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In this paper we present the results of experiments and computational analyses of trading in decentralized markets with asymmetric information. We consider three trading configurations, namely the ring, the small-world, and the Erdös-Rényi random network, which allow us to introduce heterogeneity in nodes degree, centrality and clustering, while keeping the number of possible trading relationships fixed. We analyze how the prices of a traded risky asset and the profits of differently informed traders are affected by the distribution of the trading links, and by the location of the traders in the network. This allows us to infer key features in the dynamics of learning and information diffusion through the market. Experimental results show that learning is enhanced locally by clustering rather than degree, pointing to a learning dynamic driven by interdependent, successive trading events, rather than independent exposures to informed traders. By calibrating a behavioural agent-based model to the experimental data we are able to estimate the speed at which agents learn and to locate where information accumulates in the market. Interestingly, simulations indicate that proximity to the insiders leads to more information in regular networks but not so in random networks.

Keywords
OTC markets; Asymmetric information; Learning; Information diffusion; Networks; Insider trading

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Learning and information diffusion in OTC markets: experiments and a computational model

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Abstract

In this paper we present the results of experiments and computational analyses of trading in decentralized markets with asymmetric information. We consider three trading configurations, namely the ring, the small-world, and the Erdös-Rényi random network, which allow us to introduce heterogeneity in nodes degree, centrality and clustering, while keeping the number of possible trading relationships fixed. We analyze how the prices of a traded risky asset and the profits of differently informed traders are affected by the distribution of the trading links, and by the location of the traders in the network. This allows us to infer key features in the dynamics of learning and information diffusion through the market. Experimental results show that learning is enhanced locally by clustering rather than degree, pointing to a learning dynamic driven by interdependent, successive trading events, rather than independent exposures to informed traders. By calibrating a behavioural agent-based model to the experimental data we are able to estimate the speed at which agents learn and to locate where information accumulates in the market. Interestingly, simulations indicate that proximity to the insiders leads to more information in regular networks but not so in random networks.

Keywords: OTC markets; Asymmetric information; Learning; Information diffusion; Networks; Insider trading.

1 Introduction

The last few decades have seen an increasing interest in the study of trading and information diffusion in decentralized markets where trading occurs via bilateral negotiations rather than through the posting of public bid and ask quotes (see, e.g., Babus and Kondor, 2018; Choi et al., 2017; Condorelli et al., 2017; Gale and Kariv, 2007; Gofman, 2011; Grimm and Mengel, 2020; Kranton and Minehart, 2001; Malamud and Rostek, 2017; Manea, 2018; Nava, 2015; Rahi and Zigrand, 2013). In decentralized markets prices are dispersed and pre-trade and post-trade transparency is limited. Investors negotiate the terms of their trades with imperfect and often asymmetric information about overall market conditions. This lack of transparency has been identified as a potential source of systemic risk and a driver of unfair pricing. The Global Financial Crisis, for example, sparkled in 2008 from the disruption of a number of OTC markets, was exacerbated by the inability of traders to quickly identify the fair price of assets under the opaque mechanisms of decentralized trading, leading to a collapse in trading volume. In order to inform market design and regulatory intervention, and to establish a level playing field for all market participants, it is of critical importance to understand under what conditions agents can learn the value of an asset in decentralized markets, how the organization of the trading relationships may affect learning, and how the learning dynamics may in turn affect market efficiency and fairness.

To answer these questions, we study, via laboratory experiments and computer simulations, markets in which agents can engage in multiple, bilateral, transactions of a single risky asset. Agents are organized in a trading network where links between pairs of agents indicate potential counterparts to a trade. The final value of the asset is uncertain and agents have private signals, of heterogeneous quality, about its common value. Some agents may have perfect information about the value of the asset and in this case they are called insiders. Our aim is to understand how agents learn information via trading and how private information diffuses through the market.

In the paper we argue that some features of the learning process can be inferred by pinning down which agents become more informed, and which markets become more efficient as trading progresses. Specifically, we can deduce if learning is driven primarily by independent interactions with informed traders, in which case information diffuses in markets via simple contagion, analogously to the propagation of infectious diseases, or if learning is achieved synergistically, thought mutual reinforcement of beliefs among neighbours, in which case information diffuses as a complex form of contagion. These different forms of contagion are in fact enhanced by different network structures. Networks which are heterogeneous in nodes' degree, so that some nodes are hubs connected to many other nodes in the networks, while others only have few links, have been shown to facilitate the diffusion of simple contagious processes (Pastor-Satorras and Vespignani (2002)). More complex form of diffusion, however, like social learning, can be enhanced by less heterogeneous, but more clustered[1] networks(Centola and Macy (2007)).

The relationship between degree, clustering and the spread of information is in general complex and may depend on the nature of the information being spread and the characteristics of the individuals in the network. High degree, influential nodes are typically able to spread information quickly and efficiently even in networks with low clustering. In our context, if the informed agents, or the insiders, could be easily discovered, they would become the main influencers of agents beliefs. A few highly connected insiders would in this case be a very effective channel for information transmission, and more heterogeneous networks would lead to more efficient markets. This is because traders who have early interactions with the insiders would become quickly informed themselves, and, if highly connected, could turn into new information hubs and spread information further through the market. However, if insiders are not easily detectable, they would be less influential and uninformed agents may need multiple interactions with the insiders themselves, and/or other neighbours, to learn. In this case learning would be slow and heterogeneous networks may loose their competitive advantage in favour of more regular, clustered networks. In clustered networks information

[1]Clustering measures the extent to which nodes in a graph create tightly knit groups.

can spread faster in the neighbourhood of the insider. This is because the neighbours of an insider are likely to belong to the same cluster, and the many short paths connecting the nodes in the neighborhood facilitate achieving a critical mass of traders who hold a similar opinion within the cluster. This in turn may cause a rapid adoption of the information by all the traders in the cluster as they reinforce each other beliefs by quoting and trading in a correlated fashion. However, information generally propagate slowly in clustered networks, since the clusters themselves may be relatively sparsely connected. Nonetheless, if the speed gains in terms of learning within a cluster compensate for the slower diffusion across clusters, regular networks could lead to more efficient markets than heterogeneous ones.

Our laboratory and computational experiments provide support to the theory that information diffusion is affected by the network structure and by the number and position of insiders. Experimental outcomes point to a situation in which insiders do not compete aggressively and, as a result, their presence and location is unlikely to be detected. Markets do not converge to the fully revealing equilibrium in the laboratory. Better informed agents profit from information advantages and more so when they are better connected, in line with theoretical predictions and empirical observations (Babus and Kondor, 2018; Di Maggio et al., 2017; Hollifield et al., 2017; Li and Schürhoff, 2019). At individual level we observe that belonging to a clustered neighbourhood around an insider facilitates learning more than occupying a high degree or central position. At the same time, insiders profit less when they are part of a clustered neighbourhood. In some experimental configurations, clustered networks are overall more efficient and fair than random networks. All together, these findings support the hypothesis that learning is alike a complex contagion process, reinforced by synergistic interactions, rather than a simple contagion process, driven by independent exposures to insiders.

In the paper we also investigate if the trading behaviour of insiders, and their ability to extract a surplus from trading, is affected by the position they occupy in the network, and if competition among insiders has different implications for the price discovery process and for market fairness under different network architectures. The empirical literature has documented that choosing the source of information randomly typically performs worse than targeting more central nodes (Banerjee et al. 2013, Banerjee et al. 2019, Banerjee et al. 2020). We compare market efficiency and fairness when placing the insider(s) in more or less central nodes of the network. Our experiments confirm that when the insider occupies the most central position higher efficiency and lower inequality is achieved in Random Networks, but not so in regular networks. Further, similar levels of efficiency do not necessarily lead to comparable levels of inequality. Interestingly, proximity to the insiders does not necessarily lead to better learning and profit opportunities.

The rest of the paper is organized as follows. In section 2 we review the theoretical and experimental literature on information diffusion in trading markets. In section 3 we formulate the hypothesis. In section 4, we outline the experimental design and experimental results. Section B describes the ABM and the computational experiments' results. Conclusions follow in section 6. Additional results are presented in the Appendices.

2 Related literatures

Our paper contributes to the literature on trading in decentralized markets. Wolinsky (1990), Blouin and Serrano (2001), Duffie and Manso (2007), Duffie et al. (2009, 2010a,b), and Golosov et al. (2014), have investigated learning in OTC markets using search and random matching. In this setting, participants meet randomly and trade bilaterally, without an explicit network structure being assumed. A limitation of search models is that counterparties are only likely to meet and trade once. While this set up is also common to some network models, networks, in general, allow for stable trading relationships, either exogenously imposed or endogenously determined. Crucially, this makes some modelling choices, such as that information is revealed by word-of-mouth, inappropriate in this setting.

The problem of information diffusion in networked decentralized markets has been analyzed by Babus and Kondor (2018). The central results of this work is that dealers in an OTC market do not normally learn all the relevant information from prices, except in the common value case where decentralization does not hamper the information transmission process in any network

Babus and Kondor (2018), as most of the papers in this branch of the literature, assume that private information is incorporated rationally into individual beliefs via Bayes' rule. However, when learning is mediated by social networks and the actions and information of agents can only be partially observed, Bayesian updating poses unrealistic cognitive demands on individuals. When there is only partial observability of the structure of the social network, bayesian updating becomes computationally prohibitive. To address these criticisms, a bounded rational paradigm has been proposed which, building on the DeGroot (1974) model, introduces simple heuristics to incorporate the opinions of others into one's own. This bounded rational approach is often employed in settings of repeated interactions in social networks[2]. Various authors have analyzed which networks of social interactions and what learning rules lead successfully to information aggregation (DeMarzo, Vayanos, and Zwiebel (2003), Golub and Jackson (2010), Jadbabaie, Molavi, Sandroni, and Tahbaz-Salehi (2012)). Other scholars have studied how the characteristics of the network can affect the speed of diffusion. This body of work has shown that the speed at which information, behaviour or a disease, propagates, depends on the size and location of the initial seed, the diffusion rule, and the connectivity of the underlying network. Our paper contributes to this literature and in particular relates to studies which measure the effect of clustering on diffusion over social networks. The simplest model of social influence (e.g. Bass 1969) assumes, analogously to

[2]In the standard social learning models individuals are allocated signals of varying precision on the true state of a variable and update their priors by sharing their best guess with each other. In this framework, learners truthfully communicate their best guesses about the state of the world to their social connections. In some formulations of the model, at each time step, agents update their believes as a weighted average of their current belief and the beliefs of all their neighbours, with weights representing the trust, or influence, they repose in them. In alternative versions, individuals meet one person at a time within their social circle, and dynamically update their belief as a convex combination of their current belief and the belief of the last person they have met. Rather then communicating beliefs in some formulation of the models agents can only observe the actions of their neighbours (see Acemoglu and Ozdaglar (2011) for a review some of the literature on both the Bayesian and non Bayesian learning models).

the spread of an infectious disease, that agents adopt a behaviour, or belief, with constant probability each time they have an independent exposure to an earlier adopter. Given that only the absolute number of observable adopters matters in these models, the effectiveness of a network in propagating a belief can be shown to be negatively correlated with the variance of the connectivity distribution of its nodes' (see Pastor-Satorras and Vespignani (2002) for a review). However, in many social phenomena (such as the adoption of innovation, conforming to costly social behaviours, or learning), not only does the total number of adopters matter, but so does how this number compares with the number of non-adopters. In these more complex models, such as the Granovetter (1978) threshold model (where agents become active only if enough other agents in their reference group are already active), the information cascade model of Bikhchandani, Hirshleifer, and Welch (1992) (where learning is affected by the particular order in which the actions of others are observed), or the generalized contagion models of Dodds and Watts (2004, 2005) (which interpolates between simple contagion and threshold models) the probability that an additional positive signal triggers adoption depends on how many other signals have been observed, and possibly their order. Thus, multiple interdependent exposures, from the same, or different, active agents, are needed in these models to induce an agent to change behaviour, or learn. Research has shown that these slower and more complex forms of contagion may diffuse better within different types of networks to those in which simple contagion flourishes (Centola and Macy, 2007; Watts, 2003; Watts and Dodds, 2007; **?**; **?**). For example, Jackson and Yariv (2005) and Lopez-Pintado (2008) have shown that for more general diffusion rules low variance networks may have lower diffusion thresholds than high variance ones. Further, Centola and Macy (2007) have illustrated how clustered networks can better promote complex contagion. More recent studies have shown that the extent to which an innovation diffuse depends not only of the cohesion of groups but also on the adoption threshold. As the threshold of adoption increases, more and more clustered networks become superior at diffusing the innovation.

An experimental paper related to ours is Halim et al. (2019) which studies information aggregation in markets where traders share the information they can purchase on their social network via word-of-mouth communication. The experiment shows that, while social communication leads to more trades and improves market liquidity, the ability of prices to correctly predict the true state of nature does not improve with information sharing. Our setup is different in that agents cannot purchase information and do not engage in direct communication but can only update their beliefs from observing the actions of their neighbours. Another recent experimental paper related to ours is Alfarano et al. (2019), which analyzes the interplay between network density and informational asymmetries in decentralized markets where prices are determined via a networked continuous double auction. Results show that trading volume increases significantly when connectivity among traders increases, but market efficiency and fairness do not improve when additional links are added to the network. Our paper differs from Alfarano et al. (2019) in that in our setting prices are determined via a bilateral bargaining mechanism and, rather than changing the network density, we change the distribution of links, varying from regular to random networks, but keeping the overall number of links constant.

3 Formulation of Hypothesis

In our experiments we test the effect of the trading network structure on information diffusion in the context of decentralized markets. The main treatments are three network structures: Circle, Small World, and Random Network. For each treatment we consider sub-treatments with zero, one or two insiders, located in more or less central nodes in the network.

In formulating our hypothesis we draw a parallel between learning and the diffusion of contagion processes in random networks. In contagion types of models, agents can typically be in two possible states, usually referred to as active/inactive, infected/susceptible, adopter/non-adopter etc. The two states in our context can be interpreted as agents being correctly informed or not about the true value of the dividend, and trading accordingly, i.e.

buying when the dividend is high and selling when the dividend is low. Our agents do not communicate directly with each other by word-of-mouth but try and infer the fundamental value of the asset from the order flow they observe.

In order for information to spread in the market, agents have to be able to learn it first and then to influence others. If each trading interaction with informed agents could independently lead to the discovery of the fundamental value, more connected nodes would have a double advantage: they would be more likely to be connected to the insider, and thus more likely to learn the correct price, and could spread the information to others more effectively. As a result, in analogy with epidemiological models, heterogeneous networks would always be more conducive to information diffusion. When learning is fast, for example because insiders quickly reveal their information, information advantages fade away very quickly and more efficient markets are normally also more equal in terms of profit opportunities. Thus, heterogeneous networks would lead not only to greater price efficiency abut also to greater fairness in profits than networks of homogeneous agents. This leads to the following hypothesis:

Hypothesis 1 (Simple contagion): Learning occurs via independent interactions with better informed traders, as in simple contagion models. Learning is locally enhanced by degree. Random networks lead to markets that are more efficient and fair, and even more so when two insiders compete in the same market as they independently contribute to the spreading of information.

If this hypothesis holds it would indicate that insiders can easily be identified. However identifying the insiders may not be easy. Traders may face uncertainty about whether others are informed or not, and could only learn by aggregating the orders submitted by all their neighbours. In this case learning would be alike a complex contagion process, building up slowly and in a path dependent way. While high degree nodes would still be more effective in propagating information, they could become less "vulnerable" to learning in this context. High degree nodes in fact are likely to be connected to agents located in distant part of the network. While some of these neighbours may be informed, others, particularly in the early stages of trading, are likely to be still uninformed. As a result, the observed order flow may be noisy and extracting the signal from the noise may be difficult for high degree agents[3]. Agents in a clustered neighbourhood instead are tightly connected to each other and tend to learn simultaneously. This interdependence can lead locally to orders submitted consistently on the same side of the market, generating a large order flow imbalance that can reinforce each others' beliefs. Thus, a more regular, clustered, network may become more informative around an insider than a random network configuration, particularly if insiders cannot be immediately identified. Centola and Macy (2007) has discussed how increasing the probability of rewiring links in small world networks[4] slows down diffusion in threshold models. Higher levels of rewiring, in fact, create bridges across distant nodes reducing the mean distance between arbitrarily chosen nodes in the network. Few long ties can dramatically enhance simple contagions, which is why small world networks are very effective at spreading diseases even at a low level of rewiring. Complex contagion, however, requires contact with several active neighbours, and depends not only on the length of a bridge (how distant are neighbourhoods that become connected by the bridge) but also on its width (i.e. the number of ties between neighbourhoods). As a result, complex contagion is locally enhanced by network topologies that provide social reinforcement via high clustering. However, clustering implies redundancy which may override the benefit of multiple influences and may slow down the learning process overall. This is particularly the case if information spreads from a single source but may be mitigated by the presence of multiple insiders who could spread information simultaneously from different parts of the network. Overall, the networks that lead to greater market efficiency are determined by the balance between the speed of individual learning and the speed of diffusion. However, if learning is slow, non informed agents become exposed to exploitation by better-informed ones and information advantages can lead to high profit opportunities. More efficiency does

[3]Sunder (1992) for example described how the double auction mechanism creates enough endogenous noise to prevent an instantaneous revelation of the available information.

[4]Random networks can be generated by rewiring links in small world networks. In the process clustering declines as well as the diameter of the network.

not necessarily lead to more fairness in this context. This is because efficiency is driven by the average amount of learning that takes place in the market, while profit inequality is affected by where information is located in the networks. The relative precision of agents' information at layers of increasing distance from the insider, determines which market leads may to larger profit inequalities.

In addition to clustering, centrality could also be more valuable than degree for agents if learning is a complex contagion process. When agents learn from all their neighbours and, through them, from their neighbours' neighbours, and so on, more central agents can potentially aggregate private information dispersed through the market faster that high degree nodes. This would be the case, particularly for agents distant from the source of information, who cannot learn directly from the insider(s) but only from their neighbours.

These considerations lead to the following alternative hypothesis:

Hypothesis 2 (Complex contagion): Learning occurs via interdependent interactions and is enhanced by social reinforcement, in analogy to complex contagion models. Nodes with high clustering and/or high centrality learn faster than high degree nodes. Regular clustered networks may become more efficient, particularly when two insiders trade in the same market. More efficient markets are not necessarily more fair.

4 Laboratory experiments

4.1 Experimental design and execution

We consider a trading network consisting of 14 participants. The structure of the network varies across treatments. Figure 1 shows the three network structures, circle network (left), small world network (middle), and Erdös-Rényi random network (right), considered in our experiment.[5] All three network structures have the same average degree, i.e. the average

[5] Starting with a circle networks, the small world properties of low diameter and high clustering are recovered for a rewiring probability of about 1% of the links. For higher values of the rewiring probability random networks are recovered.

[h]

	Circle) (c=0.46, b=7.5, cc=0.50)			Small World (c=0.49, b=6.9, cc=0.46)			Random (c=0.55, b=5.5, cc=0.29)		
Node number	Betweenness	Closeness	CC	Betweenness	Closeness	CC	Betwenness	Closeness	CC
1	7.5	0.464	0.5	11.21	0.565	0.33	7.27	0.565	0.16
2	7.5	0.464	0.5	7.74	0.500	0.50	0.97	**0.433**	**0.00**
3	7.5	0.464	0.5	3.70	0.464	0.50	4.65	0.565	0.33
4	7.5	0.464	0.5	3.89	0.464	0.50	**13.80**	**0.619**	0.20
5	7.5	0.464	0.5	3.64	0.448	0.50	3.70	0.565	0.40
6	7.5	0.464	0.5	4.89	0.481	0.50	1.64	0.448	**0.00**
7	7.5	0.464	0.5	6.48	0.500	0.50	6.95	0.565	0.33
8	7.5	0.464	0.5	**17.07**	**0.590**	**0.30**	8.90	0.541	**0.00**
9	7.5	0.464	0.5	7.82	0.500	0.50	3.90	0.590	0.40
10	7.5	0.464	0.5	6.07	0.500	0.50	**0.00**	0.448	**1.00**
11	7.5	0.464	0.5	5.22	0.433	0.50	7.96	**0.619**	0.30
12	7.5	0.464	0.5	4.61	0.464	0.50	3.54	0.541	0.33
13	7.5	0.464	0.5	**1.95**	**0.419**	**0.66**	7.15	**0.619**	0.33
14	7.5	0.464	0.5	12.67	0.500	0.33	6.54	0.565	0.30

Table 1: Betweenness centrality, closeness (normalized) centrality, and (local) clustering coefficient (CC) of the nodes in the experimental markets of Figure 1. Global measures are reported in the table headings: c=closeness, b=betweenness, cc=clustering coefficient. Minima and maxima of each column are in bold.

number of trading links for each node is the same across networks, and equal to 4. Degree is a local measure and does not necessarily indicate the importance of a node in connecting others. Measures of centrality, such as closeness centrality and betweenness centrality, are more indicative of how well information can flow from one part of the network to another. The average centrality measures and global clustering coefficient for each experimental network, in addition to the centrality and local clustering coefficient of each node, are reported in Table 1[6]. Values reflect the well-known fact that the more rigid the shape of the network is, such as the ring, the higher the clustering coefficient and the betweenness centrality are (all nodes are important for information flow, which is forced to follow a strict path) but the lower is the closeness (nodes are farther away to each other on average).

In our experiment, participants can trade only with others who are directly connected in the network. Participants are informed of their "Player ID" as well as those of his/her counter-parties in the network. Thus agents know their own degree but are not informed of the entire network structure, or the degree of their neighbours.

[6]Closeness centrality of a node is calculated as the inverse of the average length of the shortest paths from a node to every other node in the network. The most central nodes are the ones with the highest closeness centrality. Closeness can be regarded as a measure of how fast it will take to spread information from a node to all other nodes sequentially. Betweenness centrality measures how many shortest paths between vertices in the network pass through a given vertex. Thus it measures how important a node is to the shortest paths through the network. The most central nodes are the ones with the highest betweenness centrality. Betweenness captures how important a node is in spreading information across different parts of the network.Another metric commonly used to describe the structure of a network is clustering which measures the extent to which nodes in a graph create tightly knit groups. The global clustering coefficient is defined by the number of closed triplets over the total number of triplets in the network.

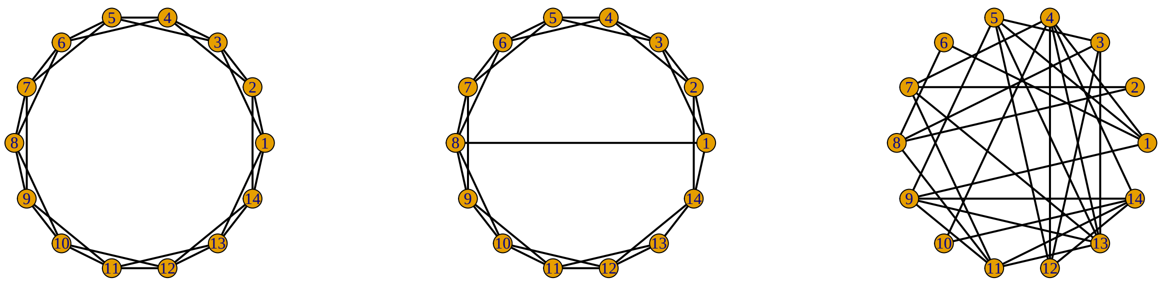


Figure 1: Network structures considered in the experiment: the circle (ring) network (left), the small world network (center), and the Ervos-Renyi random network (right).

At the beginning of the game, each participant is endowed with 20 units of asset and 10,000 of Experimental Currency Units (ECUs) that they can use to trade. Each unit of the asset can payoff a dividend of 200 ("high") or 100 ("low") with equal probability. The value of the dividend is determined at the beginning of the game before the market opens. Conditional on the realization of the dividend, each participant receives a private signal which informs him/her about the true value of the dividend with a probability $P = 0.6$ unless s/he is an insider. If the participant is in the role of an insider, $P = 1.0$.

A market is open for 7.5 minutes. During these 7.5 minutes, participants can, at any time, submit orders by specifying a counter-party (among those who are directly connected in the network), type of order (either to buy from or to sell to), and the price. If there already exists an outstanding offer submitted by a participant to a counter-party, the participant can either improve upon the existing offer or cancel it before it is accepted by the counter-party, before submitting a new one. Participants can trade as many times as they wish within their budget constraints (i.e., participants cannot borrow money or short-sell the asset).

Once the market is closed, participants are informed of the value of the realized dividend and payoffs that they have obtained. The payoff of each participant is computed as the difference between the value of their final portfolio (cash + dividend earning from their asset holding) and the initial endowment evaluated at the realized dividend. Thus, if they do not trade, their payoff is zero.

In each experimental session, we repeat this OTC market game 8 times holding the structure of network fixed. We call one play of OTC market game a round. At the beginning of each round, participants' position in the network is randomly re-assigned (i.e., they are given a new Player ID), and the true value of dividend is reset. The number and the position of insiders within a network are varied across rounds according to a pre-specified order. In particular, we set up markets with 0, 1, or 2 insiders, and they may be "strong" (if their betweenness centrality is the highest in the network) or "weak" (if their betweenness centrality is the lowest in the network).[7] Participants are told that there can be insiders (who receives a signal with $P = 1.0$) in the market, but are not told how many of them exist.

Upon completion of 8 rounds of OTC market games, 2 rounds will be randomly selected for payment. Participants receive a cash reward based on the payoffs they earned in these two selected rounds according to an exchange rate of 20 ECU=10JPY ($\approx$ 0.08EUR) in addition to 2000 JPY endowment for the OTC game. If one's payoff is negative, it is subtracted from their endowment.

Before the 8 rounds of OTC market game, we have elicited participants' risk preference based on an investment game (Gneezy and Potters, 1997) where they are given 1,500 ECU to invest and with probability 50% it is multiplied by 2.5 and with 50% chance it is lost. The result of this game is not communicated to the participants until the end of the session. After the completion of the OTC market game, participants answered 16 questions (in 8 minutes) from Raven Advanced Progress Matrix test (Raven, 1998), as well as a 3-question version of the Cognitive Reflection Test (Frederick, 2005). In addition to the participation fee of 500 JPY, participants are paid for the rewards they earned in the investment game and the OTC market game. See Online Appendix for an English translation of the instruction

[7] In case of the circle network, all the positions in the network are symmetric. Thus, there is no distinction between "strong" or "weak" insider. Instead, we distinguish, in case there are two insiders in the circle network, whether two insiders are directly connected or not.

of the experiment as well as a comprehension quiz.

We conducted computerized experiments[8] at the Institute of Social and Economic Research, Osaka University, from February to June 2019. A total of 16 experimental sessions were carried out. In each session, we recruited 28 students to participate from our participants database (Greiner, 2015). Before the OTC market game, the 28 participants are randomly split into two groups with 14 participants in each.[9] A total of 420 subjects participated over 16 sessions. Experiments lasted 2.5 hours on average including payments. Participants earned on average 3340 JPY including a participation fee of 500 JPY.

We discarded from the analysis the markets where either technical problems or students' incomprehension of the rules meant we could not guarantee the validity of the experiment.[10] As a result, there are 216 valid markets in total. A summary description of laboratory markets is reported in Table 2. In small world and random networks, insiders are located in the most central (*strong*) or least central (*weak*) node. In circle networks, the first insider occupies a random node in the network while with two insiders we consider the cases where they are directly connected or not connected. In what remains of this paper we use the labels in Table 2 to refer to network treatments.

4.2 Experimental results

We first perform an analysis at the agent level, separately for different agent types, namely insiders, correctly informed agents, and incorrectly informed agents, of their: (1) posted quotes, (2) profits, and (3) order flows. In this way, we investigate how the individual profits, trading strategies, and learning opportunities of agents depend on the network type,

[8] Experiments were computerized with z-Tree (Fischbacher, 2007).

[9] In three sessions, due to absentees, we had less than 28 participants. In these sessions, we had only 14 participants.

[10] In a total of 5 rounds across 3 sessions, some participants were not able to enter their orders, at least for a noticeable length of time, during a part of the 7.5 minutes of trading due to their computers freezing. In one group in one session, there was a participant who, even in the role of an insider, consistently entered orders that resulted in a loss (thus 8 rounds are dropped). Furthermore, we have dropped 11 more rounds across 9 sessions because the insider in the market made a loss or the transaction prices were below 5 (despite the lowest possible FV of the asset being 100).

Label	*Treatment*	*Num of markets*	*Num of traders*	*% high dividend*	*% correct private signal*
C_0	Circle network with no insiders.	20	14	0.500	0.610
C_1	Circle network with one insiders.	19	14	0.579	0.607
C_c	Circle network with two connected insiders.	17	14	0.353	0.568
C_{nc}	Circle network with two not connected insiders.	17	14	0.529	0.583
R_0	Random network with no insiders.	20	14	0.500	0.557
R_w	Random network with one weak insider.	19	14	0.631	0.595
R_s	Random network with one strong insider.	20	14	0.300	0.573
R_2	Random network with two insiders.	18	14	0.666	0.638
S_0	Small-world network with no insiders.	16	14	0.437	0.571
S_w	Small-world network with one weak insider.	16	14	0.437	0.615
S_s	Small-world network with one strong insider.	18	14	0.777	0.619
S_2	Small-world network with two insiders.	16	14	0.500	0.645

Table 2: Treatment labels used throughout the text, and descriptive statistics across treatments.

the type of the initial private signal owned by agents, the number of insiders in the market, as well as the degree, centrality, and clustering of the nodes occupied by the agents in the trading network. We then investigate the effects of network topology, number and position of insiders on market level variables: (1) market efficiency, (2) price convergence, and (3) inequality of agents' profits. While in the market level regressions we include markets with no insiders, in the individual level regressions we concentrate on markets with at least one insider.

4.2.1 Individual posted quotes

Given that we cannot directly observe learning in the experiments, as a proxy for learning we use the deviation of individual quotes from the fundamental, or individual mis-pricing. We interpret the posting of quotes closer to the fundamental value as evidence that agents are better informed. However this is an imperfect measure as agents' quotes are blurred by their strategic motives and reflect their market power and outside options.

Table 3 reports the results of regressions where we regress agents' (quoted) mispricing on their signal, treatment characteristics, as well as measures of their network positions (degree, betweenness, and local clustering) using five subsets of the data in laboratory markets: all agents; insiders' neighbours (with right and wrong private signal); insiders' non-neighbours (with right and wrong private signal).

The column (1) in Table 3 shows that better informed agents (insiders and those with right signal) do quote closer to the fundamental, which gives credibility to our choice of proxy. Clustering reduces individual mispricing overall, indicating that agents post more informative quotes when they belong to closely knitted groups. This effect is particularly true for those agents with a wrong signal who are further away from the insider (column 5). Interestingly insiders do not quote more aggressively when they belong to a clustered neighbourhood, indicating that learning is enhanced by social reinforcement rather than a more revealing behaviour of the insiders. Social reinforcement in fact can create a positive feedback as

	(1)	(2)	(3)	(4)	(5)
Individual Mispricing (quoted)	All agents	Insiders' neighbours		Insiders' non-neighbours	
		Right	Wrong	Right	Wrong
(Intercept)	49.69***	49.07***	43.14***	43.35***	49.47***
insider	-14.41***	-	-	-	-
right	-2.71***	-	-	-	-
degree	0.69	-0.58	0.26	1.01	2.70
betweenness	-0.19	0.39	0.21	-0.21	-0.98**
clustering	-7.44**	-8.62	0.68	-2.81	-22.47**
Clustering*insider	1.26	-	-	-	-
% right	-0.85	-2.78	-2.57	3.10	-0.55
Circle	2.61*	0.38	5.51	-0.15	9.75**
Small-World	3.83***	1.31	3.48	2.25	10.94***
NumInsiders 2	0.19	4.77**	-1.59	-0.46	-1.84
Circle*NumInsiders 2	3.02*	0.07	3.06	5.87*	5.89†
Small-World*NumInsiders 2	-2.80*	-4.23	-1.69	-3.80	0.05
Circle*InsidersConnected	-4.81***	-7.06***	-10.82***	-4.83*	-0.97
N	2,132	459	298	691	469

Significance: 0.15 † 0.1 * 0.05 ** 0.01 *** 0.

Table 3: Regression on the (quoted) mispricing using five subsets of the data: all agents; insiders' neighbours (with right and wrong private signal); insiders' non-neighbours (with right and wrong private signal).

posting of more informative quotes facilitates learning for all agents in a neighbourhood of a clustered node and, in turn, more coordinated learning induces agents to post more informative quotes as they all compete more aggressively to secure a trade. This is confirmed by the analysis in section 4.2.3.

On the other hand, degree has no significant effect on mispricing for any agents, but betweenness has a small favourable effect for agents with wrong signal further away from the insider (column 5). These far away nodes appear to infer information better when more clustered and/or central rather than when more connected, consistently with the complex contagion hypothesis.

Quotes in Circle and Small World network are overall less informative (column 1), and this is true particularly for those agents with a wrong signal who are far away from the insiders (column 5), and even more so in circles networks with two disconnected insiders.

This indicates that, while agents may infer information more effectively when clustered around its source, information takes longer to reach distant nodes in regular networks and overall these distant agents become better informed in random networks. On the contrary, agents close to the insiders are not generally affected by the network structure, but they appear to learn much better in circle networks with two connected insiders (column 2 and 3). This is the configuration where social reinforcement would have the strongest effects.

4.2.2 Individual profits

Table 4 reports the results of regressions where we regress agents' profits on their signal, treatment characteristics, and measures of their network positions (degree, betweenness, and local clustering) using five subsets of the data in laboratory markets: all agents; insiders' neighbours (with right and wrong private signal); and insiders' non-neighbours (with right and wrong private signal).

From regressions in column (1) of Table 4, we observe that insiders earn more than non-insiders, and those agents who receive a correct private signal earn more than agents who receive a wrong private signal. This shows that information is always valuable, even when it is not perfect. However, the higher the proportion of correct private signals in the market the lower are the profits of agents overall. Insiders' profits are lower when they have a high clustering coefficient (column 1, Clustering*insider) reflecting that, when learning happens collectively in the neighbourhood of the insider, the informed have fewer opportunities to exploit the uninformed. Overall degree, betweenness and clustering do not have a significant effect on profits. However, degree affect negatively the profits of the most disadvantaged agents (i.e. the one not connected to insiders and with a wrong signal, column 5) while clustering enhance their profit (or reduces their losses). Together these effects indicate that a higher connectivity does not deliver more learning opportunities to these agents. Rather they become vulnerable to be exploited by a larger number of neighbours. The learning of this group appears to be enhanced instead by social reinforcement.

	(1)	(2)	(3)	(4)	(5)
Individual Profits	All agents	Insiders' neighbours		Insiders' non-neighbours	
		Right	Wrong	Right	Wrong
(Intercept)	-39.30	23.99	-16.09	275.65***	315.97**
insider	830.63***	-	-	-	-
right	298.54***	-	-	-	-
degree	-0.66	-2.24	4.33	-33.24	-87.38*
betweenness	0.38	9.46	-10.64	6.18	13.75
clustering	-36.26	-35.75	-96.49	166.81	450.75*
Clustering*insider	-363.79***	-	-	-	-
% right	-266.82***	-47.10	-104.44	-232.60***	-486.23***
FV-High	1.06	17.77	41.11	-15.69	-33.41
Circle	3.95	25.05	-173.82†	-2.17	-187.00*
Small-World	2.35	-13.32	-71.20	-8.63	-177.37*
NumInsiders 2	-30.64	18.07	-155.20*	-6.57	-89.53†
Circle*NumInsiders 2	-2.95	-20.08	145.31	-53.98	-10.33
Small-World*NumInsiders 2	-2.24	-52.11	214.75*	3.28	26.14
Circle*InsidersConnected	0.02	-25.90	99.12	26.55	61.66
N	2,240	486	308	730	488

Significance: 0.15 † 0.1 * 0.05 ** 0.01 *** 0.

Table 4: Regression on the agents' profits using five subsets of the data in laboratory markets: all agents; insiders' neighbours (with right and wrong private signal); insiders' non-neighbours (with right and wrong private signal).

The network structure does not have a significant effect overall and no variable significantly affect the profits of the neighbours of the insiders which have a correct private signal. However, wrongly informed agents (column 3 and 5), independently of their position, typically profit less in more regular networks and when two insiders trade in the market. The wrongly informed neighbours of the insiders (column 3), instead, profit more when two insiders trade in Small World networks. These results suggest that different networks topologies may affect different types of agents differently.

4.2.3 Order flow imbalance

Finally, we investigate if order flow imbalance could be a valid channel through which learning can take place, despite this not necessarily being the only possible one. Absolute order imbalance has been used to capture the presence of informed trading in the literature. For example, absolute order imbalance is used as a proxy for the probability of informed trading (PIN) measure in Easley et al. (1996). Ahern (2020) shows that the absolute order imbalance and the autocorrelation of order flows, and not prices or quotes, are the most statistically significant and economically meaningful predictors of informed trading, at least when information is short-lived.

We define the quantity "Flow Imbalance" as the number of orders to buy minus the number of orders to sell when the dividend is high and the number of orders to sell minus the number of order to buy when the dividend is low. Thus a large and positive imbalance would provide an informative trading signal. We compute this imbalance, for each agent, by summing all received (signed) quotes from the opening of the market.

	(1)	(2)	(3)	(4)	(5)
Absolute Imbalance	All agents	Insiders' neighbours		Insiders' non-neighbours	
		Right	Wrong	Right	Wrong
(Intercept)	-2.72**	-3.11	-4.62	-4.19**	-9.08***
insider	-14.37***	-	-	-	-
right	-3.72***	-	-	-	-
degree	0.66**	0.80	0.72	0.98	2.60***
betweenness	0.07	-0.06	0.41	-0.15	-0.31†
clustering	2.09†	1.87	2.58	-0.88	-8.95†
Clustering*insider	6.63**	-	-	-	-
% right	6.66***	2.61	7.08**	4.07**	10.88***
Circle	-1.63**	-0.17	0.16	-1.21	1.36
Small-World	-0.39	1.85*	0.76	-0.62	2.93†
NumInsiders 2	1.77***	0.36	4.87***	1.30†	0.53
Circle*NumInsiders 2	-0.71	1.29	-7.09***	-0.16	1.43
Small-World*NumInsiders 2	0.55	0.27	-4.92**	0.84	2.32
Circle*InsidersConnected	1.25*	1.32	6.20***	-0.07	0.14
N	2,240	486	308	730	488

Significance: 0.15 † 0.1 * 0.05 ** 0.01 *** 0.

Table 5: Regression on the order book informativeness using five subsets of the data: all agents; insiders' neighbours (with right and wrong private signal); insiders' non-neighbours (with right and wrong private signal).

Table 5 reports the results of regressions where we regress agents' absolute imbalance on their signal, treatment characteristics, as well as measures of their network positions (degree, betweenness, and local clustering) using five subsets of the data in laboratory markets: all agents; insiders' neighbours (with right and wrong private signal); insiders' non-neighbours (with right and wrong private signal). From column (1) of Table 5, we observe that the absolute imbalance is positively correlated to the number of insiders present in the market, and to the proportion of correct signals. Thus the imbalance is larger when more information is available overall in the market and in this sense it is a plausible channel for learning. Clustering has a positive, even is significative only at 15%, overall effect on the size of the order book imbalance. Insiders also observe a higher imbalance when they have a high clustering coefficient. This supports the conjecture that agents clustered around an insider learn at the same pace and submit coherent orders in the same direction. The imbalance is more informative when two insiders are connected in circle networks, again supporting the social reinforcing hypothesis.

The effect of degree is strong and positive overall and for the distant agents with a wrong signal (column 5), indicating that a high degree can lead to more informative trading signals. These however do not results in enhanced profits or learning opportunities (as discussed earlier).This is possibly because the imbalance is not sufficiently persistent and fails to deliver a consistent message agents can learn from. This provides support to our intuition that learning is slow, and independent encounters with informed agents, who may lead to large order imbalances, are not sufficient for agents to learn, unless such imbalances are sustained over time.

4.2.4 Interpretation of agent level results

Our analysis has shown that: (i) traders who belong to close knitted communities quote closer to the fundamental value; (ii) insiders belonging clustered neighbourhood make lower profits; (iii) distant agents with a wrong signal quote closer to the fundamental and profit more when belonging to clustered neighbourhoods; (v) individual mis-pricing is lower when two insiders are connected. Higher degree leads to a larger order flow imbalance, which potentially could lead to better learning opportunities. However, degree is negatively correlated with profits, suggesting that the risk of trading with better informed traders outweighs the potential benefits of enhanced learning opportunities. In fact, betweenness rather than degree decreases mis-pricing for distant agents. This combined evidence supports overall the hypothesis that learning is a complex contagion process enhanced by social reinforcing.

In the next section we move away from individual learning dynamics and focus on the overall efficiency and fairness of the considered markets.

4.2.5 Market efficiency

We use the average absolute mis-pricing as a measure of market inefficiency: the higher this measure, the higher the difference between traded prices P_i and the fundamental (FV) in the market. Specifically, market inefficiency in market m is defined as the average deviation in absolute value of the price of each of the V_m transactions from the fundamental, i.e.,

$$\mathrm{AMP}_m = \frac{1}{\mathrm{V}_m} \sum_{i=1}^{\mathrm{V}_m} |\mathrm{P}_{i,m} - \mathrm{FV}_m| \tag{1}$$

To test for convergence we regress the price deviations against the networks and information variables, separating transactions in two blocks of trading of 3.5 minutes duration each. From Table 6 we can see that convergence, as captured by the "second block" variable, is significant overall and separately for each of the three cases considered with 0, 1, and 2 insiders, even though it is only significant at 15% with zero insiders. Markets are overall more efficient with insiders. However, increasing the number of insiders does not make a notable difference, neither in terms of efficiency levels nor in terms of convergence, suggesting that competition among insiders is not the main driver of information discovery. The total number of correct signals on the contrary is strongly significant, in particular in the absence of insiders. Regression also shows that Circle networks are overall the most efficient. Without insiders, Circle and Small World networks are more efficient than random networks. Random networks deliver higher efficiency when only one insider is presents. With two insiders Circle networks with two connected insiders are the most efficient overall and achieve the highest efficiency gains in the second part of the market.

Inefficiency	All	0 insiders	1 insider	2 insiders
(Intercept)	56.01***	59.99***	46.02***	45.31***
Circle	-2.71***	-3.11***	3.01***	3.27***
Small-World	-0.95	-2.85***	1.52**	-1.51
Second block	-2.13***	-1.47†	-2.48***	-2.01**
NumInsider 1	-9.22***			
NumInsider 2	-9.66***			
perc. right	-7.54***	-15.16***	-5.89***	-6.02***
Circle*Second block	-0.69	0.53	0.57	-1.98*
Small-World*Second block	0.02	3.88***	-0.22	-2.05
Circle*NumInsider 1	6.44***			
Small-World*NumInsider 1	2.44**			
Circle*NumInsider 2	5.26***			
Small-World*NumInsider 2	-1.58			
Circle*Insiders_Connected	-4.00***			-3.96***
N	12,520	2,563	5,292	4,665

Significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Table 6: Estimated regression coefficients for the absolute distance of prices from the FV in all laboratory markets, conditioning markets on the number of insiders.

4.2.6 Profits inequality

We measure the inequality among traders' profits using the standard deviation of profits, which quantifies the extent of heterogeneity of agents' profits.[11]

In Table 7 we regress the profit inequalities against the networks and information variables, separating by two blocks of transactions of 3.5 minutes each. Profit inequality is reset to zero in the second block. Comparable amount of profit inequalities are generated in the second block as in the first block despite the markets becoming more efficient over time. This shows that information remain valuable throughout the whole market. The percentage

[11] An alternative is to compute extended versions of normalized Gini coefficient that take into account the possibility of negative profits. However, these measures are not free of deficiencies (De Battisti et al., 2019).

of private signal reduces inequalities significantly overall, and in the case of a single insider. Profit inequalities are higher overall with two insiders. Random networks do not show significant difference in terms of fairness from Small World networks. Circle networks, instead, generate higher profit inequality both with one or two insiders (significant at 15%). However, Circle networks become more fair when the two insiders are connected.

Inequality	All	0 insiders	1 insider	2 insiders
(Intercept)	204.77***	217.48***	223.06***	231.36***
Circle	21.22	14.79	42.63†	52.51†
Small-World	-8.41	-10.34	29.36	-28.50
Second block	-21.13	-20.86	-27.42	-7.79
NumInsider 1	4.13			
NumInsider 2	58.08***			
perc. right	-70.86*	-93.92	-89.73*	-32.01
Circle*Second block	-10.58	4.73	3.21	-37.28
Small-World*Second block	10.93	15.47	9.30	9.64
Circle*NumInsider 1	27.87			
Small-World*NumInsider 1	36.31			
Circle*NumInsider 2	15.78			
Small-World*NumInsider 2	-20.47			
Circle*Insiders_Connected	-53.03**			-52.46**
N	432	112	184	136

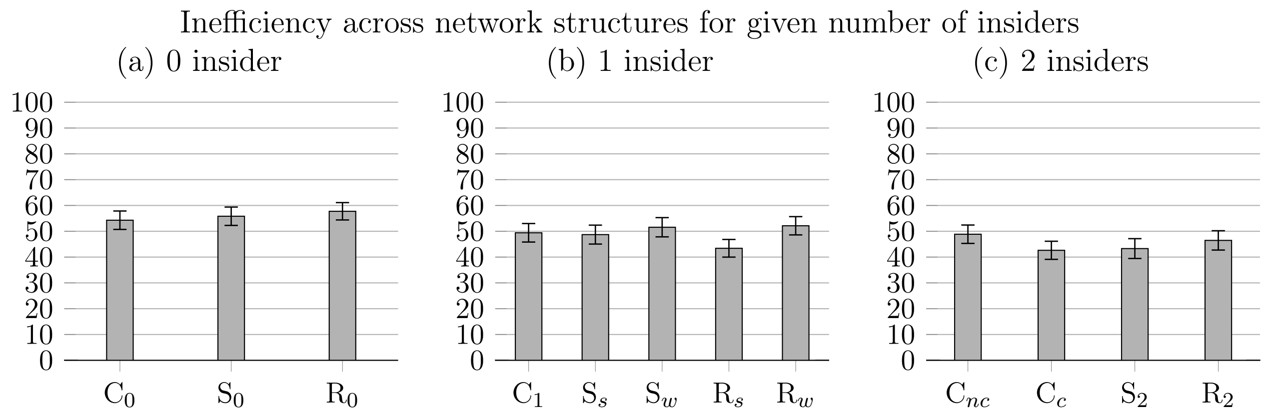
Significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Table 7: Estimated regression coefficients for the profit inequality in all laboratory markets, conditioning markets on the number of insiders.

4.2.7 Market level results conditioning on the position of insiders

In this subsection Figure 2 and Figure 3 provide a graphical representation of market level results when conditioning both on the number and the location of insiders.

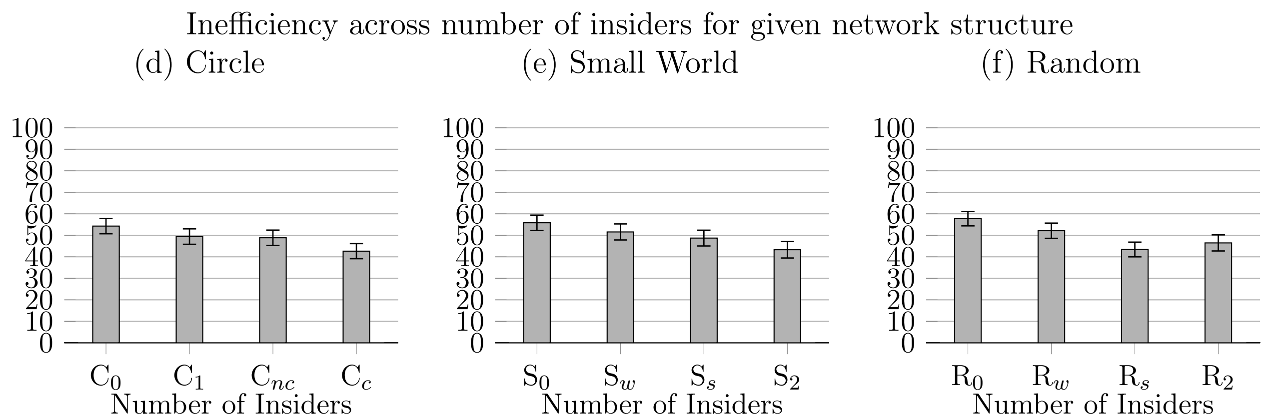
The top panels of Figure 2 show the conditional means of AMP across network structures, circle, small world, random, for 0, 1, and 2 insider cases (in panels (a), (b), and (c), respectively). These conditional means are based on the estimated coefficients of the linear regression model of Table 9 in Appendix A that controls for the percentage of non-insider agents receiving correct signals. The error bars correspond to a range equal to two standard



	S_0	R_0
C_0	ns	ns
S_0		ns

	S_s	S_w	R_s	R_w
C_1	ns	ns	$+^{**}$	ns
S_s		ns	$+^{*}$	ns
S_w			$+^{***}$	ns
R_s				$-^{***}$

	C_c	S_2	R_2
C_{nc}	$+^{**}$	$+^{*}$	ns
C_c		ns	ns
S_2			ns



	C_1	C_{nc}	C_c
C_0	$+^{*}$	$+^{*}$	$+^{***}$
C_1		ns	$+^{**}$
C_{nc}			$+^{**}$

	S_w	S_s	S_2
S_0	ns	$+^{**}$	$+^{***}$
S_w		ns	$+^{***}$
S_s			$+^{*}$

	R_w	R_s	R_2
R_0	$+^{*}$	$+^{***}$	$+^{***}$
R_w		$+^{***}$	$+^{*}$
R_s			ns

Note: Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 2: Conditional means of the average mis-pricing in laboratory markets.

error around the mean. Tables under each plot show the significance of pair-wise comparisons based on an F-test.[12] As one can observe from these panels, there is no significant

[12] In particular, the full model with all 12 treatment variables (without intercept) is compared with the restricted model, which satisfies the constraint that any two treatment dummies are equal, which leads to a model that has 11 variables. We have also conducted regressions based on mixed linear model controlling for average and standard deviation of within group individual characteristics, namely CRT score, Raven score, and share investment (tendency for risk-taking) in the investment game (Gneezy and Potters, 1997). These variables are not statistically significant, and therefore we have dropped them from the analysis to allow a better comparison of the results with the computational experiment presented in the next section. Results of these regressions are available from the authors upon request.

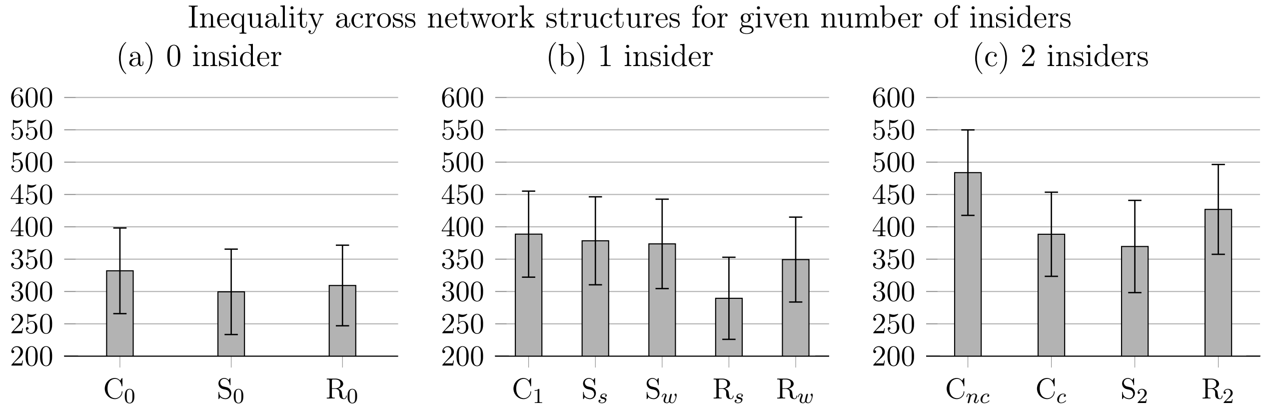
difference across three network structure when there is no insider. With one insider, the random network leads to the most efficient markets when the insider is placed in most central position (strong insider). With two insiders, differences across cases are not significant except for C_{nc} exhibiting a higher AMP than C_c and S_2.

The bottom three panels of Figure 2 compares, for each of the three network structures separately, the conditional means of AMP across the number and the position of the insiders. In random networks with one insider, the AMP is significantly lower when there the insider is in the most central node. However, adding a second insider does not lead to additional efficiency gains in these networks. In Small World networks instead two insiders lead to significant more efficiency than one insider. In Circle networks, the AMP is lower when the two insiders are connected (C_c).

The top three panels of Figure 3 show the conditional mean of the standard deviation of profits (estimated by the linear model reported in Table 10 in Appendix A) varying the network structure while holding constant the number of insiders. The bottom panels of Figure 3 show the same for each network structure varying the number of insiders.

Among the treatments with one insider (panel b), R_s leads to the lowest profit inequality. Note that R_s also resulted in the highest efficiency among these five treatments as seen in panel b of Figure 2. Among the four treatments with two insiders (panel c), S_2 and C_c have lower inequality than the other two, but due to the high variances they are only significantly so with respect to C_{nc} but not against R_2.

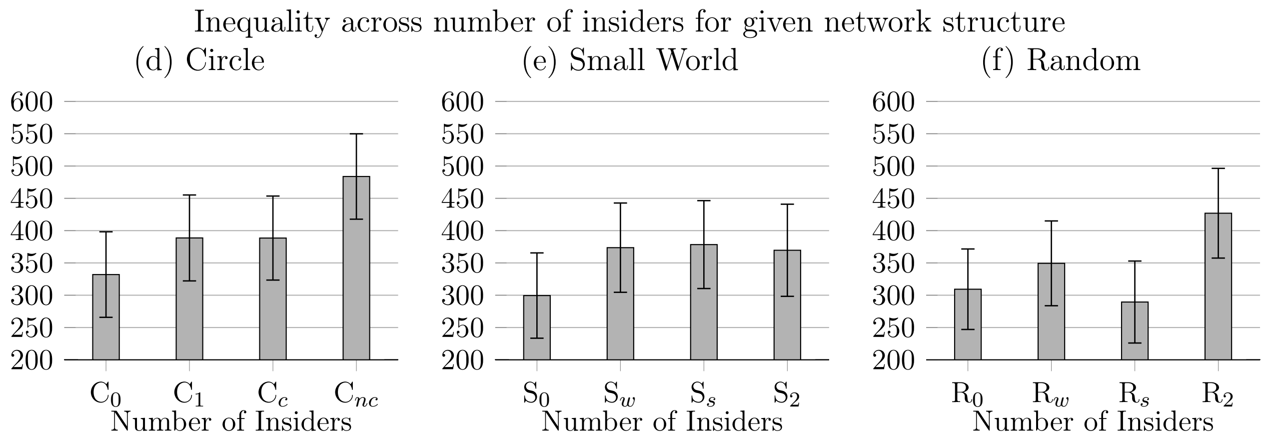
Panels (e) and (f) show an interesting contrast between Small World and Random networks. On one hand, in panel (e), profit inequality is very similar among S_w, S_s, and S_2. On the other hand, in panel (f), profit inequality in R_2 is significantly higher than that of R_s despite their similar levels of efficiency (Figure 2, panel f).



	S_0	R_0
C_0	ns	ns
S_0		ns

	S_s	S_w	R_s	R_w
C_1	ns	ns	$+^*$	ns
S_s		ns	$+^\dagger$	ns
S_w			$+^\dagger$	ns
R_s				ns

	C_c	S_2	R_2
C_{nc}	$+^*$	$+^*$	ns
C_c		ns	ns
S_2			ns



	C_1	C_{nc}	C_c
C_0	ns	$-^{***}$	ns
C_1		$-^*$	ns
C_{nc}			$+^*$

	S_w	S_s	S_2
S_0	ns	ns	ns
S_w		ns	ns
S_s			ns

	R_w	R_s	R_2
R_0	ns	ns	$-^{**}$
R_w		ns	ns
R_s			$-^*$

Note: Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 3: Conditional means of the profit inequality in laboratory markets.

4.2.8 Interpretation of market level results

At market level, the experiments reveal that, independently on the network structure, prices do not converge to the fully revealing price, but some learning takes place. Two insiders do not substantially enhance agents' learning opportunities in Random Networks, as we can see from the similar levels of market efficiency gained with one or two insiders (Table 6).

This suggests that competition among insiders is not aggressive and is not sufficient to accelerate learning and price convergence. This may be because of the decentralized nature of the market and the network structure, which affects the insiders competitive position. The insiders in fact do not necessarily compete for the same neighbours in decentralized markets and thus may not need to trade more aggressively to secure a trade. Another possible explanation is that the number of insiders is not known in the experiments and, as evidenced by Schnitzlein (2002) and Bossaerts et al. (2014), when the presence of insiders must be inferred, insiders do not compete aggressively. Either way, identifying the insiders does not appear to be an easy task for market participants and learning is unlikely to happen (only) via independent interactions with the insiders. In fact, Random Networks do not always have a competitive advantage in the experiments. With a single insider they do, and it appears that the length of the bridge is more important than its width in this case (even if this may be specific to the networks we have implemented). In C_1, only about 60% of the nodes are at distance one or two from the insider and the average distance from the insider is much higher than in R_s (Table 8). In S_s and R_s the average distance from the insider is similar but the ratio of nodes at distance one from the insider to the nodes at distance two is substantially higher in R_s. As a result R_s is more effective in diffusing information further away from its source. Despite agents learning better in clustered neighbourhoods (as shown in Subsection 4.2.1), information propagates slowly from its source in regular networks, and random networks overall dominate in the experiments. However with two insiders Random

Treatment	Distance 1	Distance 2	Distance 3	Distance 4	Average Distance
C_1	0.308	0.308	0.308	0.077	2.15
C_c	0.333	0.333	0.333	0	2.00
C_{nc}	0.667	0.333	0	0	1.33
S_s	0.385	0.538	0.077	0	1.69
S_w	0.231	0.308	0.308	0.154	2.38
S_2	0.667	0.333	0	0	1.33
R_s	0.462	0.462	0.077	0	1.61
R_w	0.154	0.462	0.385	0	2.23
R_2	0.417	0.500	0.083	0	1.67

Table 8: First four columns: proportion of non-insider nodes at given distance from insider. Last column: average distance of agents from the closest insider.

networks and regular networks perform similarly. For example, in R_2, as in C_c, the two insiders are connected to each other. Even if the average distance from the closest insider is lower in R_2, and despite the fact that, together, the two insiders can reach 5 agents in R_2 versus 4 in C_c, C_c markets are not less efficient than R_2 markets (see panel (c) of Figure 2), nor more unequal (see panel (c) of Figure 3). This suggests that speed gains in learning due to clustering balance out speed losses due to the local spreading of information in Circle networks and these market architectures experience overall comparable levels of efficiency and fairness to random networks. Profit inequalities however surge with two insiders in random networks as both can realise high profits by exploiting their neighbours before they learn. In fact R_2 leads to significatively higher levels of inequality than R_s despite the two markets achieving comparable levels of efficiency (Panel (f), Figures 2 and 3) indicating that these two market quality indicators are not always aligned. Interestingly, Circle networks with two connected insiders (C_c) exhibit a lower level of inefficiency and of profit inequality than Circle networks with disconnected insiders C_{nc} despite the average distance of agents from the closest insiders being higher in the former. This provides an example of the tension between the strength of individual learning (which is stronger with two connected insiders via the social reinforcement mechanism) and outreaching opportunities (which are enhanced by two non-connected insiders). In clustered networks agents tend to learn collectively in their neighbourhood which reduces the opportunity of profiting from each other. This is even more the case if the insiders are connected, as in C_c. While information in C_{nc} can spread further quicker, agents individually learn less in this configuration, and as a result can be exploited more easily than in C_c. This suggests that, in clustered networks, the same amount of insider information is more valuable, in terms of market outcomes, when concentrated rather than distributed.

Overall these results support our second hypothesis, that learning is better described by a complex contagion process.

5 Computational Model

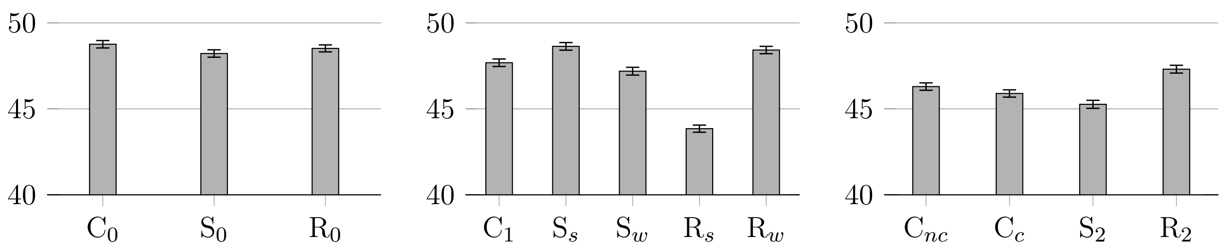
Given the complexity of the dynamics of information diffusion in networked trading markets, theoretical models are not available to provide testable predictions for our experiments. For this reason, in this section we introduce a simple agent-based model (ABM) of social learning with heterogeneous agents and study, via simulations, the extent to which the experimental results can be reproduced and further explained by the model. The ABM in particular allows us to estimate the speed at which agents learn as well as monitor the localization of information in the market. The ABM simulates the same trading environment implemented in the laboratory experiments, however, while in the laboratory time is continuous, the ABM markets run in a discrete time frame. In order to increase the sample size, we create 100 replicas of each of the 216 markets run in the laboratory experiment, keeping the network type, the number and location of the insiders, the realization of the private signals at each node, and the fundamental value the same, but changing the random order in which agents enter the market and trade in the simulated model.

In the ABM we assume, for simplicity, that the order flow imbalance is the only channel through which agents can learn. A large imbalance can be generated either by repeated orders from the insider(s) or by the correlated trading activity of all neighbours as they learn synchronously. Agents update their beliefs as new quotes arrive, in a form of complex contagion dynamics in which the sequence in which orders are received matters. Guided by the experimental results, we allow learning to happen slowly, building up as the imbalance grows persistently in the same direction. The speed at which the agents learn from the order imbalance is calibrated from the experimental data. We estimate that an imbalance of four is needed for agents to achieve a 100% confidence on the value of the random dividend. Interestingly, this is equal to the average degree of nodes in the experimental networks. The model is described in details in Appendix B. We only report the main results of the simulations below.

5.1 Results of computational experiments: market efficiency and profit inequality

Inefficiency across network structures for given number of insiders

(a) 0 insider (b) 1 insider (c) 2 insiders



	S_0	R_0
C_0	$+^{***}$	ns
S_0		$+^{\dagger}$

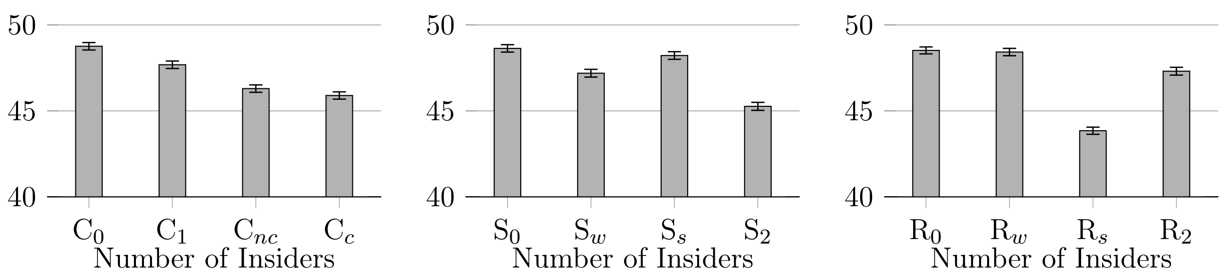
	S_s	S_w	R_s	R_w
C_1	$-^{***}$	$+^{***}$	$+^{***}$	$-^{***}$
S_s		$+^{***}$	$+^{***}$	ns
S_w			$+^{***}$	$-^{***}$
R_s				$-^{***}$

	C_c	S_2	R_2
C_{nc}	$+^{**}$	$+^{***}$	$-^{***}$
C_c		$+^{***}$	$-^{***}$
S_2			$-^{***}$

Note:

Inefficiency cross number of insiders for given network structure

(d) Circle (e) Small World (f) Random



	C_1	C_{nc}	C_c
C_0	$+^{***}$	$+^{***}$	$+^{***}$
C_1		$+^{***}$	$+^{***}$
C_{nc}			$+^{**}$

	S_w	S_s	S_2
S_0	$+^{***}$	$+^{**}$	$+^{***}$
S_w		$-^{***}$	$+^{***}$
S_s			$+^{***}$

	R_w	R_s	R_2
R_0	ns	$+^{***}$	$+^{***}$
R_w		$+^{***}$	$+^{***}$
R_s			$-^{***}$

Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 4: Conditional means of the average mispricing. Simulation experiments with 21,600 ABM markets with experimental structure.

Figure 4 shows the conditional means of the average mispricing in the simulated markets. Computational experiments replicate the patterns observed in the laboratory (Figure 2) for experimental markets. However, thanks to the large sample size, most binary comparisons are now significant, as reported in the table below each panel. In these tables + and −

indicate Row>Column and Row<Column, respectively). In particular simulations confirm that R_s are the most efficient markets with one central insider. With two insiders we find that clustered networks are significantly more efficient than Random networks.

Figure 5 shows the conditional means of the profit inequality. Again, computational experiments replicate the patterns observed in the laboratory (Figure 3 in Appendix xxx) and pairwise differences are significant. In particular we recover that R_s is the least unequal treatment with one insider. The S_2 and C_c networks are significantly less unequal with two insiders, while the C_{nc} networks remain the ones which lead to the highest inequality in profits across all treatments.

5.2 Results of computational experiments: Learning

One advantage of the computational experiments is that they allow us to directly monitor the beliefs of simulated agents. We measure the degree of agent misinformation, or average misbelief, in each market m, by computing how much non-insider agents' beliefs deviate from the fundamental value:

$$\mathrm{AMB}_m(t) = \frac{1}{\mathrm{N}_m} \sum_{i=1}^{\mathrm{N}_m} |\mathbb{E}_{i,m}(\mathrm{FV}_m, \mathrm{t}) - \mathrm{FV}_m| \tag{2}$$

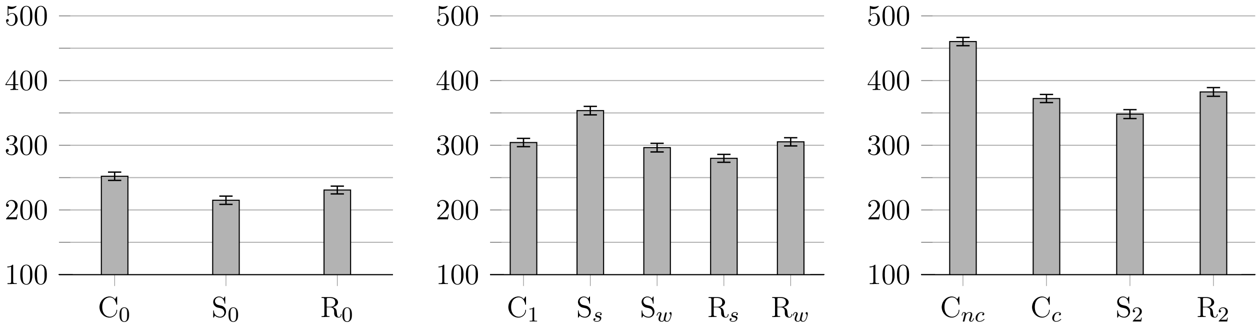
where N_m is the number of non-insiders in each market m. The lower the AMB is, the higher the convergence of belief toward the FV.

Figure 6 shows the values of average misbelief, at the end of the simulation, across network structures, and for each network structure varying the number and the position of the insider(s), conditional on the initial distribution of the private signals.

Consistently with results on efficiency and inequality, we find that without insiders, there is no significant difference across the three network structures in terms of misbeliefs (panel a). With one insider whose centrality is high, the misbelief is lower in the random network (panel b). With two insiders, misbelief is lower in the small-world (panel c). Interestingly though, C_{nc} achieves a lower level of misbelief than C_c despite these markets being less

Inequality across network structures for given number of insiders

(a) 0 insider (b) 1 insider (c) 2 insiders



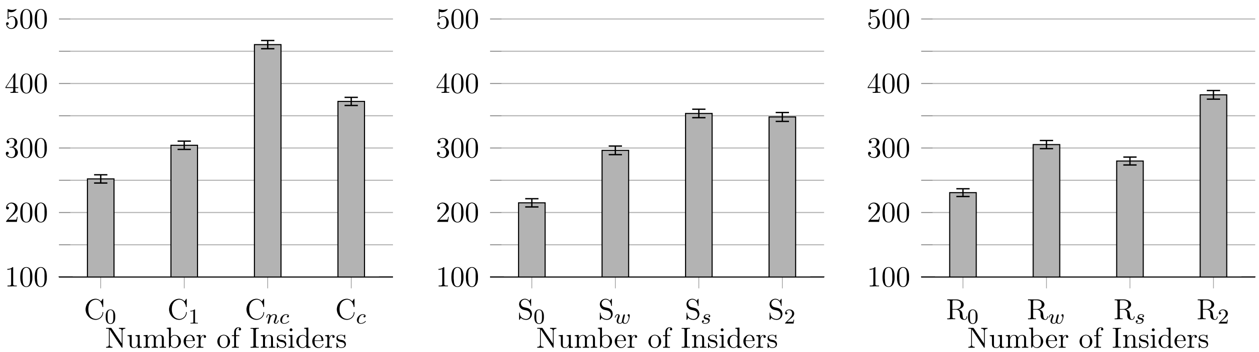
	S_0	R_0
C_0	$+^{***}$	$+^{***}$
S_0		$-^{***}$

	S_s	S_w	R_s	R_w
C_1	$-^{***}$	ns	$+^{***}$	ns
S_s		$+^{***}$	$+^{***}$	$+^{***}$
S_w			$+^{***}$	$-^{\dagger}$
R_s				$-^{***}$

	C_c	S_2	R_2
C_{nc}	$+^{***}$	$+^{***}$	$+^{***}$
C_c		$+^{***}$	$-^{*}$
S_2			$-^{***}$

Inequality across number of insiders for given network structure

(d) Circle (e) Small World (f) Random



	C_1	C_{nc}	C_c
C_0	$-^{***}$	$-^{***}$	$-^{***}$
C_1		$-^{***}$	$-^{***}$
C_{nc}			$+^{***}$

	S_w	S_s	S_2
S_0	$-^{***}$	$-^{***}$	$-^{***}$
S_w		$-^{***}$	$-^{***}$
S_s			ns

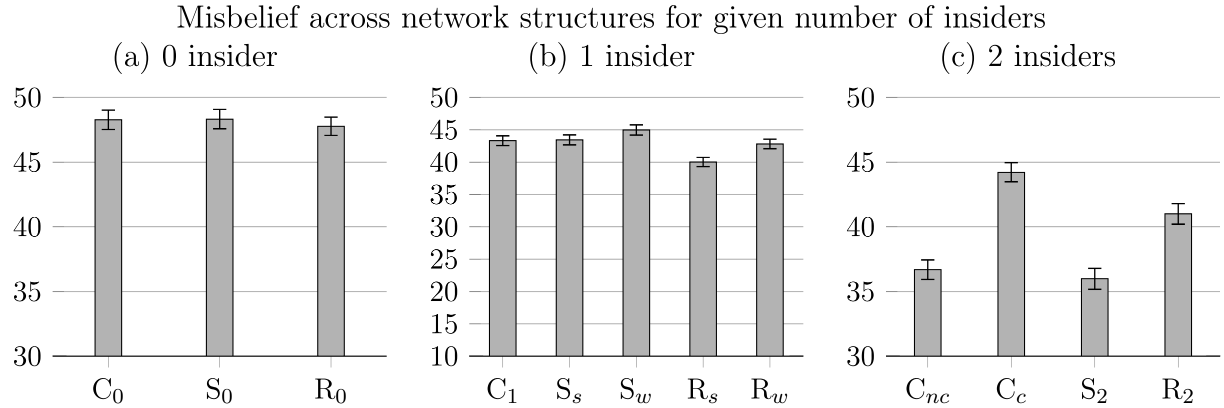
	R_w	R_s	R_2
R_0	$-^{***}$	$-^{***}$	$-^{***}$
R_w		$+^{***}$	$-^{***}$
Rs_s			$-^{***}$

Note: Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 5: Conditional means of the profit inequality. Simulation experiments with 21,600 ABM markets with experimental structure.

efficient and more unequal.

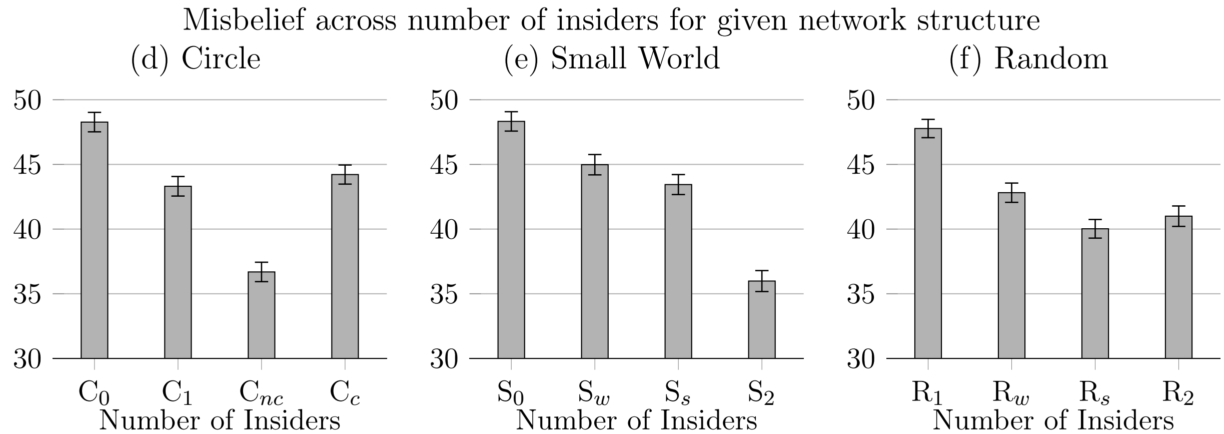
In Figure 7, we plot the misbelief of agents as a function of their private signals (R or W) and their distance from the insiders (1 or >1) across treatments. Results show that agents closer to the insider (R_1 and W_1) learn slightly more (thus misbelief is smaller) in Circle networks than in Small World networks (compare panel a vs panels d and e), and even more compared to those in Random networks (panel a vs panels g and h). Both in



	S_0	R_0
C_0	ns	ns
S_0		ns

	S_s	S_w	R_s	R_w
C_1	ns	$-^{***}$	$+^{***}$	ns
S_s		$-^{**}$	$+^{***}$	ns
S_w			$+^{***}$	$+^{***}$
R_s				$-^{***}$

	C_c	S_2	R_2
C_{nc}	$-^{***}$	ns	$-^{***}$
C_c		$+^{***}$	$+^{***}$
S_2			$-^{***}$



	C_1	C_{nc}	C_c
C_0	$+^{***}$	$+^{***}$	$+^{***}$
C_1		$+^{***}$	ns
C_{nc}			$-^{***}$

	S_w	S_s	S_2
S_0	$+^{***}$	$+^{***}$	$+^{***}$
S_w		$+^{**}$	$+^{***}$
S_s			$+^{***}$

	R_w	R_s	R_2
R_0	$+^{***}$	$+^{***}$	$+^{***}$
R_w		$+^{***}$	$+^{***}$
R_s			$-^{\dagger}$

Note: Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 6: Conditional means of the average misbelief. Simulation experiments with 21,600 markets with experimental structure.

Random and Small World networks agents learn slightly more when connected to a weak insider than when connected to the strong insider (comparison for panel d vs panel e, and panel g vs panel h). This could be because the weak insider quotes more often to each of its fewer neighbours, revealing information to them faster. R_1 and W_1 agents learn on average more in C_c (panel c) than in C_{nc} (panel b). However, more agents are located at distance one from the insider in C_{nc} and as a result average misbelief is lower in C_{nc} (panel (c) of

Figure 6). Nonetheless, these more numerous distance-one agents can all exploit the less informed agents at distance two leading overall to larger profit inequalities in C_{nc} than C_c (panel c, Figure 5).

In clustered networks, agents closer to the insider learn more than agents who are further away. However, the opposite is true in Random networks. These results illustrate the tension between the different factors that affect information diffusion. In clustered networks, thanks to the reinforcement mechanism induced by clustering, agents can learn very effectively within the insider's neighbourhood. In Random networks learning from the insider still occurs, but to a lesser extent as it is not supported by peer reinforcement. However, agents at distance one from the insider can reach fewer agents at distance two compared to those in Random networks (see Table 8). Thus more agents further from the insider have the opportunity to learn in Random networks and the average misinformation of the $R_{>1}$ and $W_{>1}$ group is lower. In fact the $R_{>1}$ and $W_{>1}$ group learns more than the R_1 and W_1 group, respectively, in the Random network. This is because $R_{>1}$ and $W_{>1}$ agents are connected to several R_1 agents and, by aggregating the R_1's order flows, they learn more from them collectively, even if the R_1 information is less precise than the insider, than each R_1 and W_1 agent learn from the insider itself. This is consistent with evidence from the experiments that centrality reduces mis-pricing in $W_{>1}$ agents (in Table 3, column 5).

6 Conclusions

In this paper we have show that the way potential trading links are organized in a decentralized market plays an important role in terms of market efficiency and fairness in profits. By comparing the way information propagates through differently networked markets, we are able to distinguish between possible learning rules and shed light on the antagonist role of clustering versus heterogeneity in degree and centrality in networks. We show that learning is alike a complex contagion process, enabled by synergistic interactions, rather than independent exposures to insiders.

At agent level, we provide evidence that learning is not an individual process, arising from pairwise interactions with better informed agents, but a collaborative, network process eased by clustering rather than by degree or centrality. However, for information to propagate through the network, nodes have to be able to reach out to others after they have learnt. While regular, clustered, networks facilitate learning locally around the insiders, the higher closeness centrality of random networks better supports information spreading. The competition between these two effects determines which market is more efficient and fair.

Overall, our experimental and computational results show that information remains more localized, and is more accurate, around the insider in clustered networks, and more dispersed, but less precise, in random networks. The relative precision of agents' information at layers of increasing distance from the insider determines which traders can achieve larger profits. Regulatory interventions aimed at enhancing market outcomes, and to limit unfair profit opportunities from insider trading, need to consider the global structural property of the trading network. In clustered networks, not only the insiders, but also their neighbours can extract profits from less informed distant agents. In random networks, it is the agents further away who can profit more at the expense of the insider's neighbours. Clustered markets can lead to outcomes that are more efficient and fair with two insiders trading, as long as insiders are close enough to compete. In random networks, instead, two insiders can lead to market outcomes that are worse than a single insider, because insiders do not normally share many neighbours and insider competition is limited in these markets. As a result efficiency is not enhanced by the presence of two insiders but inequality is worsen as both can profit at the expense of their neighbours. The position of the insider also matters in random networks and a strong insider, while earning more, can lead to more efficient and fair markets than a weak insider.

Our findings are relevant beyond financial markets and could provide useful insights in general signal extractions problems (Bao and Duffy, 2021); in industrial organization theory, for example to further understand the effects of the social network's structure on the market penetration of innovation or role of industrial districts in contributing to regional development and growth (Fleming et al., 2007; Lorenzen and Mudambi, 2013); in marketing, and to identify strategies that could be used to counteract the spreading of fake news.

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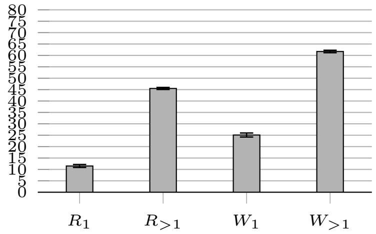
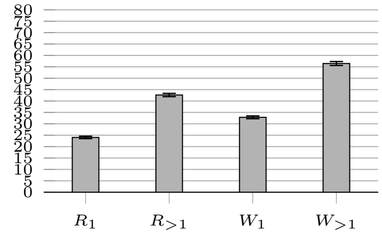
Conditional mean misbelief in circle network

(a) 1 insider



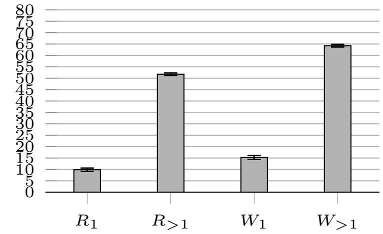
	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

(b) 2 insiders (n.c.)



	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

(c) 2 insiders (c)

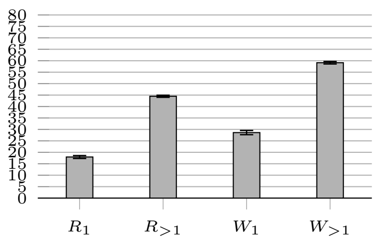


	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

Note: R: traders with right signal. W: traders with wrong signal.

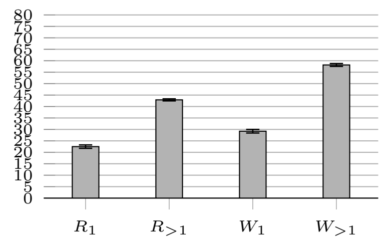
Conditional mean misbelief in small world network.

(d) 1 weak insider



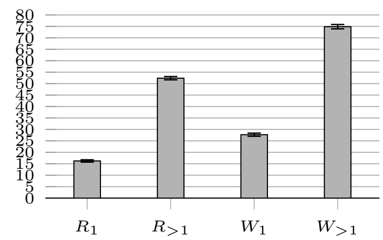
	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

(e) 1 strong insider



	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

(f) 2 insiders

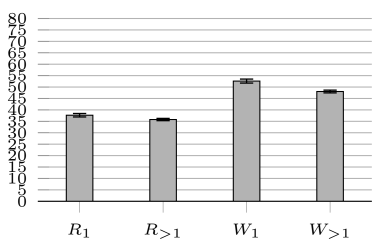


	$R_{>1}$	W_1	$W_{>1}$
R_1	$-^{***}$	$-^{***}$	$-^{***}$
$R_{>1}$		$+^{***}$	$-^{***}$
W_1			$-^{***}$

Note: R: traders with right signal. W: traders with wrong signal.

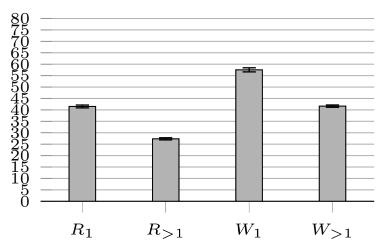
Conditional mean misbelief in random network.

(g) 1 weak insider



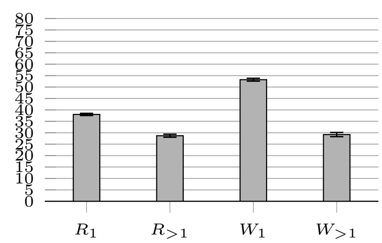
	$R_{>1}$	W_1	$W_{>1}$
R_1	$+^{**}$	$-^{***}$	$-^{***}$
$R_{>1}$		$-^{***}$	$-^{***}$
W_1			$+^{***}$

(h) 1 strong insider



	$R_{>1}$	W_1	$W_{>1}$
R_1	$+^{***}$	$-^{***}$	ns
$R_{>1}$		$-^{***}$	$-^{***}$
W_1			$+^{***}$

(i) 2 insiders



	$R_{>1}$	W_1	$W_{>1}$
R_1	$+^{***}$	$-^{***}$	$+^{***}$
$R_{>1}$		$-^{***}$	ns
W_1			$+^{***}$

Note: R_1 (W_1) indicates agents with correct (wrong) private signal at distance one from the insider; $R_{>1}$ ($W_{>1}$) indicates agents with correct (wrong) private signal at distance larger than one from the insider). Tables below each plot show the significance of pair-wise comparison. ns: not significant, +: Row>Column, −: Row<Column. Statistical significance: 0.15 † 0.10 * 0.05 ** 0.01 *** 0.

Figure 7: Conditional means of individual misbelief by distance from closest insider and type of agent in 21,600 ABM markets with experimental configuration.

References

Kenneth R Ahern. Do proxies for informed trading measure informed trading? evidence from illegal insider trades. *The Review of Asset Pricing Studies*, 10(3):397–440, 2020.

S Alfarano, A Banal-Estanol, E Camacho, G Iori, and G Kapar. Centralised vs decentralised markets in the laboratory: The role of connectivity. *Working Paper*, 2019.

Ana Babus and Peter Kondor. Trading and information diffusion in over-the-counter markets. *Econometrica*, 86(5):1727–1769, 2018.

Snehal Banerjee and Brett Green. Signal or noise? uncertainty and learning about whether other traders are informed. *Journal of Financial Economics*, 117(2):398–423, 2015.

Te Bao and John Duffy. Signal extraction: experimental evidence. *Theory and Decision*, 90 (2):219–232, 2021.

Max R Blouin and Roberto Serrano. A decentralized market with common values uncertainty: Non-steady states. *The Review of Economic Studies*, 68(2):323–346, 2001.

Peter Bossaerts, Cary Frydman, and John Ledyard. The speed of information revelation and eventual price quality in markets with insiders: comparing two theories. *Review of Finance*, 18(1):1–22, 2014.

Damon Centola and Michael Macy. Complex contagions and the weakness of long ties. *American journal of Sociology*, 113(3):702–734, 2007.

Syngjoo Choi, Andrea Galeotti, and Sanjeev Goyal. Trading in networks: theory and experiments. *Journal of the European Economic Association*, 15(4):784–817, 2017.

Daniele Condorelli, Andrea Galeotti, and Ludovic Renou. Bilateral trading in networks. *The Review of Economic Studies*, 84(1):82–105, 2017.

Francesca De Battisti, Francesco Porro, and Achille Vernizzi. The gini coefficient and the case of negative values. *Electronic Journal of Applied Statistical Analysis (EJASA)*, 12 (1):85–107, 2019.

Marco Di Maggio, Amir Kermani, and Zhaogang Song. The value of trading relations in turbulent times. *Journal of Financial Economics*, 124(2):266–284, 2017.

Darrell Duffie and Gustavo Manso. Information percolation in large markets. *American Economic Review*, 97(2):203–209, 2007.

Darrell Duffie, Semyon Malamud, and Gustavo Manso. Information percolation with equilibrium search dynamics. *Econometrica*, 77(5):1513–1574, 2009.

Darrell Duffie, Gaston Giroux, and Gustavo Manso. Information percolation. *American Economic Journal: Microeconomics*, 2(1):100–111, 2010a.

Darrell Duffie, Semyon Malamud, and Gustavo Manso. The relative contributions of private information sharing and public information releases to information aggregation. *Journal of Economic Theory*, 145(4):1574–1601, 2010b.

David Easley, Nicholas M Kiefer, Maureen O'hara, and Joseph B Paperman. Liquidity, information, and infrequently traded stocks. *The Journal of Finance*, 51(4):1405–1436, 1996.

Urs Fischbacher. z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, 10(2):171–178, 2007.

Lee Fleming, Charles King III, and Adam I Juda. Small worlds and regional innovation. *Organization Science*, 18(6):938–954, 2007.

Shane Frederick. Cognitive reflection and decision making. *Journal of Economic Perspectives*, 19(4):25–42, 2005.

Douglas M Gale and Shachar Kariv. Financial networks. *American Economic Review*, 97 (2):99–103, 2007.

Uri Gneezy and Jan Potters. An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2):631–645, 1997.

Michael Gofman. A network-based analysis of over-the-counter markets. In *AFA 2012 Chicago meetings paper*, 2011.

Mikhail Golosov, Guido Lorenzoni, and Aleh Tsyvinski. Decentralized trading with private information. *Econometrica*, 82(3):1055–1091, 2014.

Ben Greiner. An online recruitment system for economic experiments. *Journal of the Economic Science Association*, 1(1):114–125, 2015.

Veronika Grimm and Friederike Mengel. Experiments on belief formation in networks. *Journal of the European Economic Association*, 18(1):49–82, 2020.

Edward Halim, Yohanes E Riyanto, and Nilanjan Roy. Costly information acquisition, social networks, and asset prices: Experimental evidence. *The Journal of Finance*, 74(4):1975–2010, 2019.

Burton Hollifield, Artem Neklyudov, and Chester Spatt. Bid-ask spreads, trading networks, and the pricing of securitizations. *The Review of Financial Studies*, 30(9):3048–3085, 2017.

Matthew O Jackson and Leeat Yariv. Diffusion on social networks. *Economie Publique*, (16):3–6, 2005.

Polina Kovaleva and Giulia Iori. The impact of reduced pre-trade transparency regimes on market quality. *Journal of Economic Dynamics and Control*, 57:145–162, 2015.

Rachel E Kranton and Deborah F Minehart. A theory of buyer-seller networks. *American economic review*, 91(3):485–508, 2001.

Dan Li and Norman Schürhoff. Dealer networks. *The Journal of Finance*, 74(1):91–144, 2019.

Dunia Lopez-Pintado. Diffusion in complex social networks. *Games and Economic Behavior*, 62(2):573–590, 2008.

Mark Lorenzen and Ram Mudambi. Clusters, connectivity and catch-up: Bollywood and bangalore in the global economy. *Journal of Economic Geography*, 13(3):501–534, 2013.

Semyon Malamud and Marzena Rostek. Decentralized exchange. *American Economic Review*, 107(11):3320–62, 2017.

Mihai Manea. Intermediation and resale in networks. *Journal of Political Economy*, 126(3): 1250–1301, 2018.

Francesco Nava. Efficiency in decentralized oligopolistic markets. *Journal of Economic Theory*, 157:315–348, 2015.

Romualdo Pastor-Satorras and Alessandro Vespignani. Epidemic spreading in scale-free networks. *Physical review letters*, 86(14):3200, 2002.

Rohit Rahi and Jean-Pierre Zigrand. Arbitrage networks. Available at ssrn: https://ssrn.com/abstract=1430560, 2013.

J. C. Raven. *Raven's Advanced Progressive Matrices (APM)*. Pearson, San Antonio, TX, 2003 edition, 1998.

Charles R Schnitzlein. Price formation and market quality when the number and presence of insiders is unknown. *The Review of Financial Studies*, 15(4):1077–1109, 2002.

Duncan J. Watts. *Six Degrees: The Science of a Connected Age*. W.W. Norton & Company, New York, NY, 2003.

Duncan J Watts and Peter Sheridan Dodds. Influentials, networks, and public opinion formation. *Journal of consumer research*, 34(4):441–458, 2007.

Asher Wolinsky. Information revelation in a market with pairwise meetings. *Econometrica: Journal of the Econometric Society*, pages 1–23, 1990.

A Additional results for laboratory experiments

This appendix reports results of linear regression based on which Figures 2 and 3 are created.

Treatment	Estimate	Std. Error	t value	Pr(>|t|)
C_0	54.2865	3.5690	15.21	0.0000***
C_1	49.4115	3.5850	13.78	0.0000***
C_c	42.6306	3.5054	12.16	0.0000***
C_{nc}	48.8576	3.5614	13.72	0.0000***
R_0	57.7437	3.3580	17.20	0.0000***
R_w	52.1331	3.5371	14.74	0.0000***
R_s	43.4072	3.4200	12.69	0.0000***
R_2	46.4639	3.7427	12.41	0.0000***
S_0	55.8266	3.5578	15.69	0.0000***
S_w	51.5608	3.7252	13.84	0.0000***
S_s	48.7086	3.6663	13.29	0.0000***
S_2	43.2932	3.8438	11.26	0.0000***
% correct signal	-10.2261	4.8342	-2.12	0.0356**

N= 216. Significance: 0.15 † 0.1 * 0.05 ** 0.01 *** 0.

Table 9: Estimated regression coefficients for absolute mispricing AMP in laboratory markets.

Treatment	Estimate	Std. Error	t value	Pr(>|t|)
C_0	331.9929	66.2210	5.01	0.0000***
C_1	388.6753	66.5170	5.84	0.0000***
C_c	388.4992	65.0401	5.97	0.0000***
C_{nc}	483.7918	66.0796	7.32	0.0000***
R_0	309.2891	62.3047	4.96	0.0000***
R_w	349.3657	65.6278	5.32	0.0000***
R_s	289.4695	63.4568	4.56	0.0000***
R_2	426.9414	69.4429	6.15	0.0000***
S_0	299.4917	66.0130	4.54	0.0000***
S_w	373.6316	69.1189	5.41	0.0000***
S_s	378.3889	68.0264	5.56	0.0000***
S_2	369.5906	71.3189	5.18	0.0000***
% correct signal	-47.8159	89.6962	-0.53	0.5946

N=216. Significance: 0.15 † 0.1 * 0.05 ** 0.01 *** 0

Table 10: Estimated regression coefficients for profit inequality in laboratory markets.

B Agent Based Model

B.1 The agents

We assume that agents are homogeneous in terms of the behavioural rule they follow. As in the experiments, at the beginning of the market ($t = 0$), agents receive a private signal about the value of the fundamental, FV, that is correct with probability $P^i_{FV}(t = 0) = 0.6$ unless the agent i is an insider, in which case $P^i_{FV}(t = 0) = 1.0$ for all t.

Thus, if a non-insider receives a signal indicating that the true dividend is $FV = 100$, s/he assumes that $P^i_{FV=100}(0) = 0.6$ and $P^i_{FV=200}(0) = 0.4$. Similarly if the agent receives a signal indicating that the true dividend is $FV = 200$, s/he assumes that $P^i_{FV=200}(0) = 0.6$ and $P^i_{FV=100}(0) = 0.4$. The agent's expected belief about FV, $\mathbb{E}^i(FV, t)$, is calculated as the weighted average of the two possible values of FV, {100, 200} and given by

$$\mathbb{E}^i(\mathrm{FV}, t) = 100\, P^i_{FV=100}(t) + 200\,[1 - P^i_{FV=100}(t)] \tag{3}$$

B.2 Trading rules

In the trading mechanism employed in the ABM, agents are activated randomly and make a take-it-or-leave-it offer to one of their counter-parties also selected at random, who can either accept or reject the offer.

Number of Insiders	Right signal agent	Wrong signal agent	Insider
0	0.573	0.427	-
1	0.532	0.382	0.086
2	0.491	0.345	0.164

Table 11: Probabilities of node activation, which are set equal to the proportions from the laboratory data. Note that we assume these parameters are network-independent since agents do not know a priori what the network structure of the market is. Also, note that these are the aggregate probabilities for the agent type in the network, so that the sum of the probabilities over the 14 nodes is 1. The average activation probability of a non insider is 0.070. The activation probability for the insiders is about 20% higher than this value.

The probabilities of activation of agents depend on their type (I, R, W), i.e. the signal they receive at the beginning of the market, and are determined by the proportion of quotes submitted by all agents of the same type in the experiments (Table 11). Form the table we can see that insiders trade about 20% more aggressively on average than non insiders but the wo insiders do not trade on average more frequently than a single insider.

Once activated, agents can submit a bid or an ask at a specific price p^i over a given price range, also determined by the experimental values (Table 12), to the chosen neighbour. The direction of agents' quote is determined by the following rule:

$$\begin{cases} \text{Bid}, & \text{if } U \leq P_{FV=200}(t) \\ \text{Ask}, & \text{if } U > P_{FV=200}(t) \end{cases}$$

where $U \sim (0, 1)$ is the realization of a uniform (standard) random variable. Thus, if agents assess that the dividend is high with a high probability they are more likely to buy and vice versa.

	FV=100		FV=200	
Type of agent	**Ask**	**Bid**	**Ask**	**Bid**
Insider	[101; 198] *(135.9; 18.0)*	[101; 180] *(127.9; 16.2)*	[130; 195] *(171.5; 16.99)*	[110; 199] *(166.9; 19.0)*
Right signal agent	[101; 199] *(150.2; 15.6)*	[101; 190] *(131.5; 14.0)*	[110; 199] *(162.4; 16.5)*	[101; 190] *(143.2; 15.6)*
Wrong signal agent	[105; 199] *(158.8; 15.2)*	[101; 195] *(140.1; 15.4)*	[110; 199] *(155.5; 16.9)*	[105; 199] *(135.7; 15.9)*

Table 12: Ranges of experimental quoted prices are replicated in the ABM. Mean and standard deviations in parentheses.

Non-insiders quoted prices are sampled from a bounded gaussian generating process, as given by equations:

$$p^i_{ask} = \max\left\{ m;\ \min\left\{ \mathcal{N}\left(\frac{\mathbb{E}^i(\text{FV}, t) + M^*}{2}; \sigma_p^2 \right); M \right\} \right\} \tag{4}$$

$$p^i_{bid} = \min\left\{ \max\left\{ \mathcal{N}\left(\frac{\mathbb{E}^i(\text{FV}, t) + m^*}{2}; \sigma_p^2 \right); m \right\};\ M \right\}, \tag{5}$$

with mean that depends on the agent's belief, and variance σ_p^2 that is replicated from the experiments (on average for each agent type and direction of quote) as reported in Table 12. The lower and upper bounds, m and M, are the minimum and maximum of the price ranges reported in Table 12. Parameters m^* and M^* are estimated in a way that the mean prices quoted in the ABM equal the mean prices quoted in the experiments at the opening of the market, for each agent type and separately for bids and asks. In the ABM model non-insiders act as noise traders in the Banerjee and Green (2015) model, in the sense that they trade on their signals as if the signals were correct. However, as we will see in the next subsection, expectations of non-insiders are updated over time as new information comes in. In this respect non-insiders share the characteristics of noise traders and uninformed in the Banerjee and Green (2015) model. Agents, however, do not try to identify the insiders but attempt to learn the fundamental by aggregating the order flow generated by all their neighbours over time, weighting all orders equally.

Insiders, whose $\mathbb{E}^i(\mathrm{FV}, t) = \mathrm{FV}$ for all t, quote a bid (or accept an ask offer) when $FV = 200$ and quote an ask (or accept a bid offer) when $FV = 100$[13]. The insider's price is determined according to the following rule:

$$p_{ask}^{insider} = \max\left\{m;\ \min\left\{\mathcal{N}\left(\frac{\tau^{bid} + M}{2}; \sigma_p^2\right); M\right\}\right\} \tag{6}$$

$$p_{bid}^{insider} = \min\left\{\max\left\{\mathcal{N}\left(\frac{m + \tau^{ask}}{2}; \sigma_p^2\right); m\right\};\ M\right\} \tag{7}$$

where initially $\tau^{bid} = 160$ and $\tau^{ask} = 140$.

On the other hand, each counterpart j is willing to accept the offer only if $p^i < \mathbb{E}^j(FV, t)$ when buying (and $p^i > \mathbb{E}^j(FV, t)$ when selling). Thus agents sell at prices above their beliefs to more optimistic counterparts and buy at prices below their beliefs from more pessimistic ones, which results in price dispersion.

[13] In experimental markets insiders quote a bid when FV=100 and an ask when FV=200 only in 6% and 5% of the times respectively, see Table 15. Insiders may be making mistakes or play strategically in these case. As these events are very rare, we ignore them in the simulations).

B.3 Learning rules

Each agent has a prior belief of the value of the asset, given by the signal they receive. As new information arrives over time non-insiders update their beliefs. Unlike social influence models, we assume that agents take into account the cumulative information generated by the actions of their neighbours, which is the relevant variable in the context of learning.

For non-insiders, $P^i_{FV}(t)$ is updated over time as agents try to infer the value of the fundamental by observing the imbalance in their individual order flow. To make the model simple, we assume that only the direction of the order, but not its price, affects non-insiders' beliefs. We denote $\Delta^i_B(t)$, the difference between the number of bids and the number of asks received by an agent from the beginning of the market until the current time t. Kovaleva and Iori (2015) proposed a similar learning dynamic.

For simplicity, we assume a bounded linear relationship between $P^i_{FV}(t)$ and $\Delta^i_B(t)$ as shown in Figure 8. Thus, if the order imbalance is positive (more orders to buy than to sell) the agents increase $P^i_{FV=200}(t)$ and decrease $P^i_{FV=100}(t)$. Vice-versa, if the imbalance is negative, the agents decrease $P^i_{FV=200}(t)$ and increase $P^i_{FV=100}(t)$. $P^i_{FV}(t)$ converges to either 0 or 1 when $\Delta^i_B(t)$ reaches a particular value $\Delta^{opt}_B(t)$.

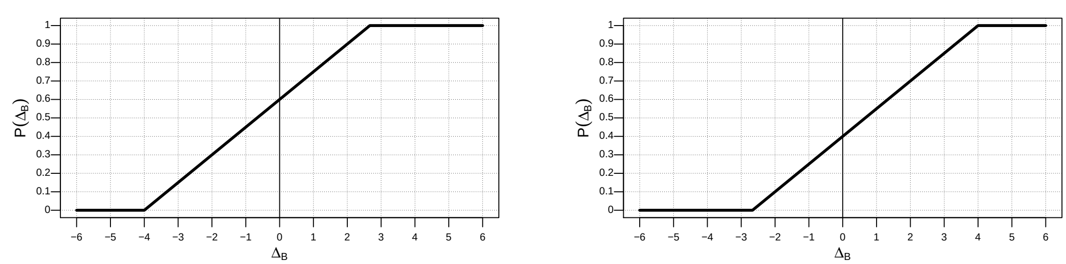


Figure 8: Relationship between $P_{FV}(t)$ and $\Delta_B(t)$ for a generic market through the learning function. *Left panel*: $\Delta_B(t)$ is in agreement with the initial private signal; *Right panel*: $\Delta_B(t)$ is in disagreement with the initial private signal. The labels in the x-axis are by way of example and vary depending on the length of real experimental markets.

This assumption, combined with the trading rules previously described, implies that as traders become more confident in their beliefs (i.e. the probability reaches the values 0 or

1) they are more likely to trade in the right direction and at more aggressive prices. While the quoted price does not affect the ability of other agents to learn, it affects both price efficiency and agent's profit.

Insiders also adjust their quotes over time in response to the order flow they observe. If the insider(s) observe a predominance of orders to sell from their neighbours, they will lower their selling price and if they observes a predominance of orders to buy from the neighbours, they will increase their buying price. Thus the insiders trade more aggressively when competition is stronger by updating τ^{bid} and τ^{ask} as follows: $\tau^{bid} = 160 + \frac{|\Delta^i_B|}{\Delta^{opt}_B}(M - 160)$ and $\tau^{ask} = 140 - \frac{|\Delta^i_B|}{\Delta^{opt}_B}(140 - m)$. When $\Delta^i_B = 0$ insiders quote prices with means of 160 and 140 for bids and asks respectively. Variances σ^2_p are replicated from the experiments (Table 12).

B.4 Calibration

The calibration of the ABM to the experiments relies on only one parameter, Δ^{opt}_B, which is the value of the private order book imbalance observed by agents that leads to the identification with certainty the value of the fundamental (i.e. the fundamental is deemed correct or wrong with 100% probabilities).

The parameter Δ^{opt}_B is calibrated so that: (i) trading volume in the ABM matches exactly the one observed in each experimental market reported in Table 13 ; (ii) the difference between the regression coefficients for the average mispricing in the laboratory and computational experiments is minimized. In other words, we aim to replicate the mean of prices and the trading volume observed in the laboratory the best we can via numerical simulations.

To this aim we have simulated each of the 216 markets in the laboratory experiments (i.e., with identical network structure and distribution of private information at each node) with values of the parameter Δ_B chosen over a grid of values from 2 to 100 with a step of 1. The optimal Δ_B is computed as the one that minimizes the objective (loss) function given in Eq. 8 defined as the sum of squared differences of the average mispricing coefficients

Treatment	n. trades (mean and sd)	n. quotes (mean and sd)
C_0	50.95 (3.03)	203.15 (6.19)
C_1	58.73 (5.52)	206.73 (9.93)
C_c	71.52 (5.07)	219.52 (8.19)
C_{nc}	80.17 (4.90)	222.70 (6.12)
R_0	44.70 (5.98)	178.10 (9.43)
R_w	56.57 (6.41)	196.21 (9.25)
R_s	54.30 (5.67)	180.25 (9.32)
R_2	69.33 (6.25)	215.16 (9.51)
S_0	43.75 (5.01)	190.43 (11.30)
S_w	59.00 (4.84)	208.68 (11.66)
S_s	63.83 (7.10)	224.33 (12.35)
S_2	61.31 (6.76)	215.50 (13.45)

Table 13: Mean and standard deviation (in parentheses) of the number of trades (left column) and quotes (right column) in laboratory experiments by treatment.

(β) observed in the laboratory and computational markets for each market and treatment (Figure 9):

$$\Delta_B^{opt} = \arg\min_{\Delta_B} f(\Delta_B) \propto \arg\min_{\Delta_B} \sum_{i \in treatment} (\beta_{i;lab}^{mispricing} - \beta_{i;ABM}^{mispricing})^2 \tag{8}$$

Figure 9: Estimation of parameter Δ_B: mispricing regression coefficients and mean price volatility are best replicated with $\Delta_B^{opt} = 4$. Note that a value of $\Delta_B = 1$ is unrealistic. In particular, in this case the ABM markets are illiquid and can not replicate the trade volume observed in the laboratory markets.

From Figure 9 we observe that the calibration provides an optimal value for Δ_B^{opt} equal to 4. This result confirms that learning is not driven by independent encounters with informed agents, in which case learning would occur independently from the order flow imbalance and an optimal value could not be determined for Δ_B^{opt}. Learning is rather enabled by sequences of coherent quotes that build up an imbalance comparable is size to the average degree of agents.

The calibrated model generates similar results to those from the experimental data.

We report the magnitude of mispricing obtained in the calibrated model in Table 14, next to the experimental values for comparison. While not identical, the coefficients produce the same ranking of treatments.

Treatment	**Laboratory coefficients**	**ABM coefficients**
C_0	54.29***	52.13***
C_1	49.41***	50.31***
C_c	42.63***	48.66***
C_{nc}	48.86***	48.53***
R_0	57.74***	49.07***
R_w	52.13***	51.58***
R_s	43.41***	45.71***
R_2	46.46***	48.96***
S_0	55.83***	52.38***
S_w	51.56***	49.19***
S_s	48.71***	50.99***
S_2	43.29***	47.57***

N= 216. Significance: 0.1 * 0.05 ** 0.01 *** 0.

Table 14: Comparison between laboratory and ABM coefficients on mispricing. The chosen learning function leads to a minimum loss value of 14.15 and $\Delta^{opt} = 4$.

The model also generates a good agreement for the proportion of quotes proposed by the different types of agents (see Table 15) and their completed trades (see Table 16).

	FV=100		FV=200	
LAB	ASK	BID	ASK	BID
Insider	0.93	0.07	0.05	0.95
Right agent	0.62	0.38	0.39	0.61
Wrong agent	0.40	0.60	0.57	0.43

	FV=100		FV=200	
ABM	ASK	BID	ASK	BID
Insider	1.00	0.00	0.00	1.00
Right agent	0.60	0.40	0.40	0.60
Wrong agent	0.45	0.55	0.55	0.45

Table 15: Proportion of quotes proposed in laboratory and ABM markets.

Furthermore, the difference of quoted prices from the fundamental by treatment and type of agent (Table 17) and the number and proportion of trades is in the correct direction given the dividend, and disaggregated at treatment level (Table 18) also show good agreements between the calibrated model and the experimental data.

	FV=100		FV=200	
LAB	ASK	BID	ASK	BID
Insider	0.96	0.04	0.01	0.99
right agent	0.62	0.38	0.46	0.54
wrong agent	0.24	0.76	0.80	0.20

	FV=100		FV=200	
ABM	ASK	BID	ASK	BID
Insider	1.00	0.00	0.00	1.00
right agent	0.61	0.39	0.49	0.51
wrong agent	0.36	0.64	0.71	0.29

Table 16: Proportion of completed trades in laboratory and ABM markets.

	REAL DATA			ABM DATA		
Treatment	INSIDER	RIGHT	WRONG	INSIDER	RIGHT	WRONG
C_0	-	46.07 (0.362)	49.05 (0.464)	-	48.65 (0.405)	51.30 (0.465)
C_1	36.58 (1.26)	44.82 (0.406)	51.27 (0.484)	28.84 (0.380)	48.38 (0.371)	51.62 (0.456)
C_c	29.39 (0.698)	44.40 (0.448)	49.54 (0.556)	25.52 (0.223)	47.86 (0.376)	48.44 (0.434)
C_{nc}	36.32 (0.841)	47.92 (0.454)	51.35 (0.494)	33.71 (0.313)	46.28 (0.386)	49.60 (0.461)
S_0	-	46.48 (0.475)	51.48 (0.554)	-	47.48 (0.489)	50.79 (0.583)
S_w	28.86 (1.37)	46.95 (0.500)	52.87 (0.540)	28.51 (0.494)	45.59 (0.453)	50.27 (0.524)
S_s	35.08 (1.02)	47.61 (0.398)	51.73 (0.543)	32.25 (0.415)	49.61 (0.404)	51.86 (0.485)
S_2	33.06 (0.784)	45.05 (0.483)	47.91 (0.648)	30.17 (0.354)	46.31 (0.442)	48.27 (0.533)
R_0	-	48.34 (0.413)	53.17 (0.453)	-	47.42 (0.446)	49.69 (0.539)
R_w	33.35 (1.17)	48.08 (0.416)	50.42 (0.482)	32.65 (0.404)	48.64 (0.423)	51.38 (0.496)
R_s	36.94 (0.773)	42.66 (0.447)	45.51 (0.475)	29.11 (0.487)	45.35 (0.402)	48.53 (0.482)
R_2	34.73 (0.679)	47.86 (0.392)	46.80 (0.550)	28.89 (0.242)	49.39 (0.385)	50.59 (0.451)

Table 17: Quoted prices distance from the fundamental by treatment and type of agent for the laboratory experiments and numerical simulations. Standard deviation in parenthesis.

	REAL DATA			ABM DATA		
Treatment	INSIDER	RIGHT	WRONG	INSIDER	RIGHT	WRONG
C_0	-	20.55/30.35 (0.677)	4.4/19.45 (0.226)	-	20.00/29.40 (0.680)	11.70/25.10 (0.466)
C_1	5.52/5.68 (0.972)	16.10/26.84 (0.600)	5.58/25.42 (0.219)	5.47/5.47 (1.00)	13.89/29.52 (0.470)	12.00/27.52 (0.436)
C_c	11.23/11.47 (0.979)	14.23/27.53 (0.517)	4.64/27.76 (0.167)	4.94/4.94 (1.00)	19.29/37.70 (0.511)	13.76/33.00 (0.416)
C_{nc}	13.29/13.64 (0.974)	16.47/33.82 (0.486)	3.76/31.82 (0.118)	14.76/14.76 (1.00)	16.29/38.05 (0.428)	7.58/31.52 (0.240)
S_0	-	15.81/22.50 (0.702)	5.00/19.87 (0.251)	-	16.68/29.81 (0.560)	8.25/18.50 (0.445)
S_w	5.50/5.75 (0.956)	13.93/30.18 (0.461)	4.62/22.06 (0.209)	3.31/3.31 (1.00)	16.87/35.31 (0.477)	9.62/24.75 (0.388)
S_s	9.61/9.61 (1.00)	21.16/33.05 (0.640)	3.00/19.77 (0.151)	5.00/5.00 (1.00)	17.55/33.88 (0.518)	7.83/28.88 (0.271)
S_2	13.75/14.18 (0.969)	11.81/23.62 (0.500)	4.50/20.87 (0.215)	8.81/8.81 (1.00)	15.43/33.43 (0.461)	7.62/25.00 (0.304)
R_0	-	18.45/24.85 (0.742)	6.75/19.60 (0.344)	-	15.25/26.75 (0.570)	7.60/21.50 (0.353)
R_w	5.84/5.89 (0.991)	21.31/32.68 (0.652)	6.26/17.42 (0.359)	3.31/3.31 (1.00)	20.10/33.47 (0.600)	8.63/22.52 (0.383)
R_s	7.00/7.10 (0.985)	10.75/24.55 (0.437)	5.60/22.10 (0.253)	5.00/5.00 (1.00)	13.20/27.35 (0.482)	8.40/26.15 (0.321)
R_2	14.66/15.16 (0.967)	13.66/28.77 (0.474)	3.83/25.11 (0.152)	10.00/10.00 (1.00)	16.15/37.88 (0.426)	9.11/27.55 (0.330)

Table 18: Number (and proportion) of transactions in the right direction by treatment and type of agent.