Agents interaction and price dynamics: evidence from the lab

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Abstract

Using data collected from an experimental double auction market, we study the dynamics of interaction among traders. Our focus is on the effect the trading network has on price dynamics and price-fundamental convergence. At the aggregate level, the network of empirical exchanges reveals properties that are dissimilar from random graphs and, in particular, high centrality and high clustering. Precisely, these properties are identifiable as the cause of price volatility and divergence from the fundamental value. At the microscopic level, we find out how the topological properties of the network derive from the behavior of traders. In fact, our findings show that it is the unbridled trading action of very centralized players who implement a minority game, to give rise to volatility clustering and arbitrage opportunities.

JEL codes: D03 · D53 · D85 · G12

Keywords: herding; price dynamics; experimental double action market; network theory.

Statements and Declarations

- **Competing Interests** The authors declare that they have no conflict of interest.

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1. Introduction

The hard core of mainstream economics relies on the hypothesis that the exhaustiveness of prices ensures the efficiency of the market and, therefore, it makes unnecessary to comprehend its functioning (see Fama, 1965). Moreover, even in a context of incomplete information, uninformed traders can achieve full knowledge through the pricing system in such a way that private information is aggregated correctly and efficiently (see Grossman and Stiglitz (1976) and Smith et al., 1982). However, "this approach reduces, via reductionism, aggregate entities to concepts and knowledge for the lower-level domain of the individual agent. By doing so, the reductionist paradigm blocks from the outset any understanding of the interplay between the micro and macro levels. As a consequence, the differences between the overall system and its parts remain simply incomprehensible given the assumption of equilibrium" (see Tedeschi et al., 2012).

Decades of empirical evidence have undermined these assumptions and demonstrated that "markets do not automatically work well and that design matters" (see Stiglitz, 2004). Among the first to show the importance of the markets institutional structure and the exchange linkages to gather the price formation mechanism, we should remember the seminal papers of North (1991) and Kirman (1991). In this vein, several papers have shown that prices dynamics reflect the interaction among agents and are not, instead, the result of a central coordination (see Kirman (2010) for a review). Since interaction depends on differences in information, motives, knowledge and capabilities, this implies heterogeneity of agents and, as a consequence, for externalities. Therefore, the literature has focused on two key aspects capable of generating heterogeneity and, consequently, moving prices away from equilibrium, namely the aggregation of information and the individual behavior. About the first element, the research has focused on the effect that agents' reaction to signals has on the price informativeness (see, for instance, Smith et al., 1988; Morris and Shin, 2002; Allen et al., 2006; Ferri and Morone, 2014; Halim et al., 2019; Steiger and Pelster, 2020; Steiger and Pelster, 2020; Ruiz-Buforn et al., 2021). Regarding the second aspect, a vast literature has shown how markets are dominated by "epidemic attitudes". These "mass-uniform" behaviors that cause coordination of expectations and collective beliefs lead to large aggregate fluctuations (see Banerjee, 1992; Bikhchandani et al., 1992; Kirman, 1993; Smith et al., 1988; Hey and Morone, 2004).

Some insights into fluctuations in prices and agents coordination have been provided by agent-based models. These models, replacing the isolated representative agent with heterogeneous interacting agents in a context of dynamic markets, are able to generate price hikes, out of equilibrium patterns and many other financial stylized facts (see Hommes, 2006; LeBaron, 2006; LeBaron, 2006; Grilli and Tedeschi, 2016, for extensive surveys). In whatever way coordination is represented, via behavioral switching models (see Brock et al., 1997;Brock and Hommes (1997); Brock and Hommes (1998); Lux and Marchesi, 2000; Chiarella et al., 2009) or herding mechanisms (see Banerjee, 1992; Banerjee, 1993; Yamamoto and Lebaron, 2010 ; Tedeschi et al., 2009; Tedeschi et al., 2012), it generates strong synchronization in the individual actions that affect price dynamics. Furthermore, a more recent literature has focused on the relationship between agents' coordination and price fluctuations using network theory. This tool has proved to be particularly suitable for describing the relationship between the organization of interaction among individuals within different components of the economy (see Bargigli and Tedeschi (2014) for a review) In light of this, some papers have studied the effects that static or dynamic networks have on price dynamics, information dissemination and price convergence to the fundamental (see Tedeschi et al., 2009; Tedeschi et al., 2012; Panchenko et al., 2013; Wang et al., 2019). In fact, depending on the adopted/obtained network topology, these works have highlighted the impact that the interaction between traders has on market efficiency and financial time series. Also experimental economics has recently incorporated into laboratory experiments different network architectures to better understand, in a controlled environment, how several mechanisms of information spreading impact the financial markets dynamics. Specifically, these studies have focused on agents' strategies (Hanaki et al., 2007) and the effects that different levels of attachment probability between players have on market efficiency (see Attanasi et al., 2016; Alfarno et al., 2019; Halim et al., 2019) . Most of these studies have exogenously determined the network structure (Duffy et al., 2019), while some others have introduced endogeneity letting participants free to choose links (Corbae and Duffy, 2008). Experimental literature is lacking of paper examining the endogenous network formation via market mechanism. Following this line of research, this work analyzes two important aspects related to interaction in an experimental double action market. **Firstly**, we analyze the network architecture emerging from the buying and selling transactions among individuals in the lab. Therefore, differently from the previously mentioned works, we do not introduce a network topology into the experimental design, but we reconstruct the network architecture through players' transactions. The reason behind this modeling choice is simple: we are not interested in understanding how an ex-ante graph impacts on the information dissemination, but what the emerging market structure is and its impact on price dynamics. Our results reveal a very centralized network topology made up of few but populous communities. Precisely, these network characteristics are shown to impact prices and generate volatility clustering and price divergence from the fundamental. Furthermore, to better understand the topology of the network generated through empirical exchanges, we compare it with a random network simulated by taking into account the key characteristics introduced in the experimental design, namely the number of players and the probability of the dividend signal accuracy. Specifically, we use a two step Bayesian approach to formalize the probability of attachment **(i.e. the probability to observe a trading between two agents)** of the trading network and, thus, to reconstruct the theoretical random graph. Interestingly, the empirical and theoretical networks (i.e. the network derived from the exchanges in the lab and the one reconstructed with the Bayesian approach) considerably diverge in terms of topological characteristics. This highlights that exchanges are not random as in the case in which agents just use prices to decide whether to buy or sell, but follow different behavioral rules (for example loyalty relationships as shown in Kirman and Vriend, 2000;Kirman and Vriend, 2001; Cirillo et al., 2012). **Secondly**, we study the behavioral rules that determine the creation of the exchange links and, consequently, define the architecture of the network. Curiously, our findings highlight the emergence of a player who make a high number of transactions. The presence of this subject (called hub or attacker) who plays against the crowd implementing a minority game, explains on the one hand the network centrality and, on the other hand, motivates the divergence of the price from the fundamental and the creation of volatility. On this point a clarification is appropriate. Although our links are created by merely matching orders, we are able to infer, ex post, some characteristics on the behaviour of the agents issuing these orders. Even behind an apparently anonymous market structure, therefore, agents reveal behavioural peculiarities detectable through the study of interaction. In this respect, our perspective is very similar to other work on order-driven markets where treading strategies are identified from the topology of the emerging network (see Moro et al. (2009), Vaglica et al. (2008) and Vaglica et al. (2010)).

In conclusion this work aims i) to highlight how the dynamics that define the interactions among economic agents are essential to explain financial stylized facts; ii) to enrich the vast literature revealing that the market design matters and is the result of the endogenous interaction among the elements that compose it.

The rest of the paper is organized as follows. In Section 2, we present the experimental design and reconstruct the theoretical random network associated with it. In Section 3, we present the empirical results on aggregate dynamics and micro behaviors. Finally, in Section 4, we draw conclusions.

2. The experimental double action market: expected vs empirical trading network architecture

In this section we present an experimental double action market where participants may make public offers both to buy ("bids") and to sell ("asks"). The goal is to investigate how the emerging market topology impacts on price dynamics and individual behavior. To this end, we compare the empirical transactions network, emerging from agents trade, with an expected theoretical graph, and verify if agents act independently of each other and link only through the price system or apply different behavioral rules in the exchange process.

2.1. Experimental Design

We run a double action market experiment where a population of N traders can either place market orders, which are immediately executed at the current best listed price, or they can place limit orders. Limit orders are stored in the exchange's book and executed using time priority at a given price and price priority across prices. A transaction occurs when a market order hits a quote on the opposite side of the market.
The experiment, programmed using the Z-tree software (see Fischbacher, 2007), is run at the laboratory LEE at the University Jaume I of Castellon. After reading the instructions, participants get involved in a test session where they become familiar with the exchange mechanism. This preliminary session, which includes reading the instructions, answering any doubts and testing the auction, takes approximately 20 minutes. After the test, the double action market experiment begins, and it includes 48 students who play about 21 minutes and earn an average of 14 euros.
Let us now describe the details of the experimental design. $N = 8$ agents trades, over a time span of 7 periods, ~~one-period life asset~~ **an asset that lives for one period only**, which pays an uncertain dividend. Each period consists in 180 seconds of trading activity. Consequently, there are $T = 7$ periods, and $\tau = 180$ intra-period trading activities. At the beginning of each period, T, the experimenter i) endows each agent with the same balance-sheet, composed by cash, $C = 2000$ experimental Currency Unit, and $S = 10$ **shares of** stocks; ii) draws, with probability 0.5, the dividend value d, which might be either 10 or 20; iii) gives each player a signal on the value of the dividend. Regarding this last point, two different scenarios (Treatments) are considered, and they vary depending on the signal accuracy: in the first scenario, T1, the probability of receiving the correct dividend value is $p(d) = 75\% = 6/8$, while, in the second scenario, T2, $p(d) = 62.5\% = 5/8$.[1,2] Whereas the signal on the dividend value received by each agent is a private

[1]Here, we show the expected rate of correct signals from which the percentage is derived. Firstly, 62.5 % is the percentage determined considering an expected fraction of 5 over 8 signals correct. Secondly 75 % derives from 6 over 8 correct signals.

[2]The value $p(d)$ is based on the number of subjects. To reach a proper level of market informativeness, we keep the expected value of the fraction correct signal higher that the one of incorrect (i.e. higher than 50%) in order to have enough information

information, the probability of the signal accuracy, p(d), is common knowledge. At the end of each period, i.e. in $\tau = 180$, the dividend true value is publicly announced.

Finally, in order to check the robustness of our qualitative results, three independent sessions for each scenario are run, using different subjects. Therefore, the experiments is composed by two different treatments (T1,T2) with 3 sessions for each treatment (i.e. 6 total sessions) and 8 agents per session (48 total subjects) involved in a within design of 7 trading periods.[3]

2.2. The expected theoretical trading network formation

Keeping in mind the experiment design described above, and remembering that the traded stocks are homogeneous goods and the probability of the dividend signal accuracy, p(d), is common knowledge, one could conjecture that linkages among agents and, consequently, exchanges, take place randomly and just considering prices. On the basis of these simple considerations, we model the trading connections among subjects as a random network and, specifically we hypothesize that the expected theoretical network is the Erdős and Rényi (1959) model.

Let us now explain the approach used to reconstruct the exchange relationships. As already mentioned, the probabilistic distribution of the dividend signal accuracy, p(d), is common knowledge, while the realization coming from that distribution is agent specific. In fact, some subjects, with probability p(d), receive an information reveling the dividend true value, while others, with probability $(1 - p(d))$, have a wrong information. We assume that traders trust (or not) the agent-specific signal received on the dividend value with a probability corresponding to $p(d)$ (or 1-p(d)). In our context, two naive strategies are hypothesized. On the one hand, agents following their signal (regardless of its correctness) submit a buy (sell) order when receiving the signal $d = 20$ ($d = 10$). On the other hand, players refusing the received information apply the opposite strategy.

Basically, among all the possible strategies identifying traders' behavior in experimental financial market contexts (see Merl (2021) for a review), this work is inspired by the Prior Information setting of Plott and Sunder (1982). In this case, agents act considering the signal received as unique informative source. The combination of the flat uniformative prior (i.e. the dividend random draw) and the informative private

to predict the dividend at market level. On the other side, we exclude the possibility to have very high level of informativeness and precision to observe trading activity (as can be observed in the Fig.3). This lead us to opt for 5 or 6 expected correct signals per period.

[3]We are aware that our number of traders per market (i.e. 8), the number of sessions (i.e. 6) and the number of repetitions (i.e. 8) may be elements of weakness in this work. However, we are in line with other experimental work. Indeed, on the one hand, there are numerous studies with similar numbers of players per market (see for example Morone and Caferra (2020), Huber et al. (2008) and Noussair and Xu (2015), with 8, 10 and 14 players, respectively). On the other hand, other studies use a similar number of sessions and repetitions (see, Noussair and Xu (2015), with 8 and 10 sessions and repetitions). There are other studies following a lower number of sessions per treatment in market context (3), as in List and Price (2005).

agent-specific signal received syntethizes the expectation of each agents' action. Specifically, we model the different inferences made on the received signal considering its level of accuracy. This assumption comes from both the empirical analysis obtained by our experimental data and the literature on trader belief heterogeneity inferring the same information (see Harris and Raviv, 1993; Carlé et al., 2019; Bao and Duffy, 2021). A trading connection is created when a buyer meets a seller.

Let us now formalize how the expected theoretical trading network is formed. We define with $D \sim \{10{,}20;0.5,\, 0.5\}$ the dividend distribution, d the dividend realization and $\bar{d}$ the opposite event. Moreover, let I=$\{I_m | I_m \sim (d, \bar{d}; p(d), 1-p(d))\}$ be the generic signal informational distribution received by each agent. I_m is the signal realization coming from the distribution, where $m = 1$ ($m = 0$) indicates the coincidence (divergence) between signal and dividend[4]. Once received the signal, the trader can choose the action A_m=$\{A_1, A_0\}$, where $m = 1$ ($m = 0$) refers to an action consistent (not consistent) with the signal. Consequently, we define "coherent" the player who acts in accordance with her signal regardless of its correctness, that is received the correct (incorrect) signal, I_1 (I_0), her action follows the signal A_1. Symmetrically, an incoherent trader is the one who discards her signal, that is received the correct (incorrect) signal, I_1 (I_0), she always takes the opposite action, A_0. Let us suppose the signal on the dividend to be 20 (10), the coherent player will place an order to buy (sell), at any price, p $\leq$ 20 (p $\geq$ 10). Otherwise the incoherent agent, received the signal of a dividend equal to 20 (10), will not trust the information truthfulness and place a sell (buy) order, at any price p $\geq$ 10 (p $\leq$ 20).

By using a Bayesian approach, and in particular a two step methodology, we can now formalize the trading network bayesian probability of attachment, $p(g)$. In the first step, we assume that the probability to follow the received signal (I_m) coincides with the signal precision ($p(d)$). In other words, we hypothesize that the signal is given without including its distribution. In the second step, we incorporate in the equation obtained in the first step, the signal distribution, that is the probability to receive a signal (in)coherent, (I_0) I_1, with the dividend true value. In this way, agents behavior jointly considers i) the probability to follow the received signal and ii) the probability to receive a signal in line with the dividend true value.

Let us start by describing the first step. As known agents' actions lead to a binomial outcome, that is a buy or sell order. Both orders can be modeled with the following Bayesian distribution:

$$P(A = A_m | I = I_m) = \frac{P(A) \times P(I = I_m | A = A_m)}{P(I)} \propto P(A) \times P(I = I_m | A = A_m), \tag{1}$$

[4] Specifically, if the dividend is 20, d=20, $\bar{d}$=10, I_1=20 and I_0=10

where the probability to take an action on the basis of the received signal, P(A=A_m|I=I_m), is given by the prior distribution, $P(A)$, that represents the probability to do the action independently from the received signal, the likelihood, $P(I = I_m|A = A_m)$, that is the probability to correctly infer the signal, and the marginal probability, $P(I)$, that is the probability to choose one of the two actions. Firstly, $P(A)$ can be defined as a flat uninformative prior distribution, since traders have no preference between the two actions. $P(A)$ is uninformative due to the fact that the only available information is both dividends to have an equal chance of happening. Secondly, $P(I)$ is equal to 1 since, in line with the empirical analysis on our experimental data, traders always take an action. Consequently, Eq. 2 becomes:

$$P(A = A_m|I = I_m) = P(I = I_m|A = A_m) = \begin{cases} p(d), & \text{if } A_m = A_1 \ \forall\ I_m \in I, \\ 1 - p(d), & \text{if } A_m = A_0 \ \forall\ I_m \in I, \end{cases} \tag{2}$$

where the first (second) line of Eq. 2 right hand side denotes the coherent (incoherent) strategy.

Let us now move to the second step, where we reintroduce I_m, that is the probability to receive a signal (in)coherent, (I_0) I_1, with the dividend true value. This implies a modification of Eq. 2 in such a way as to introduce $P(I = I_m)$, that is the probability to receive a specific signal. Consequently, by multiplying Eq.(2) by $P(I = I_m)$, we obtain the joint probability to take a specific action, that is $P(I = I_m) \times P(A = A_m|I = I_m)$. Theoretically the probability to create a trading link, $p(g)$, depends on the probability of drawing two players making different actions. The different possible combinations in the links' creation depend i) on the information received ii) on the strategy adopted by traders (coherent vs incoherent). Tab. 1 summarizes all the essential ingredients to reconstruct the links. Moving from left to right we find: the probability to receive a signal coinciding or not with the dividend; the probability to make a specific action (buy or sell) depending on the coherency (incoherency) of the player (see Eq. 2); the joint probability; the agent market position and, finally the trader strategy profile.

Signal received	Probability to make a specific action (Eq. 2)	Joint probability	Market Order		Strategy profile
$P(I = I_m)$	$P(A = A_m \vert I = I_m)$	$P(I = I_m) \times P(A = A_m \vert I = I_m)$	$d = 10$	$d = 20$	
$P(I_1) = p(d)$	$P(A_1 \vert I_1) = p(d)$	$p(d) \times p(d)$	Sell	Buy	W1
$P(I_1) = p(d)$	$P(A_0 \vert I_1) = 1 - p(d)$	$p(d) \times (1 - p(d))$	Buy	Sell	W2
$P(I_0) = 1 - p(d)$	$P(A_1 \vert I_0) = p(d)$	$(1 - p(d)) \times p(d)$	Buy	Sell	B1
$P(I_0) = 1 - p(d)$	$P(A_0 \vert I_0) = 1 - p(d)$	$(1 - p(d)) \times (1 - p(d))$	Sell	Buy	B2

Table 1: Summary table of the probability to make a buy or a sell order. Specifically, the first column identifies the different signal realizations; the second one models the probability to make an action based on the given signal. The third column summarizes the joint probability of these events, shaping the signal-coherent (or signal-incoherent) strategy profile (fifth column) and the corresponding market order (fourth column).

Basically, four options are possible: coherent players who may be well (badly) informed, i.e. W1 (B1). These traders, who always follow the signal, buy (sell) if the information reveals a dividend equal to 20 (10). Incoherent players who may be well (badly) informed, i.e. W2 (B2). These traders, who never follow the signal, sell (buy) if the information reveals a dividend equal to 20 (10).

Let us now compute the probability of attachment $p(g)$, that is the probability that two nodes (i.e. two agents) are linked (i.e. the probability that a trade exchange takes place between two traders). In this case, we consider all the available combinations and the compatibility of events. This implies that all possible events, occurring simultaneously in the market, can be added together. Specifically, trading happens when a couple of agents belonging to one of these two trading strategy profiles groups, (W1, W2, B1) or (W2, B2), meet. Obviously there is no interaction between a couple of agents with the same strategy profile belonging to the same group. Hence the probability of attachment is given by:

$$p(g) = W1 \times B1 + W1 \times W2 + W2 \times B1 + W2 \times B2. \tag{3}$$

By substituting each strategy profile with the corresponding joint probability in Tab. 1, and after some algebra, we obtain:

$$p(g) = 2 \times p(d)(1 - p(d))[p(d)^2 + (1 - (p(d))^2)]. \tag{4}$$

Recalling that in the first scenario p(d)=75% and in the second one p(d)=62.5%, we easily obtain the probability of attachments, that are $p(g)$=0.234 in T1, and $p(g)$=0.249 in T2.

3. Empirical results

In this session we analyze the emerging market structure and the arising trading strategies. Firstly, our study deals with the market microstructure. Here we mainly focus on the similarities/differences between the theoretical network (see Sec. 2.2) and the empirical exchanges. The goal is to understand the impact of the network topology on price dynamics, its volatility and equilibrium (reported in Fig. 1). Secondly, we look at agents strategies, focusing on those behaviors that move the price away from equilibrium and motivate the discrepancies between the theoretical and the empirical network. It is worthy of note that agents' tactics are inferred ex post on the basis of their position in the exchange network (see Tumminello et al. (2012), for a similar approach).

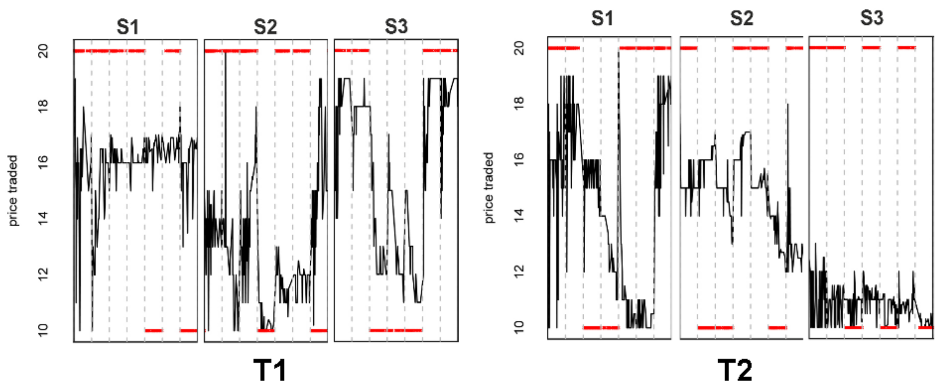

Figure 1: Experimental time series. Horizontal red bars show the dividend drawn, while the black solide lines represent the price evolution across sessions (S1,S2,S3) and treatments (T1,T2).Vertical dashed grey lines divide the different trading periods.

3.1. Market microstructure: theoretical vs empirical configuration

Using the attachment probability $p(g)$ that we have calculated in Sec. 2.2, we simulate, for the two treatments, the Erdòs-Renyi theoretical networks with $N = 8$ vertices and study their topological properties.

In Fig.2 we plot one shot of the configuration of the theoretical network for T1 & T2 (left side) and the corresponding degree distribution (right side). The graphs show that the network architecture depends on the probability of attachment: the higher p(g), the more connected the network. Obviously, the simulated degrees follows a poisson distribution in both scenarios, as shown by the decumulative distribution functions (DDF). By applying the well-known properties of random graphs (see Newman, 2003), we identify other important characteristics of the theoretical trading network. Firstly, we define the approximate mean degree, z, for each of the N vertexes as $z = p(g)(N - 1)$. The mean degree, which coincides with the network average degree and its degree centrality, is equal to 1.638 (1.743) in T1 (T2). Once the mean degree and the probability of attachment are known, we can calculate the fraction of nodes (traders) joined together

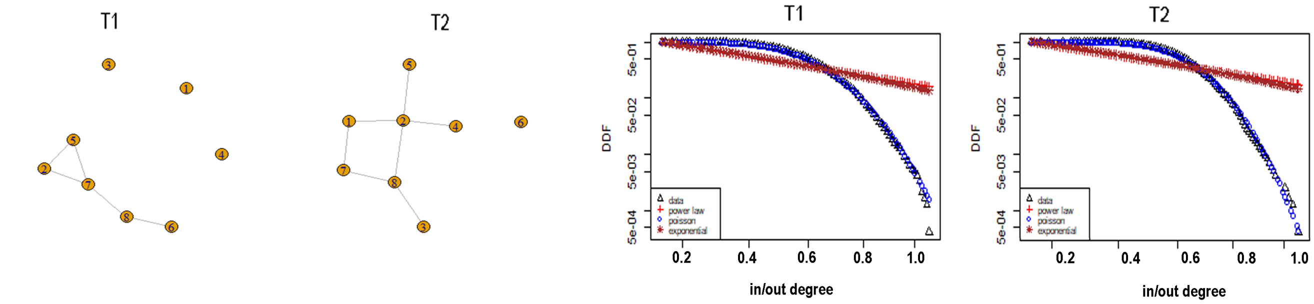

Figure 2: Theoretical network configuration (left side), and decumulative distribution function (DDF) of the degree (right side), for $p(g) = 0.234$ in T1 and $p(g) = 0.249$ in T2.

in a single giant component. The size of the largest component S, is numerically[5] obtained by solving $S = 1 - e^{-zS}$. Our theoretical graph exhibits a giant component made up of 66% (70%) of agents in T1 (T2), demonstrating the network to cross the percolation threshold. Finally, we focus our attention on the diameter index, d, which shows the shortest distance between the two most distant nodes in the network. This index, defined as $d = log(N)/log(z)$, is equal to 4.213 (3.742) in T1 (T2).

In summary, theoretical exchanges generate a high connected network with a high probability of trading between each pair of agents. Obviously this result strongly depends on the attachment probability described in Sec. 2.2. The expected structure of the random graph, in fact, varies with the value of the connectivity $p(g)$. The links join nodes (i.e traders) together to form components, i.e., (maximal) subsets of nodes that are connected by paths through the network. Random graphs possess an important property, called phase transition, from a low-density, low-$p(g)$ state in which there are few edges and all components are small, to a high-density, high-$p(g)$ state in which an extensive fraction of all traders is joined together in a single giant component. As we have seen, our theoretical network crosses this threshold by displaying a giant component. The impact of the attachment probability on the network topology is shown in Fig 3. The black solid line in Fig 3 (left side) shows the dependence of the attachment probability, $p(g)$, on the probability of the dividend signal accuracy, $p(d)$. It is worthy of note that the probability of creating a trading link is a symmetrical function with respect to the informativeness of the dividend signal, with a maximum in $p(d) = 0.5$ and two minima in $p(d) = 0$ and $p(d) = 1$. Intuitively, when half of the players think the dividend is 20 and the other half it is 10, 50% of agents buys and the other 50% sells, thus reaching the maximum number of exchanges. Instead, in the case of missing or complete information (i.e. $p(d) = 0$ and $p(d) = 1$), traders assume the same market position, thus leaving no room for transactions. Finally, a signal corrected to 25% or 75%

[5] Numerical solutions are obtained by applying the Newton-Rapson algorithm.

generates exactly the same number of transactions given the reciprocity between the number of buyers and sellers. Obviously, the motion of the giant component is strictly correlated with the connectivity dynamics, as shown in the black dashed line of Fig.3, left side. The variation of the network properties as a function of connectivity are shown in the right side of the Fig 3. As expected, as $p(g)$ grows, the network centrality increases and its diameter decreases.

Having shown the topological characteristics for the expected theoretical trading network, we can test affinities and dissimilarities with experimental empirical exchanges. The empirical network is simply defined as the sell/buy orders matrix recorded during the experiment, between the players. Consequently, the nodes represent the $N = 8$ traders and the links the transactions among them. Specifically, the agent i incoming links show her buying positions, while the outgoing links the selling positions. In Fig. 4 we plot one shot of the configuration of the empirical trading network (left side) and the in-out degree distribution (right side) for T1 and T2. As we can easy recognize, empirical exchanges considerably diverge from the random configuration. The network architecture, in fact, appears denser than the Erdos-Renyi graph and the degree distribution[6] well approximated by an exponential function rather than a Poisson one. The robustness of

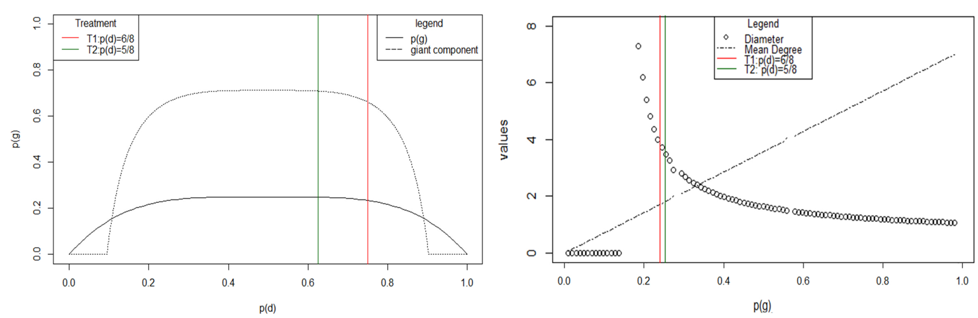

Figure 3: Left side: Evolution of attachment probability,$p(g)$, and of the giant component as a function of the dividend signal accuracy, $p(d)$. Right side: variation of the network mean degree and diameter as a function of $p(g)$. The vertical red (green) line refers to T1 (T2) where $p(d) = 75\%$ ($p(d) = 62.5\%$). Results refer to the theoretical network.

the empirical network topology is displayed in Tab.2 where we estimate the empirical degree distribution with the exponent α of the power law function and its standard error and the rate parameter λ of the exponential function and its standard error by means of the Maximum Likelihood Method (MLM) as in Clauset et al. (2009). The estimated α and λ parameters of the in/out degrees, for each treatment, are displayed in the third and fourth columns respectively. The comparison via the Vuong (1989) test between the two distributions is shown in the fifth column of Tab.2. Given the null hypothesis that the empirical

[6]The sample, made up of 168 observations, collects the information of the 8 subjects, in the 7 periods for each of the three sessions.

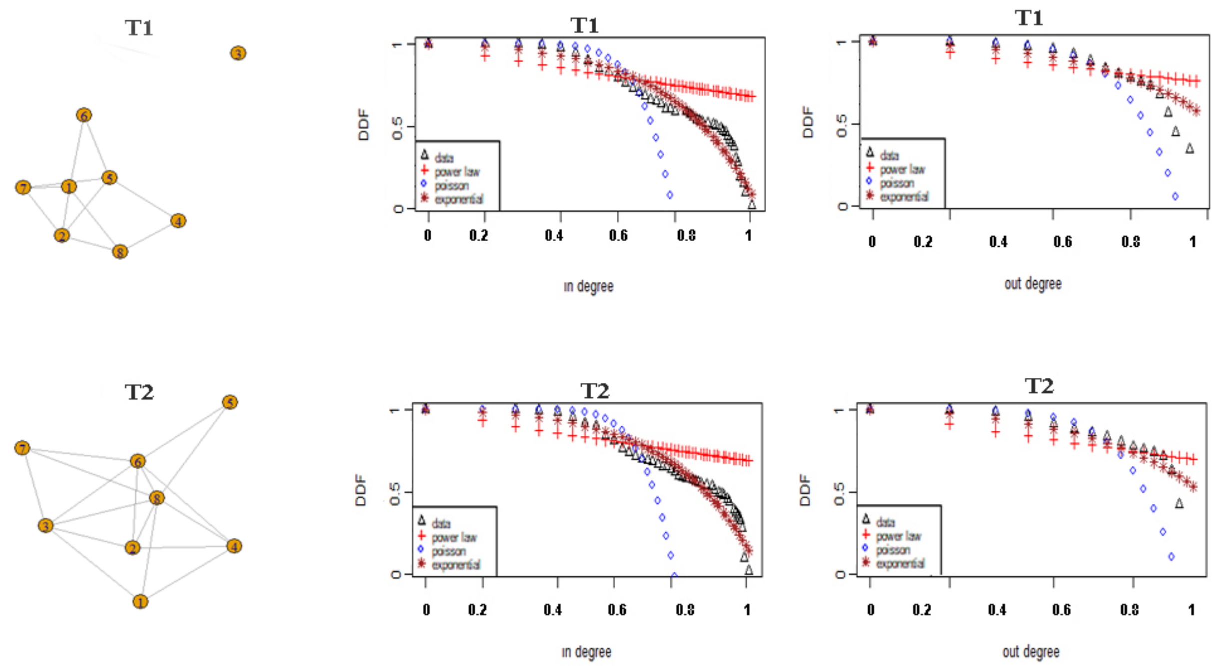

Figure 4: Empirical network configuration (left side), and decumulative distribution function (DDF) of the in-out degree (right side), in T1 and in T2.

data are equally far from a power law or an exponential distribution, and the alternative hypothesis that the exponential function best represents the "truth" degree distribution, the p-value identifies the exponential function as the degree best fit[7].

Treatment	Type	Estimated power law coefficient (MLM)	Estimated Exponential coefficient (MLM)	p-value
T1	In	1.292	0.070	0.000
T1	Out	1.429	0.148	0.045
T2	In	1.312	0.067	0.000
T2	Out	1.436	0.143	0.000

Table 2: Maximum Likelihood Method (MLM) estimation of the power law exponents α and the exponential function λ parameter of in-out degree distributions in T1 and T2. p-value of the Vuong's test, with H0 defining both classes of distributions to be equally far from the true distribution, and H1 identifying the exponential function as closer to the "truth".

Let us now focus on the other properties of the empirical exchanges network and the comparison with the theoretical graph. Tab. 3 shows the main properties of the theoretical and empirical network and their statistical comparison through the t-test for both treatments.[8] It is worthy of note that the empirical network,

[7]We also estimate the empirical degree distribution with the λ parameter of the Poisson distribution. Results, omitted here, reconfirm the supremacy of the exponential distribution.

[8]Since we have time series, there might be serial dependence among observations. We consider this aspect observing that the network metrics and price variables are not serially correlated (1 lag). Additionally, we observe that all the metrics at time t are not dependent by the dividend drawn at time t and t-1. This partially justifies our choice to treat observations as "serial independent" for T-tests.

	T1			T2		
	Theoretical	Empirical	Diff	Theoretical	Empirical	Diff
Degree Centrality	1.638	6.238 (0.95)	-4.600***	1.743	6.017 (1.422)	-4.274***
Density	0.234	0.445 (0.068)	-0.211***	0.249	0.433 (0.105)	-0.184***
Diameter	4.213	2.142 (0.654)	2.071***	3.742	1.857 (0.792)	1.885***
Giant Component	0.661	0.976 (0.050)	-0.315***	0.709	0.952 (0.062)	-0.243***

Table 3: Theoretical and empirical network properties. T-test on the statistical difference between the properties of the two networks. Results refer to both treatments.

compared to the theoretical one, is more centralized, and more than 90% of traders are clusterized in a large community and very close to each other. These aspects suggest that empirical transactions are influenced by some central traders around which the others crowd and not, instead, only by the information contained in prices. Finally, a t-test on the statistical differences between the two graphs topological properties shows the robustness of our results, that is the existence of considerable divergences between empirical exchanges and the Erdos-Renyi graph, as shown in the column "Diff" of Tab.3. Curiously, however, considering the two treatments distinguishing the empirical network, we notice a close similarity between their topological measures. The t-test, omitted here, on the statistical differences between T1 and T2 proves the two sets of data are significantly no different from each other.

Let us now analyze the effect that the empirical network topology has on market prices. Specifically, we focus on two key prices characteristics, namely the volatility and the convergence to the fundamental value. On the one hand, price volatility is a good proxy of financial and macroeconomic uncertainty, often generated by the emergence of systemic instability (see Baum et al., 2008; Berardi and Tedeschi, 2017; Ghosal and Loungani, 2000; Grilli et al., 2020; Tedeschi et al., 2020). Understanding, therefore, whether specific network configurations boost systemic risk is useful for safeguarding systemic resilience. On the other hand, the price-fundamental juxtaposition indicates the network topology ability in spreading the signal and, consequently, reveals the market efficiency (see Fama, 1965).

To create time series with a sufficient length to conduct the analysis, we sample data every 60 seconds. Since there are 7 trading periods of 180 seconds, and these 7 periods are repeated three times (i.e. there are three independent sessions) for each of the two scenarios (T1& T2), we obtain historical series of network measures, prices variance and deviation from the dividend made up of 126 observations[9]. A preliminary empirical analysis reveals that market prices are affected by great volatility and hardly converge to the dividend which, in our experiment, coincides with the fundamental. Specifically, remembering that individual prices always oscillate between 10 and 20, the average prices standard deviation is 0.99, indicating that prices have an average dispersion of about 10%. Furthermore, the dividend price deviation, defined as $e = |p - d|$, is on average equal to 4.85 (st.dev 2.65), indicating that the market prices do not match the dividend. The empirical evidence on prices indicates that, on the one hand, traders do not seem to follow mainstream rational strategies, but rather behave like keynesian animal spirits, and on the other hand, information does not properly flow into the market. The question, therefore, is whether these "anomalies" depend, in some way, on the market architecture. An affirmative answer can be found in Tab 4, where we correlate the main network measures with prices dynamics. To this end, we can compare the results found with existing ones based on empirical and computation studies. For instance, Adamic et al. (2010) compare the network segregation (with clustering coefficients), centrality and connectedness with price returns and volatility, finding higher volatility for more connected graphs. Other computational studies are in line with these findings, showing that high centralized trading networks lead to higher volatility (Grilli et al., 2015). Based on these considerations, we expect that a higher number of clusters and lower closeness (i.e. higher sparsity) reduce price fluctuations.

Market measure	**Empirical network**	**Correlation**	**p-value**
volatility	closeness centrality	0.11	0.007
volatility	mean degree	0.091	0.044
volatility	number of cluster	-0.405	0.000
Price Deviation	closeness centrality	-0.010	0.511
Price Deviation	mean degree	0.191	0.000
Price Deviation	number of cluster	-0.151	0.001

Table 4: Correlation between prices dynamics and network properties. The analysis refers to time series made up of 126 observations.

Specifically, we observe that the high centrality of the empirical network (the average closeness centrality is in fact equal to 0.375 with standard deviation of 0.031) has a positive impact on price volatility, as shown by the positive and significant correlation, equal to 0.11, between the two variables. Obviously, when the

[9] By sampling every $\tau = 60$ seconds, we obtain a minimum of 20 and a maximum of 52 transactions every τ.

network is very centralized, few communities (clusters) emerge, and traders tend to clusterize themselves into few, but very populated, groups. In particular, our market is characterized by an average number of groups[10] equal to 1.5 (st. dev. 0.01), and by the materialization of a giant component made up of 96% of players (see Tab.3). As expected, therefore, given the inverse relationship between the two network properties, we observe a negative and significant correlation between price volatility and the number of communities in the order of −40%.This result is in line with other studies showing that in high centralized trading networks, congestion phenomena can emerge and these foster volatility clustering (see Tedeschi et al., 2009; Grilli et al., 2014; Grilli et al., 2015). Furthermore, the high number of transactions, the mean degree is in fact 4.42 (st. dev. 1.45), generates a positive and significant impact on price volatility equal to 0.091. Finally, regarding the impact of network architecture on the information dissemination, in Tab 4 we observe that the separation between price and dividend depends, for 19%, on the high number of transactions and for 15% on the presence of a few communities.

The results collected so far reveal the emergence of a highly centralized market where traders clasterize into a few communities generating strong prices volatility and poor convergence to the fundamental value. However, it is worthy of note that the emerging empirical network is a dynamic process. Understanding its dependence/relationship with the strategies of the agents placing the orders is the core of the next session.

3.2. From agents behavior to trading links formation

As mentioned above, the strategies adopted by traders reveal information about their orders which define their trading links and determine the evolution of the empirical network. Understanding how players use the received signal and interpret other subjects' actions is, therefore, the key ingredient to comprehend the network dynamics. In this subsection, we study the evolution of players' strategies and the impact they have on traders' performance, on the one hand, and on the deviation of the price from the dividend on the other hand. Before starting this analysis some general remarks are essential: **i)** to create a sequence of data with a sufficient length to conduct the analysis, we sample data every 10 seconds. Since there are 7 trading periods of 180 seconds, and these 7 periods are repeated three times (i.e. there are three independent sessions) for each of the two scenarios (T1& T2), we obtain "historical series" made up of 756 observations[11] **ii)** we introduce a new agent-specific variable: the trading net position. When the dividend is equal to 20, this variable is calculated as the difference between incoming and outgoing links, since buying is the best

[10] We implements the "leading eigenvector" method.

[11] What we generate are not true time series, but more appropriately sequences of data. In fact, if it is true that there is temporal consecutiveness within each session, i.e. during the 7 trading periods that make up each session, there is no temporal consecutiveness between the different sessions. To be clear, the vertical solid lines identifying each session in Fig. 5 could be moved without modifying the analysis, which is not true for the vertical dashed lines corresponding to the trading periods.

strategy the trader can implement. Conversely, when the dividend is equal to 10, the trading net position is given by the difference between outgoing and incoming links, since selling is the best strategy the trader can implement. Consequently, this variable increases (decreases) each time the player takes the correct market position. **iii)** we rank agents according to their network centrality. Specifically, traders are sorted, within the considered time window (ie every 10 seconds), in descending order using the betweenness centrality[12] and, the most central node is named hub/attacker.

In the extant literature, there are several alternative notions of traders' centrality. These range from the "Gurus", who rise (decline) as successful (unsuccessful) traders generating herding (see Tedeschi et al., 2012), to the "large traders" considered by Bannier (2005), who are characterized by "financial market power", able to create speculative attacks (Taketa et al., 2009). In our setting, the hubs/attackers identify the most central subjects, i.e. the most aggressive subjects in the marketplace. Akin to previous studies, we ask whether "One Soros makes a difference" (Corsetti et al., 2004), hence, whether one investor might determine aggregate dynamics. Whereas the aforementioned articles introduce a pre-defined mechanism that determines the attractiveness of the hub, here we observe her appearance and ex-post trace the causes of the predominance of this player. Interestingly, in our context the hub "market power" is just obtained through the trading mechanism, where the player places the largest amount of bid/ask orders influencing the price dynamics.

In the bottom panel of Fig 5 we plot the index of the current hub with the identifier of the strategy she adopts. Following the approach used in the theoretical network, the **well** (badly) informed hub can be "coherent" and, therefore, follow the received signal, ie **W1** (B1), or "incoherent" and, consequently, not be consistent with the signal, ie **W2** (B2). The figure shows that agents alternate as the hub during the experiment. However, it is worthy of note that there are long time periods where the hub is stable, as shown, for example, in the last two experimental sessions. The persistence of this agent denotes her aggressiveness in the market, highlighted by her high volume of transactions. In fact, the hub trading volume is 28% higher than that of other players.

[12] The traders descending order is also robust using other centrality measures such as the closeness and degree centrality.

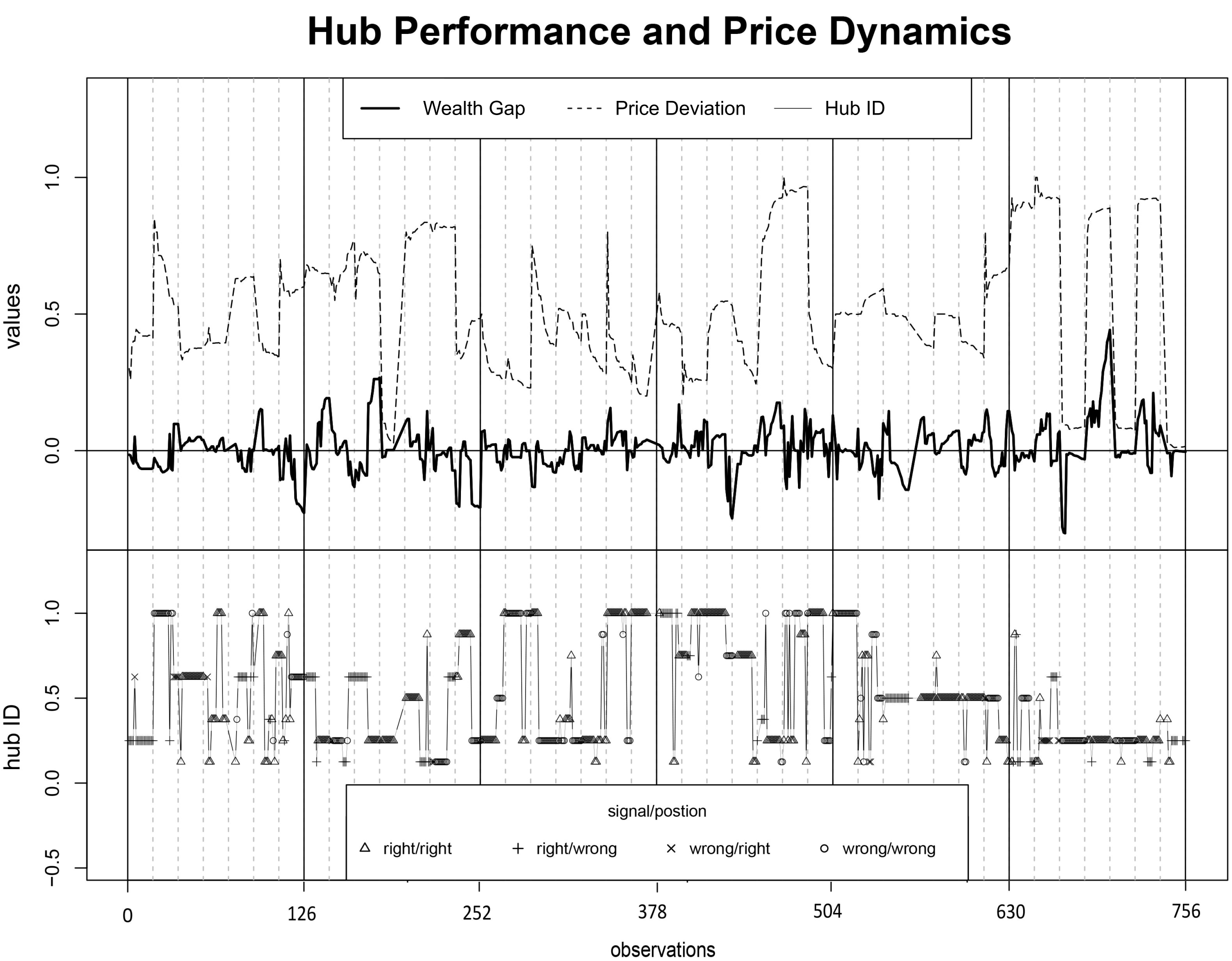

Figure 5: Top Panel: normalized time series of i) the distance between the hub wealth and that of the second most central trader (black solid line), ii) the price deviation from the fundamental value (black dotted line). Bottom Panel: the index of current hub (black line), identified by her coherence/incoherence: triangles and circles identifies coherent strategies, W1 and B1 respectively; plus and times incoherent strategies, W2 and B2 respectively. Vertical solid lines identify the independent sessions for each scenario. Dashed vertical lines refer to the 7 periods of 180 seconds making up each session.

One might expect the hub's highest volume of transactions to depend on her particular trading tactic. A possible answer is in Tab. 5, where we report the average strategy adopted by each of the 8 traders arranged in descending order with respect to their centrality (with S1 to be the attacker).[13,14] As is clear, most of the time, 66%, players follow the coherent strategy, that is, regardless of the correctness of the signal, they

[13]In this case, S1-S8 are the codes uniquely associated to each subject within each period considering the average strategy adopted by each player. Hence the code related to each subject changes depending on their order across different periods.

[14]We have also checked if the fraction of coherent agents impacts the network structure, obtaining no statistically relevant results.

follow it. This turns crucial in explaining wealths, since agents inferring the correct dividend (i.e. W1 and B2) report higher profits, as reported in Fig. 6. Despite the position taken by the player in the network, this strategy is therefore the most common. Nevertheless, a not negligible percentage of time, 25.4%, agents reject the received information. The manifestation of the non-coherent tactic has a double value. On the one hand, it legitimizes the introduction of this strategy in the calculation of the probability of attachment used in the theoretical network. On the other hand, it justifies the existence of the high volume of transactions in the market. In fact we know that the interaction between coherent agents represents only 1 out of 4 possible trading combinations. The other 3 possible interactions necessarily involve the non-coherent agents, as shown in Eq. 3. On the whole, we can conclude that the hub, which is similar to other players for the adopted strategies, differs in her "aggressiveness" in placing market orders.

Another characteristic distinguishes the hub from other traders, that is her market position.

	ALL	S1	S2	S3	S4	S5	S6	S7	S8
W1	44.1%	44.4%	41.9%	42.1%	39.0%	39.6%	49.6%	47.2%	49.5%
W2	24.5%	23.0%	21.4%	23.5%	31.2%	23.9%	25.4%	22.5%	25.7%
B1	21.9%	28.4%	31.2%	28.6%	21.8%	25.8%	13.4%	16.3%	10.1%
B2	0.09%	4.1%	5.4%	5.8%	7.9%	10.7%	11.6%	14.0%	14.8%

Table 5: % Composition of the strategy adopted by each of the 8 traders arranged in descending order with respect to their centrality (with S1 to be the hub). W1 & B1 refer to well (badly) informed agents following their signal (coherent strategy). W2 & B2 refer to well (badly) informed agents not following their signal (incoherent strategy).

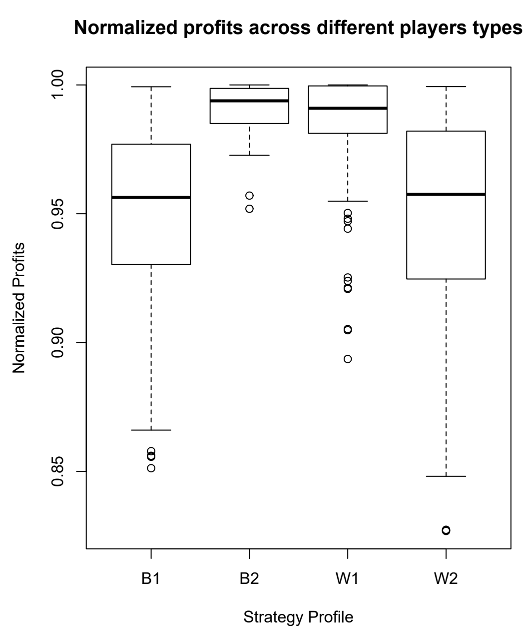

Figure 6: Profits distribution across different strategy profiles for each market period. Data have been normalized by the highest profits per period.

This peculiarity is shown in Tab. 6, where we report the correlation of trading net positions of each pair of players ranked according to their centrality[15] (with S1 to be the hub). As the reader can observe the hub trading net position is always negatively correlated with the other players one. This indicates that the hub plays against the crowd, that is when she submits a market order to buy (sell), other traders give the instruction to sell (buy). Interestingly, however, other traders are ~~perfectly~~ synchronized when placing their orders, as demonstrated by the positive and significant correlation among their trading net positions. The fact that the hub plays a minority game has important systemic consequences. On the one hand, in fact, this strategy gives rise to important stylized facts, such as fat tails and volatility clustering (see Galla and Zhang, 2009; Tedeschi et al., 2009). In this regard, it is sufficient to recall the positive and significant correlation between the volatility and the network centrality shown in Tab. 4. On the other hand, minority game allows hub for the possibility of arbitrage opportunities (see Challet et al., 2005). This second point is shown in the top panel of Fig. 5, where we display the difference between the attacker wealth and that of the second most

centrality	S1	S2	S3	S4
S1	1***			
S2	-0.453***	1***		
S3	-0.501***	0.399***	1***	
S4	-0.389***	0.202***	0.250***	1***

Table 6: Correlation matrix of traders trading net position. The first 4 traders, listed in descending order with respect to their centrality (with S1 to be the hub), are reported.

central trader, $S2$, (black solid line)[16]. As the reader can appreciate there are periods where the attacker prevails over the system (ie. $W_{S1,t} - W_{S2,t} > 0$) and others where she is dominated by it. An intuition of how the minority game played by the hub provokes arbitrage is as follows. 72% of the time the hub follows the signal, which turns out to be correct 44.4% of the time (see Tab. 5). The signal, therefore, determines the hub action and, consequently, her trading net position, which is positively correlated (84%) with her wealth. On the one hand, the well-informed attacker, who acts aggressively in the market and assumes the correct market position playing against other traders, over-performs the system and, consequently, exploits arbitrage in her favor. On the other hand, the badly-informed hub, equally vehement and in disagreement with the crowd, down-performs the market which exploits arbitrage to her detriment.

The effect of signal, trading net position and network configuration on traders wealth is better quantify via

[15] The 4 most peripheral agents have similar correlations to those reported here. Results are available upon request.

[16] S1 and S2 wealth at time t, $W_{S,t}$, is given by $W_{S,t} = C_{S,t} + A_{S,t}d_t$, where C and A is the amount of cash and stocks, respectively, and d the dividend. S2 is used as a proxy for the system due to the synchronization of the market orders of no-attacker traders. However, results are robust also compering S1 wealth with the system's average wealth without the hub.

the following gravity model:

$$ln(W_{s,t}) = \alpha + \beta_0 ln(W_{s,t-1}) + \beta_1 \mathrm{p(d)}_{s,t} + \beta_2 ln(\mathrm{C}_{s,t}) + \varepsilon_{s,t}, \tag{5}$$

where W is the wealth of $S = 1...8$ traders, $p(d)_s$ the signal on the dividend value received by each agent and C the closeness among traders[17]. Specifically, this last variable measures the distance of each treader from the most central agent in the network (ie. the hub). We estimate Eq. 5 via an Arellano and Bond (1991) dynamic model using a two step GMM procedure with robust standard error. Two alternative model's specifications are considered: the case (a) includes the agent closeness, C, regardless of the correctness of the trading net position; the case (b) controls for the type of trading net position by inserting a dummy equal to 1 (0) when the agent is assuming the correct (wrong) market position, that is when the trading net position, η, is strictly positive (negative). Tab. 7 displays the estimated results from models (a) and (b) by considering the lagged dependent variable[18].

[17] C is calculated as the reciprocal of the sum of the length of the shortest paths between a player and all other subjects in the graph.

[18] The sample is made up of 338 observations, that is N=8 subjects play two different scenarios (T1 & T2), repeated 3 independent times over a time span of 7 periods

Variable	Model (a)	Model (b)
$\ln(W_{t-1})$	-0.105	-0.026
	(0.159)	(0.161)
p(d)	0.579 ***	0.257*
	(0.114)	(0.157)
ln(C)	-1.759	
	(1.292)	
$\ln(C) \mid \eta < 0$		-7.403***
		(2.293)
$\ln(C) \mid \eta > 0$		11.790***
		(3.186)
α	7.327***	7.273***
	(1.052)	(1.058)
N × T	288	288
AR1	[0.000]	[0.002]
AR2	[0.765]	[0.852]
Hansen	[0.003]	[0.559]

Table 7: Estimated results for Eq. 5.$\ln(C) \mid \eta < 0$ is the reference coefficient for the $\ln(C) \mid \eta > 0$ effect.

As can be seen, in both models the estimated coefficients associated to the signal, p(d), are positive and statistically significant, indicating the beneficial impact that the received information has on the players' wealth. The impact of the agents' position in the network, C, on the other hand, is not significant in model (a). This result is in line with what we have said about the attacker wealth dynamics. Depending on the correctness/incorrectness of the hub market position, she can over-performs/down-performs with respect to the system. This obviously nullifies the overall effect of the market position on players' wealth. The specification made in model (b) mitigates this problem. As the reader can see, in fact, when the position is bound to the action (in)correctness, its effect clearly emerges. Specifically, when players take the correct position in the market, the centrality favors the wealth, as shown by the associated estimated coefficient equal to +11.79. This is not the case, however, in the opposite circumstance, where it can be seen that the centrality harms the players' wealth with a negative impact equal to 7.4.

It is now natural to wonder how this mechanism, linking the signal and the network position with the agent's wealth, affects price dynamics and, in particular, the convergence between price and dividend. Firstly, we observe that the system is characterized by a strong dispersion of prices from the fundamental value, thus, reveling the efficient-market hypothesis denial. This is shown in the top panel of Fig. 5, where we display the price-dividend deviation (black dashed line). Now, to connect the price-dividend gap with the hub-system wealth discrepancy, we calculate the absolute value of the latter, which is proxy of arbitrage exploited to the attacker's (dis)advantage, and correlate it with the former. We find a positive and significant correlation of 34.8%, indicating that the aggression of- or at the expense of- the hub, which impacts the wealth volatility gap, also pushes prices away from the fundamental value. Obviously, as the wealth dynamics is linked to the trading net position, the same is true for the price-dividend deviation. In this regard, we find a positive and significant correlation of 0.31 between the two variables. To sum up, the mechanism linking signal, wealth gap and price deviation is well summarized in diagram 7, where we display the time series of the attacker wealth gap (as in Fig. 5) lined up in in ascending order (black solid line) with the respective value of the price-dividend deviation (red dashed line).

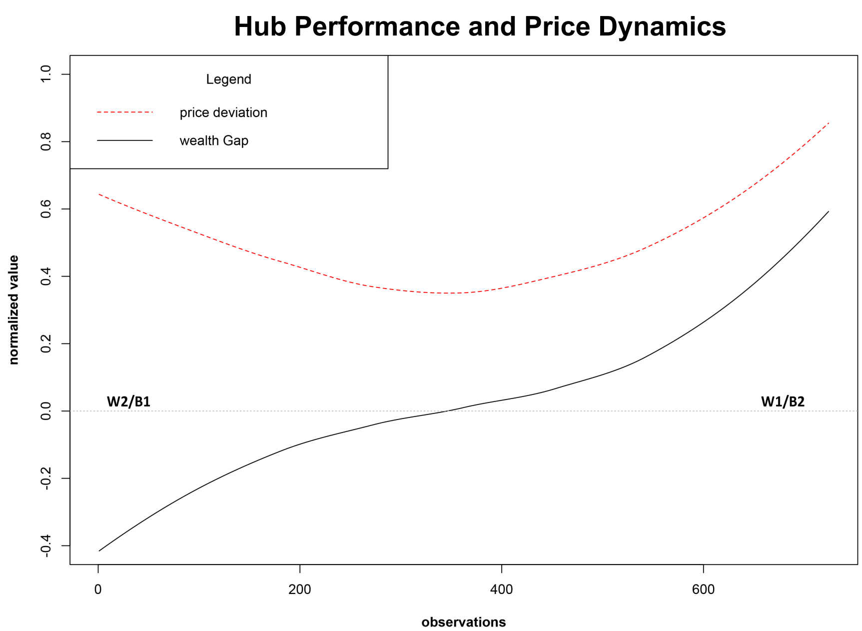

Figure 7: Time series of the hub wealth gap (as in Fig. 5) ranked in ascending order (black solid line) with the respective value of the price-dividend deviation (red dashed line). W2(B1) refers to well (badly) informed-hub who does not follow (follows) the signal, thus assuming the wrong market position. W1(B2) refers to well (badly) informed-hub who follows (does not follow) the signal, thus taking the right market position.

Moving from the center to the left we notice how the attacker, who does not perform the correct action (ie. W2-B1), sees her wealth decrease. However, as the system plays aggressively against her, the price moves away from the dividend. On the other hand, moving from the center to the right, the attacker who performs the correct action (ie. W1-B2) is enriched at the expense of the system and, this time, it is the hub herself that moves the price away from the fundamental value.

4. Concluding remarks

Using the experimental data on a double action market, we have demonstrated the importance of the architecture defining the exchange relationships among traders on the prices' dynamics. At the aggregate level, we have observed that the trading network displays very distinct characteristics from a random graph. The configuration of empirical exchanges, in fact, turned out to be highly centralized and compartmentalized in a few communities that impact on prices' volatility and price-dividend gap.

At a microscopic level our findings have suggested that traders behavior is the key element to comprehend the topology and the dynamics of the trading network. We have shown that the centrality of the empirical network is the result of the behavior of some agents who carry out a high number of transactions. These traders, defined attackers, play a minority game and are able, depending on the correctness/incorrectness of the received signal, to over-perform/down-perform the system. Moreover, the hub, regardless of her trading net position, with her impetus in buying and selling and her game dissociated from the crowd, is shown to be the engine of the price-dividend gap.

Interestingly, the proposed experimental design has allowed us to identify the behaviour of agents interacting in the market as the origin of important stylised facts such as abnormal price excursions and volatility clustering. From the modeller's point of view, this finding is not irrelevant. In fact, it gives a clear guideline in modelling that traders behaviour able to reproduce price dynamics. This particularly impacts, for instance, agent-based models, which are often accused of using ad-hoc rules of thumb to reproduce human behaviour. An interaction between the two disciplines would therefore be desirable: the experiments should provide the model with instructions on the pivotal elements on human behaviour capable to reproduce the desired phenomenon. Furthermore, our findings have shown that the interaction is complex and not random, thus demonstrating that several elements can be, or rather must be, added to the analysis. In this respect, in addition to the many characteristics of the agents (e.g. rationality, risk propensity), it can be worthy to analyze the impact of different configuration of informational distribution, such as the presence of insiders or "quasi"-insiders and their interactions with other market participants. In conclusion, an important policy recommendation can be deduced: if the interaction among traders is an essential building block for the emergence of abnormal price hikes, then **the authority can closely monitor the topology and send the market warnings if dangerous signals emerge, so avoiding the costly damages associated to this dysfunctional market architecture.** ~~the regulator should control the topology of the financial network so as to be able to limit, and possibly anticipate, avoiding the costly damage associated.~~

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