacher, 2007).



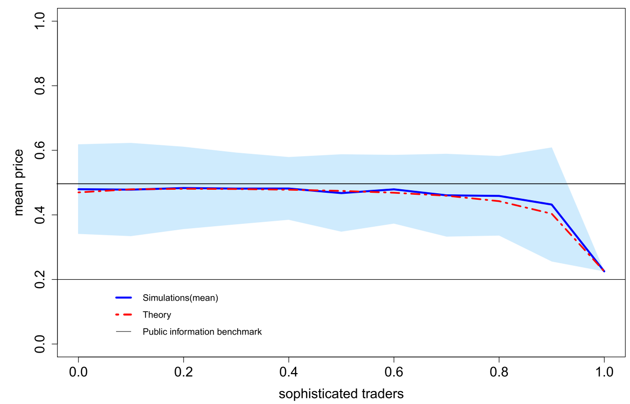
(a) PS scenario with $y = 1$



(b) CS scenario with $y = 1$



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



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

Figure 3.3 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 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.

Each market is populated by 15 subjects who are endowed with 1000 units of experimental currency (ECU)[21] 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 market, when the dividend is paid. Additionally, subjects receive noisy signals on the dividend value. Signals are partially but not totally informative and are presented to the subjects taking the value 10 or 0. If a subject observes a signal 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 (Table 3.3). 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 although one of them is identical to all of them in the market. But, unlike in the PS treatment, this signal is not common knowledge.[22]

Treatment	Released signal	Number of groups	Number of markets
B	-	1	10
PS	public	2	20
CS	common	2	20

Table 3.3 Experimental design.

At the end of each market, dividends are paid out and the subjects' profits are computed as the difference between their initial money 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.

3.4 Corroborating evidence: observed vs simulated data

This section compares the computational data, which is generated by the Monte Carlo simulations of the model, with the experimental data. The computational data are

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

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

generated following the process explained in Section 3.2.2 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:

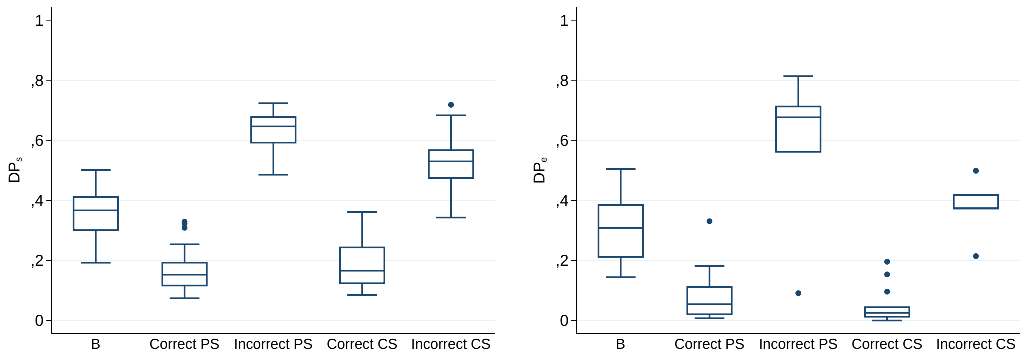
$$DP_e = \frac{1}{T_r} \sum_{tr=1}^{T_r} \frac{|D - PR_{tr}|}{10} , \tag{3.8}$$

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

$$DP_s = \frac{1}{M} \sum_{m=1}^{M} |D - \overline{P}_m| , \tag{3.9}$$

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

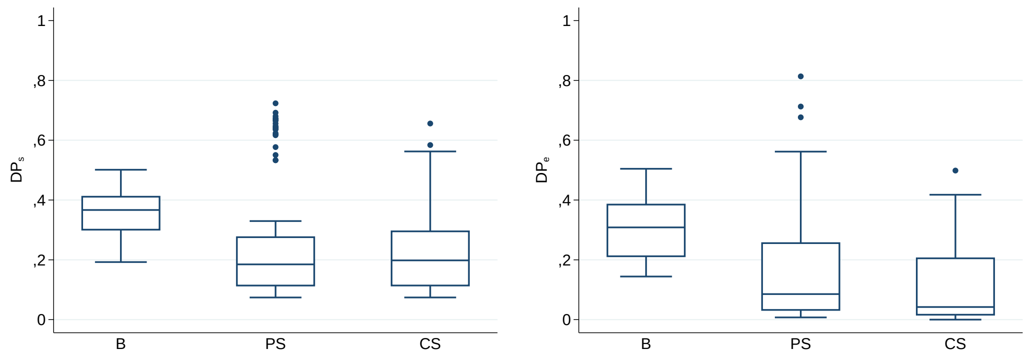
Figure 3.4(a) plots the DP_s indicator and Figure 3.4(b) plots the DP_e indicator. At a first glance, similarities are clear although a higher dispersion is present in the experimental data. Comparing to the B treatment, the release of a correct public signal helps prices to converge towards the dividend (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 traders 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 simulated traders are not able to learn. Although this is a weakness of our model, the main results of the laboratory experiment are reproduced.



(a) Simulation ($\theta = 0.2$) (b) Experimental results

Figure 3.4 Distribution of DP across markets, considering whether the released signal is correct or incorrect.

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 3.5 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. Therefore, we can conclude that public information is beneficial for market dynamics.



(a) Simulation ($\theta = 0.2$) (b) Experimental results of treatments

Figure 3.5 Distribution of DP across markets.

Finally, Figures 3.8 and 3.9 in the Appendix show similar results when the proportion of sophisticated traders is fixed to $\theta = 0.7$. These findings reveal that we do not have to fine tune the value of θ to observe similar results when comparing simulated and experimental data. In fact, any percentage of sophisticated traders in the interval $\theta \in [0.2, 0.7]$ gives similar results.

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) its limited impact if traders observe the same signal without being common knowledge.

3.5 Conclusions

We propose a simple decentralized asset market with asymmetric information populated by naive and sophisticated traders. The model aims at identifying the main effects on prices of unwarranted or mistaken public information when it interplays with noisy private information. Under bounded rationality, public information affects differently traders' behavior. Whereas naive traders only consider their information set, 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 instead of the dividend value. Whereas the distorting impact of mistaken 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 Chapter 2. Heterogeneity combined with bounded rationality generate 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.

Appendix

3.A Public signal scenario

3.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:

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

3.A.2 Sophisticated receivers

This section provides some illustrative examples to clarify the computation of expected payoffs when a sophisticated trader receives an offer. First, Table 3.4 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**
bid	$b \geq D_M$	N_H
	$D_L \leq b < D_M$	N_H, N_M
	$b < D_L$	N_H, N_M, N_L
ask	$a > D_H$	N_H, N_M, N_L
	$D_M < a \leq D_H$	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 3.4 Sophisticated receivers' inference about the expected dividend of the proposer.

Receiving buy offers: an example

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.[23]

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

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.

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

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

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

[23]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.

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.

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

Receiving sell offers: an example

Moving on to observed asks, she cannot update new information when she observes an ask at $a_{H^+} = D_H + \varepsilon$. Thus, the expected payoffs are defined by

$$\pi^S(a_{H^+}, D_L) = \begin{cases} 2D_L - a_{H^+} & \text{accepting the ask} \\ \\ D_L & \text{rejecting the ask} \end{cases}$$

In case she receives an ask at $a_{H^-} = D_H - \varepsilon$, the proposer of the offer may have an expected dividend D_M or D_L. The expected payoffs are the following:

$$\pi^S(a_{H^-}, D_L) = \begin{cases} -a_{H^-} + 2(D_{LM}\ Pr[D_M|D_M < a_{H^-}] \\ \qquad + D_{LL}\ Pr[D_L|D_L < a_{H^-}]) & \text{accepting the ask} \\ \\ D_{LM}\ Pr[D_M|D_M < a_{H^-}] \\ + D_{LL}\ Pr[D_L|D_L < a_{H^-}] & \text{rejecting the ask} \end{cases}$$

where

$$Pr[D_M|D_M < a_{H^-}] = \frac{Pr(a_{H^-}|D_M)Pr(D_M|D_L)}{Pr(a_{H^-}|D_L)} = \frac{\frac{1}{4}2pq[(1-D_L)+D_L]}{\frac{1}{4}[D_L(q^2+2pq)+(1-D_L)(p^2+2pq)]}$$

and

$$Pr[D_L|D_L < a_{H^-}] = 1 - Pr[D_M|D_M < a_{H^-}]\ .$$

Finally, in case she receives an ask at $a_{M^-} = D_M - \varepsilon$, the proposer's expected dividend must be D_L. Thus, the expected payoffs are

$$\pi^S(a_{M^-}, D_L) = \begin{cases} -a_{M^-} + 2D_L & \text{accepting the ask} \\ \\ D_L & \text{rejecting the ask} \end{cases}$$

3.A.3 Probability of transactions

	Flow	$\mathbf{S_H}$	$\mathbf{S_M}$	$\mathbf{S_L}$	$\mathbf{N_H}$	$\mathbf{N_M}$	$\mathbf{N_L}$
$\mathbf{S_H}$	μ_H	0	0	$\theta^2 p^2 (1-p)^2$	0	$\theta(1-\theta)2p^3(1-p)$	$\theta(1-\theta)p^2(1-p)^2$
$\mathbf{S_M}$	μ_M	0	0	0	$\theta(1-\theta)p^3(1-p)$	0	0
		0	0	0	0	0	$\theta(1-\theta)p(1-p)^3$
$\mathbf{S_L}$	μ_L	$\theta^2 p^2 (1-p)^2$	0	0	$\theta(1-\theta)p^2(1-p)^2$	$\theta(1-\theta)2p(1-p)^3$	0
$\mathbf{N_H}$	ν	0	0	$0.5(1-\theta)\theta p^2(1-p)^2$	0	$(1-\theta)^2 p^3 (1-p)$	$0.5(1-\theta)^2 p^2 (1-p)^2$
$\mathbf{N_M}$	ν	$(1-\theta)\theta p^3(1-p)$	0	$(1-\theta)\theta p(1-p)^3$	$(1-\theta)^2 p^3 (1-p)$	0	$(1-\theta)^2 p(1-p)^3$
$\mathbf{N_L}$	ν	$0.5(1-\theta)\theta p^2(1-p)^2$	0	0	$0.5(1-\theta)^2 p^2 (1-p)^2$	$(1-\theta)^2 p(1-p)^3$	0

Table 3.5 Probability per unit of time of trades.

3.B Common signal scenario

The analysis of common signal 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.

3.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:

$$E[D = 1|x_i, y_i] = \frac{1}{1 + \left(\frac{1-p}{p}\right)^{x_i} \left(\frac{1-q}{q}\right)^{y_i}} \tag{3.10}$$

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 $\chi_i = (x_i + y_i)$.[24] 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 $y_i = -1$. Table 3.6 lists the optimal offer of every type of trader considering the two possible realizations of the common signal. The optimal offer is computed by following the process explained in Section 3.1.2.

In case a sophisticated trader receives an offer, it provides with her 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. Table 3.7 shows which types of proposer a sophisticated trader can infer when she receives a given offer.[25]

[24] 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 $x_i = 0$.

[25] Note that there are not traders with low expected dividend D_L when the common signal is 1. Similarly, there are not traders with high expected dividend D_H when the common signal is -1.

Common signal 1				Common signal -1			
Proposer	χ_i	**Offer**		**Proposer**	χ_i	**Offer**	
S_H	3	b^*_H	$D_{\overline{M}} + \varepsilon$ $D_{\underline{M}} + \varepsilon$				
$S_{\overline{M}}$	1	$b^*_{\overline{M}}$	$D_{\underline{M}} + \varepsilon$	$S_{\overline{M}}$	1	$b^*_{\overline{M}}$	$D_{\underline{M}} + \varepsilon$
$S_{\underline{M}}$	-1	$a^*_{\underline{M}}$	$D_{\overline{M}} - \varepsilon$	$S_{\underline{M}}$	-1	$a^*_{\underline{M}}$	$D_{\overline{M}} - \varepsilon$
				S_L	-3	a^*_L	$D_{\overline{M}} - \varepsilon$ $D_{\underline{M}} - \varepsilon$

Table 3.6 Type of sophisticated traders and their optimal offers.

Observed offer		Type of the proposer
bid	$b \geq D_{\overline{M}}$	N_H
	$D_{\underline{M}} \leq b < D_{\overline{M}}$	N_H, $N_{\overline{M}}$
	$D_L \leq b < D_{\underline{M}}$	N_H, $N_{\overline{M}}$, $N_{\underline{M}}$
	$b < D_L$	N_H, $N_{\overline{M}}$, $N_{\underline{M}}$,N_L
ask	$a > D_H$	N_H, $N_{\overline{M}}$, $N_{\underline{M}}$, N_L
	$D_{\overline{M}} < a \leq D_H$	$N_{\overline{M}}$, $N_{\underline{M}}$, N_L
	$D_{\underline{M}} < a \leq D_{\overline{M}}$	$N_{\underline{M}}$,N_L
	$D_L < a \leq D_{\underline{M}}$	N_L

Table 3.7 Sophisticated receivers' inference about the expected dividend of the proposer depending on the value of the offer. First columns list the offers. The right column shows the receiver's inference about the proposers type.

3.B.2 Transactions

Tables 3.8 and 3.9 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 type of traders are $\{H, \overline{M}, \underline{M}\}$ if the common signal predicts dividend 1 (Table 3.8); otherwise $j \in \{\overline{M}, \underline{M}, L\}$ (Table 3.9). Considering the previous changes, we define a vector of market prices following the proposer's type offer in Table 3.8, $\mathbf{P} = (D_M, D_L, D_L, D_M, D_H, D_M, D_L)$. The vector of transaction prices when the common signal predicts dividend 0 is $\mathbf{P} = (D_M, D_H, D_H, D_M, D_H, D_M, D_L)$.

Tables 3.10 and 3.11 show the transaction probability per unit of time for each two specified types of traders. We distinguish again between markets with common signal 1 and common signal -1. Finally, the probability of transaction of every type of proposer is computed as the sum of columns in tables 3.10 and 3.11 and listed in tables 3.12 and 3.13, respectively.

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 3.8 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 3.9 Transactions when the common signal is -1.

	Flow	$\mathbf{S_H}$	$\mathbf{S_M}$	$\mathbf{S_L}$	$\mathbf{N_H}$	$\mathbf{N_M}$	$\mathbf{N_L}$
$\mathbf{S_H}$	μ_H	0	0	0	0	$\theta(1-\theta)p^3(1-p)$	$\theta(1-\theta)0.5p^2(1-p)^2$
		0	0	0	0	0	$\theta(1-\theta)0.5p^2(1-p)^2$
$\mathbf{S_M}$	μ_M	0	0	0	0	0	$\theta(1-\theta)2p(1-p)^3$
$\mathbf{S_L}$	μ_L	$\theta^2p^2(1-p)^2$	0	0	$\theta(1-\theta)p^2(1-p)^2$	$\theta(1-\theta)2p(1-p)^3$	0
$\mathbf{N_H}$	ν	0	0	$0.5(1-\theta)\theta p^2(1-p)^2$	0	$(1-\theta)^2p^3(1-p)$	$0.5(1-\theta)^2p^2(1-p)^2$
$\mathbf{N_M}$	ν	$(1-\theta)\theta p^3(1-p)$	0	$(1-\theta)\theta p(1-p)^3$	$(1-\theta)^2p^3(1-p)$	0	$(1-\theta)^2p(1-p)^3$
$\mathbf{N_L}$	ν	$0.5(1-\theta)\theta p^2(1-p)^2$	$\theta(1-\theta)p(1-p)^3$	0	$0.5(1-\theta)^2p^2(1-p)^2$	$(1-\theta)^2p(1-p)^3$	0

Table 3.10 Probability per unit of time of trading for two specified types of agents in case common signal is 1. First column(row) denotes the type of proposer(receiver). Second column describes the proposer's order flow.

	Flow	$\mathbf{S_H}$	$\mathbf{S_M}$	$\mathbf{S_L}$	$\mathbf{N_H}$	$\mathbf{N_M}$	$\mathbf{N_L}$
$\mathbf{S_H}$	μ_H	0	0	$\theta^2p^2(1-p)^2$	0	$2\theta(1-\theta)p^3(1-p)$	$\theta(1-\theta)p^2(1-p)^2$
$\mathbf{S_M}$	μ_M	0	0	0	$2\theta(1-\theta)p^3(1-p)$	0	0
$\mathbf{S_L}$	μ_L	0	0	0	$0.5\theta(1-\theta)(1-p)^2p^2$	0	0
		0	0	0	$0.5\theta(1-\theta)(1-p)^2p^2$	$\theta(1-\theta)p(1-p)(1-p)^3$	0
$\mathbf{N_H}$	ν	0	$(1-\theta)\theta p^3(1-p)$	$0.5(1-\theta)\theta p^2(1-p)^2$	0	$(1-\theta)^2p^3(1-p)$	$0.5(1-\theta)^2p^2(1-p)^2$
$\mathbf{N_M}$	ν	$(1-\theta)\theta p^3(1-p)$	0	$(1-\theta)\theta p(1-p)^3$	$(1-\theta)^2p^3(1-p)$	0	$(1-\theta)^2p(1-p)^3$
$\mathbf{N_L}$	ν	$0.5(1-\theta)\theta p^2(1-p)^2$	0	0	$0.5(1-\theta)^2p^2(1-p)^2$	$(1-\theta)^2p(1-p)^3$	0

Table 3.11 Probability per unit of time of trading for two specified types of agents in case common signal is -1. First column(row) denotes the type of proposer(receiver). Second column describes the proposer's order flow.

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

Table 3.12 Expected number of transactions per unit of time for every type of trader when the common signal is correct, given $D=1$ in CS scenario.

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

Table 3.13 Expected number of transactions per unit of time for every type of trader when the common signal is incorrect, given $D=1$.

3.C Robustness

3.C.1 Effects of the heterogeneous order flow

Figure 3.6 shows the mean price evolution over the proportion of sophisticated traders present in the market θ. Dark-thick lines refer to the public signal scenario whereas light-thin lines refer to the common signal scenario. Moreover, variation in sophisticated traders' relative order flow per unit of time is represented as follows: the dashed lines represent the mean price under homogeneous order flow $\mu_i = \nu = 1$ and solid-lines depict the mean price under the heterogeneous order flow defined in the main text.

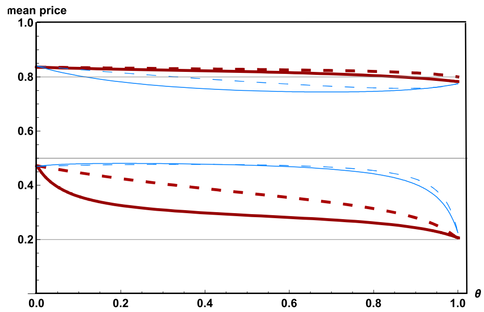


Figure 3.6 X-axis represents the proportion of sophisticated traders and Y-axis denotes market prices. Horizontal lines at $(0.8, 0.2, 0.5)$ indicate the public benchmark PB taking into account only the correct or incorrect public signal and the common signal, respectively.

At the top of the figure, one can see that there are no large differences between mean prices under homogeneous and heterogeneous order flow specifications when the signal is correct. The order flow shows has not a significant impact, except for the case with an incorrect public signal. However, the mean price is always biased towards the public signal.

3.C.2 Does market configuration matter?

This subsection aims at testing the relevance of 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 (Table 3.14) based on observed distributions of information across traders in the experiment of Chapter 2: 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.

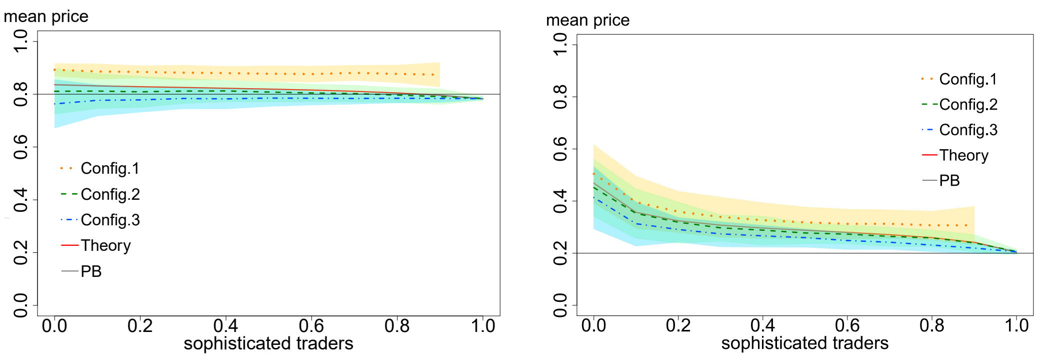
3 where markets are populated by 2 misinformed, 5 uninformed and 8 informed traders.

Configuration	informed (H)	uninformed (M)	misinformed (L)
1	10	5	0
2	7	7	1
3	8	5	2

Table 3.14 Market configurations assuming $D = 1$. H, M and L refer to *high*, *medium* and *low* expected dividend.

Figure 3.7 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.



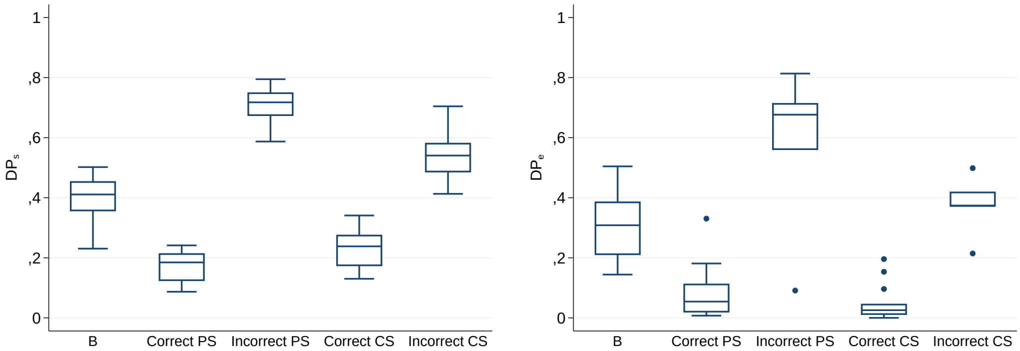
(a) Correct public signal $y = 1$

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

Figure 3.7 Mean price of the market configurations assuming dividend $D = 1$. Shaded area shows 1 standard deviation of the Monte Carlo simulations.

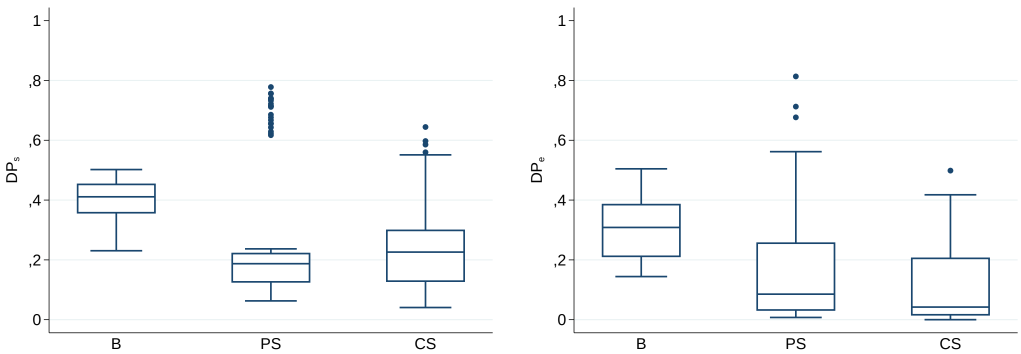
3.C.3 Computational and experimental data

Figures 3.8 (a) and (b) plot the computational data and observed data from the laboratory experiment, respectively. Contrary to Figure 3.4, we fix a high proportion of sophisticated trader $\theta = 0.7$. At a first sight, similarities between both data are evident and there are no noticeable differences between simulations with $\theta = 0.2$ and $\theta = 0.7$ proportion of sophisticated traders.



(a) Simulation ($\theta = 0.7$) (b) Experimental results

Figure 3.8 Distribution of DP of scenarios B, PS and CS, considering a correct and incorrect released signal.



(a) Simulation ($\theta = 0.7$) (b) Experimental results

Figure 3.9 Distribution of DP of scenarios B, PS and CS.

General conclusions and future perspectives

Over the years, the degree of transparency in the communication policy of regulatory institutions has been discussed without reaching a consensus view. The fact that public announcements are listened by all participants in a market may provoke traders to over-rely on this information when they make decisions. In view of this, the aim of the thesis is to investigate the impact of public information on market price in uncertain environments. More specifically, this study attempts to analyze the aggregation of information in laboratory asset markets as a function of the access of traders to heterogeneous sources of information. We design an experimental asset market that is characterized by (i) one-period risky assets that pay a dividend homogeneous among traders, and (ii) the presence of different sources of information, namely private and public information.

In the first experiment, traders can acquire costly imperfect private information about the dividend of the asset. Moreover, in some markets, a free signal is released to all traders. That signal is identical to all traders, which is explicitly explained to traders in some treatments, whereas traders are not aware of it in other treatments. The knowledge condition of the released signal allows for disentangling the dual role of public information, which is identified in the theoretical literature. Public information provides information on the fundamentals and information on the other traders' beliefs. The main findings of the theoretical literature are observed in our experiment, crowding out of private information and overweighting of public information. Indeed, both effects are measurable and empirically relevant.

After that, the second experiment is devoted to understanding the mechanism behind the overweighting of public information and the principal responsible elements of such a phenomenon. In doing so, the previous experimental design is simplified; the sole difference is that private information is exogenously allocated among traders. The exogenous distribution of information keeps constant the information available in the market and explicitly reveal the presence of uninformed traders. We find that public information helps price convergence to the fundamentals when correct. Instead, an incorrect public signal favors informed traders to make more profitable transactions than uninformed traders. The main contribution of this chapter is the identification of the asymmetric behavior of the traders according to their private information level, and how this behavior changes depending on the characteristics of the released signal. A simple beliefs approach model proves that public information strongly affects prices when they depend on traders' higher-order beliefs.

The last chapter focuses on the role of public information on traders' beliefs. We develop a model characterized by the presence of heterogeneous traders who observe imperfect private signals. Moreover, the market is populated by traders with two levels of reasoning: naive and sophisticated. The model, together with Monte Carlo simulations, qualitatively reproduces the main patterns observed in the laboratory experiments of Chapter 2.

The main contribution of the thesis is that price overweighting comes up in a non-explicit coordination setting. The fact that public information is observed by all market participants is the main responsible for the overweighting phenomenon. We find that this phenomenon emerges as a consequence of the asymmetric strategies that public information generates in heterogeneous and bounded rational traders.

Finally, this thesis provides policy advice to financial institutions. There are unintended effects of the complex interaction between private and public information on the market performance. For example, policymakers should be aware that public announcements might reduce traders' effort to invest in alternative sources of information and, then, reduce the information available in the market. As a policy advise, we recommend that ongoing reforms on the regulation of financial institutions (for instance, the credit rating agencies) should account for the complex interplay of public and private information. Institutions should determine the level of transparency considering the quality and characteristics of the private information at the disposal of traders.

In this respect, many questions remain open. How can institutions release information preserving the benefits of public information and reducing its adverse effects? Future experiments will be focused on investigating communication strategies that preserve the benefits of public information while reducing its distortive effects. For example, we conjecture that the presence of multiple sources of public information in the market, limit publicity of the announcements or the timing of releasing public information into the market may achieve this goal.

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