Believe it or Not: Experimental Evidence on Sunspot Equilibria with Social Networks

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Abstract

Models with sunspot equilibria have long been a topic of interest among economists. It then became an interesting question to ask whether there is empirical support for their existence. One approach to answer this question is through lab experiments. Such equilibria have been successfully reproduced in the lab, but little is known about their determinants and, most importantly, about their convergence dynamics: when, and how, do individuals assign a coordination role to signals which are publicly known to have no fundamental value? In order to answer this question, we run a laboratory experiment in which individuals, connected through a network, directly observe the actions of their neighbors as well as aggregated information. By manipulating both the type of information available and the structure of the network, we show that general information about other players' behavior hinders coordination, while information specifically related to the sunspot enhances it.

Keywords: sunspot equilibrium, laboratory experiment, coordination, social networks, communication.
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1 Introduction

Can factors that do not directly affect the fundamentals of an economy nevertheless affect its performance? In macroeconomics, models in which this extrinsic uncertainty is the driving force behind fluctuations have a rich history. Early work by authors such as Azariadis (1981) and Cass and Shell (1983) established the theoretical basis for the literature that followed. In these models, the extrinsic or "sunspot" shock is most easily thought of as a coordination device in choosing among multiple equilibria, i.e., through self-fulfilling expectations on the parts of agents. Benhabib and Farmer (1994) and Farmer and Guo (1994) are seminal examples. The Benhabib-Farmer-Guo model represented a huge achievement: when calibrated largely in line with its contemporary – the real business cycle model (Kydland and Prescott, 1982) – it could similarly replicate real world data. However, in order for sunspot equilibria to obtain, certain parameters of the model needed to be outside the range of empirical plausibility. Hence, much subsequent work focused on producing variations of this model that were more empirically plausible. Examples include Wen (1998) and Harrison (2001). See Benhabib and Farmer (1999) for an extensive review of the sunspot literature in macroeconomics. As a whole, then, this literature helped bring the idea of sunspot equilibria into the mainstream of macroeconomics, and to establish the foundation for the belief, now more widely held, that these models are in fact relevant for explaining the real world.

A more recent literature directly tests the hypothesis that sunspot equilibria can occur in the real world, by seeking to observe coordination on sunspot equilibria in human interaction, based on experimental evidence. The laboratory setting provides the unique ability to create an actual sunspot signal – that is, a message which (i) is random, (ii) does not directly affect fundamentals, and (iii) is known as such by participants, but is still potentially useful as a coordination device. Early work includes Marimon et al. (1993), and Duffy and Fisher (2005), which provide convincing evidence that, at least in some contexts, sunspot shocks do matter. Fehr et al. (2019) also find evidence of sunspot equilibria in the presence of noisy sunspot signals. Agents are able to coordinate with the help of sunspot shocks in each of these games. In addition, in two recent papers, Arifovic et al. (2019) and Arifovic and Jiang (2019) show the emergence of sunspot equilibria in laboratory experiments, reproducing respectively a simple macroeconomic environment, and bank runs dynamics.

In this paper, we add to this literature by improving our understanding of how sunspot equilibria emerge. We do so by manipulating the possibilities for participants to coordinate, connecting them through a predefined social network structure. Models in which agents are connected and communicate via a social network have been used widely in economics over the past decade (see for example Jackson, 2010 and Jackson and Yariv, 2011). In our experiment, each individual is a member of a network, and is able to observe her neighbors' behavior following a sunspot shock, which may aid in the coordination on a sunspot equilibrium. Agents must decide between two symmetric assets, exploiting a sunspot signal as a coordination device. The return on each asset is increasing in the number of agents who invest in it. The payoff structure we pose is based on that of Keser et al. (2012), which can be seen as a special case of models studied in the game theoretic literature on coordination.

Compared to the existing experimental literature on sunspot equilibria, we introduce the novel element of *local* information on other players' actions – which mimics the importance of private interactions and ties in a large number of investment settings, including the financial world (Fracassi, 2017). In addition, we consider a simplified but more general coordination game, where framing is very limited, but both an idiosyncratic fundamental value and a positive complementarity effect affect individual payoffs, hence requiring players to balance contrasting incentives. We focus on the roles of different types of information in helping or hindering synchronization on the sunspot signal.

It is worth mentioning that the game we analyze is a local *information* game, as opposed to the large literature on local *interaction* games: *"locality is represented by information and not necessarily by payoffs"* (Chwe, 2000). It is closely related to the literature on *global* games (Carlsson and Van Damme, 1993; Morris and Shin, 2003), but it relies on purely strategic uncertainty, rather than on individual noisy signals about an unknown state of the world. On the other hand, our setup differs from that of Chwe (2000) because the local information our agents care about concerns *actions* rather than *types*. In this sense, our work is more similar to Cassar (2007) and Battiston and Stanca (2015).

We study different treatments, manipulating two main dimensions. First, we vary the extent to which subjects see other people's actions, by changing the structure of the network, or suppressing it entirely. Second, we introduce a form of nudging which affects the *semantics* of, but is distinct from, the sunspot signal by implicitly referring to it as a potential coordination device (Duffy and Fisher, 2005).

We confirm previous evidence that the sunspot signal can spontaneously emerge as a coordination device, and we show that this coordination increases over time. We find that messages that subjects receive can substantially affect their reliance on the sunspot. In particular, while mere information about other players' actions can crowd out the sunspot signal, explicit nudging can increase its adoption. We also find that the position of a subject in the network can make her more or less important in driving the group towards the sunspot equilibrium. Specifically, subjects with more connections play a more important role in convergence to the sunspot equilibrium.

The rest of the paper proceeds as follows. In the next section, we outline our model; in Section 3, we describe the experimental design; in Section 4 we present results of our analysis; and Section 5 concludes.

2 Theory

Our model is similar to that of Keser et al. (2012). Suppose that $N \geq 2$ investors choose between two assets, A and B. The return for investor i in asset j is:

$$R_{ij} = q_j + r_{ij} + kN_j \tag{1}$$

where $j \in \{A, B\}$, $N_j \in \{0, \dots, N-1\}$ is the number of agents besides i that choose asset j, and $k > 0$. Positive externalities, or complementarities, are captured by the last term in the equation: each investor earns k times the number of other investors who invest in the same asset. The terms $q_j + r_{ij}$ form instead the base, or standalone, value for the investor. It is the return the asset would earn with no complementarities; that is, if no one else besides investor i chooses the asset,[1] and it is composed by a common term q_j and an idiosyncratic term r_{ij}. For the purpose of the present paper, where we focus on complementarities between players' actions, we assume $q_j = 0$. Future research will be devoted to the interaction between common and idiosyncratic base values.

Fehr et al. (2019) and Keser et al. (2012) also consider a context in which agents face a coordination problem in their decision between different assets, with similarly defined complementarities. But in their work, the assets are differentiated by their risk profiles; in our case, the two assets are perfectly symmetric, sharing the same k and with (r_{iA}, r_{iB}) being i.i.d. pairs of values from a common distribution.[2] For simplicity, we assume that the sum of the

[1] Equation (1) can be considered as a special case of the payoffs scheme adopted by (Chwe, 2000), in which the individual utility function is supermodular.

[2] That individual fundamental values are uncorrelated might seem like a strong departure from reality, where fundamental values might differ from investor to investor but typically share a substantial common component. This design decision sacrifices some level of realism

base values is constant, and that the difference between them, $\gamma = r_{iA} - r_{iB}$, is uniformly distributed over a set Γ of values that partition the interval $[-\gamma_M, \gamma_M]$ into intervals of equal length , where $\gamma_M = \max(r_{iA} - r_{iB}) = \max(r_{iB} - r_{iA})$.[3]

The decision to play one asset over the other will naturally depend on the expected number of other players also playing it:

$$x_i = \begin{cases} A & \text{if } \mathbb{E}[R_{iA}] \geq \mathbb{E}[R_{iB}] \\ B & \text{otherwise.} \end{cases} \tag{2}$$

where $\mathbb{E}[R_{ij}] = r_{ij} + k\mathbb{E}[N_j]$. When not specified otherwise, we will be interested in the case in which the maximum difference between base values is less than the maximum benefit from coordination:

$$\gamma_M < k(N-1). \tag{3}$$

Under this assumption, the one-shot game has exactly two pure Nash equilibria that hold for any realization of the base values: full coordination on each of the two assets.[4] Once we consider the repeated version of this game, *any* sequence of plays in $\{A, B\}^T$ is a potential pure Nash equilibrium, and the problem becomes that of coordinating on the same sequence.

Given that the two assets are perfectly symmetric, and that the base values of different players are independent, we can assume that ex ante they are expected to be played with the same probability:

$$\mathbb{E}[N_A] = \mathbb{E}[N_B] = \frac{N-1}{2}. \tag{4}$$

2.1 Introducing the sunspot

We introduce a nonfundamental *sunspot* device S, taking value $S = A$ or $S = B$ with the same probability $\frac{1}{2}$. How does introduction of the sunspot affect the equilibrium properties of the game?

We enrich the model by allowing each agent to have expectations about the influence of the sunspot on other agents' choice. We are not interested, at this stage, in modeling the mechanics of such influence; we simply capture it with a coefficient $\alpha \in [-1, 1]$, where $\alpha = 1$ represents the belief that everybody

in favor of a much clearer interpretation – one with complementarity being the only common component of different agents' payoffs.

[3]In our experiment, $r_{iA} + r_{iB} = \gamma_M = 5$. The case in which the distribution of r_{iA} and r_{iB} is continuous is analyzed in Appendix A.1.

[4]If $\gamma_M > k$, asymmetric equilibria might exist for specific combinations of base values.

follows the sunspot, $\alpha = -1$ represents the belief that everybody deviates from it, and in general $\frac{1+\alpha}{2}$ is the expected share of other group members playing the sunspot: $\mathbb{E}[N_S] = \frac{1+\alpha}{2}(N-1)$. Hence,

$$\mathbb{E}[R_{ij}] = \begin{cases} r_{ij} + k(N-1) \cdot \frac{1+\alpha}{2} & \text{if } S = j \\ r_{ij} + k(N-1) \cdot \frac{1-\alpha}{2} & \text{otherwise.} \end{cases} \tag{5}$$

Notice that $\alpha = 0$ (falling back to equation 4) represents the belief that the sunspot does not, on average, affect agents' decisions.

Given α, each subject forms $\mathbb{E}[R_{ij}]$, and hence chooses x_i, based on the value of r_{iA} and r_{iB}. Let $T \in \{A, B\}$ denote the non-sunspot asset, and $\gamma = r_{iS} - r_{iT} \in [-\gamma_M, \gamma_M]$ be the relative advantage, in terms of base value, from choosing the sunspot: strategies are mappings $\sigma : [-\gamma_M, \gamma_M] \mapsto \{S, T\}$.

Given beliefs about other players (α) and own difference between base values (γ), the condition for picking asset S is:

$$x_i = S \iff \mathbb{E}[R_{iS}] > \mathbb{E}[R_{iT}] \iff \gamma > -k(N-1)\alpha \tag{6}$$

Equation (6) guarantees that best replies are always pure strategies, and allows us to state the following.

Lemma 1. *Best replies are* monotonic *in γ: given an α, if a player chooses S for a given γ', she should do the same for $\gamma'' > \gamma'$.*

Proof. If equation (6) holds for $\gamma = \gamma'$, it holds also for $\gamma = \gamma'' > \gamma'$. □

Corollary 1. *Optimal strategies can take only three forms:*

1. Always strategy*: i.e., always play the sunspot:*

   If $\alpha = 1$, equation (6) becomes $-\gamma < k(N-1)$, which is always true by virtue of equation 3. In other words, if other players are always expected to play the sunspot, the best reply is to always play the sunspot.

2. Threshold strategy*: i.e., play the sunspot if and only if $\gamma > \bar{\gamma}$, for some $\bar{\gamma} \in \mathbb{R}$,*

   For example, if $\alpha = 0$, equation (6) becomes $\gamma > 0$. In this case, other players are expected to not take the sunspot into consideration, hence picking the asset with the larger base value (which is S if and only if $\gamma > 0$), and this is precisely the best reply.

3. Never strategy*: i.e., never play the sunspot.*

If $\alpha = -1$, equation (6) becomes $\gamma > k(N-1)$, which is always false by virtue of equation 3. In other words, if other players are expected to never play the sunspot the best reply is to never play the sunspot.

The three examples presented above, $\alpha \in \{-1, 0, 1\}$, are clearly symmetric Nash equilibria. In order to analyze all possible values for α, we state another result based on equation (6).

Lemma 2. *Best replies are* monotonic *in α: given γ, if a player chooses S for a given α', she should do the same for $\alpha'' > \alpha'$.*

Proof. The right hand side of equation (6) is decreasing in α, so if it holds for $\alpha = \alpha'$, it also holds for $\alpha = \alpha'' > \alpha'$. □

Lemma (2), combined with the analysis above for $\alpha \in \{-1, 0, 1\}$, guarantees that the possible values of α for which the best reply is to never play the sunspot (the never strategy) are an interval $[-1, \underline{\alpha}]$, and that the possible values of α for which the best reply is to always play the sunspot (the always strategy) are an interval $[\overline{\alpha}, 1]$, with $\underline{\alpha} < 0 < \overline{\alpha}$.

Lemma 3. *No value of $\alpha \in (-1, \underline{\alpha}] \cup [\overline{\alpha}, 1)$ results in a symmetric Nash equilibrium.*

Proof. If we take $\alpha \in (-1, \underline{\alpha}]$, the best reply is (by definition) to never play the sunspot, but this strategy *induces* a belief $\alpha_{BR} = -1 \neq \alpha$: hence, beliefs are not consistent. Analogously, if we take $\alpha \in [\overline{\alpha}, 1)$, then $\alpha_{BR} = 1 \neq \alpha$. □

2.1.1 Threshold Nash Equilibria

We now look for Nash equilibria in the intermediate region $\alpha \in (\underline{\alpha}, \overline{\alpha})$. In this case, strategies are defined by a threshold (see Corollary 1) being the value of γ for which equation (6) is binding, that is, $\bar{\gamma} = -k(N-1)\alpha$. In the following, we refer to symmetric Nash Equilibria with strategies of this kind as Threshold Nash Equilibria (TNE).

In a TNE, the value of α induced by $\bar{\gamma}$ is $\alpha_{\bar{\gamma}} = \alpha_{BR} = \mathbb{P}\{\gamma > \bar{\gamma}\}$: the only value of α consistent with believing that other players use $\bar{\gamma}$ as a threshold. Hence, each $\bar{\gamma}$ induces a given $\alpha_{\bar{\gamma}}$, and each $\alpha_{\bar{\gamma}}$ induces a given $\bar{\gamma}'$.

Importantly, multiple values of $\bar{\gamma}$ (or of α) can correspond to the same threshold strategy. For instance, in our experiment, $\Gamma = \{-5, -3, -1, 1, 3, 5\}$, so $\bar{\gamma} = 1.5$ and $\bar{\gamma} = 2$, which are both between 1 and 3, denote the same threshold strategy: "choose the sunspot if and only if γ is equal to 3 or 5". And, if the strategy given by $\bar{\gamma}$ is the same that best replies to $\alpha_{\bar{\gamma}}$, then it is a TNE.

The elements of Γ partition the interval $[-\gamma_M, \gamma_M]$ in H intervals of equal size: if we parametrize such elements as $\gamma_h = \gamma_M - h\frac{2\gamma_M}{H}$ for $h \in \{0, \ldots, H\}$, then the values of α they induce are clearly of the form $\alpha_h = -1 + 2\frac{h}{H}$ (notice that the γ_h are decreasing, and the α_h increasing, in h, as larger thresholds result in smaller expected shares of sunspot players). In turn, each α_h induces a γ'_h such that equation (6) is binding; that is, $\gamma'_h = k(N-1)(1 - 2\frac{h}{H})$.

The two thresholds γ_h and γ'_h represent the same strategy whenever the latter is included in the interval between the former and the subsequent element of Γ, that is, if

$$\begin{aligned} |\gamma_h - \gamma'_h| \leq \frac{2\gamma_M}{H} &\iff \left| \frac{1}{2} - \frac{h}{H} - \frac{k(N-1)(1-2\frac{h}{H})}{2\gamma_M} \right| \leq \frac{1}{H} \\ &\iff \left| \underbrace{\left(\frac{H}{2} - h\right)}_{A} \underbrace{\left(1 - \frac{k(N-1)}{\gamma_M}\right)}_{B} \right| \leq 1. \end{aligned} \tag{7}$$

Hence, equation (7) is crucial in identifying conditions for existence of non–trivial equilibria, as in the following result.

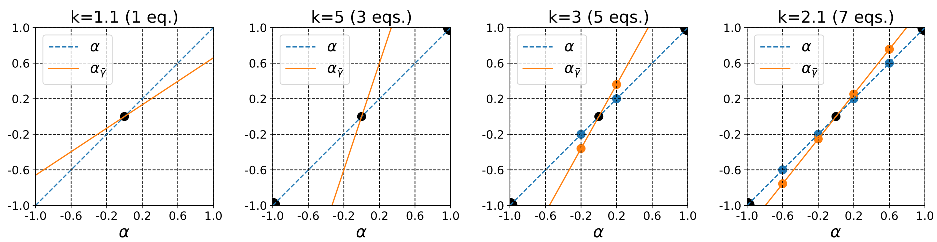
Result 1. *The coordination game admits non–trivial symmetric Nash equilibria if and only if equation* (7) *is satisfied for* $h = \lceil \frac{H}{2} \rceil - 1$.

Proof. One implication directly comes from the definition of equation (7): if it is satisfied for h, then γ_h is a TNE. For the other implication, notice that keeping all other parameters fixed, given a symmetric equilibrium at $h = \bar{h}$, then each value of h at least as close to $\frac{H}{2}$ (i.e., $\left|\frac{H}{2} - h\right| \leq \left|\frac{H}{2} - \bar{h}\right|$) also corresponds to a symmetric equilibrium (because the absolute value of the term A is smaller, or equal, while the term B is unchanged). Since $h = \lceil \frac{H}{2} \rceil - 1$ is the closest value of h to $\frac{H}{2}$, then if non–trivial equilibria exist, it corresponds to one of them. $\square$

Furthermore, we know that B is strictly negative because of equation (3), but at the limit for $k \to \frac{\gamma_M}{N-1}$, it tends to 0. Hence, for any choice of H, h, N and γ_M, we can find a value of k that satisfies equation (3) *and* equation (7), and results in a symmetric equilibrium. We can hence conclude what follows.

Result 2. *The coordination game can admit any strictly positive number of symmetric equilibria.*

Figure 1: Possible configurations of symmetric equilibria for $H = 6$



Note: $\gamma_M = 5$, $N = 4$, $H = 6$, k as specified. Black dots denote trivial symmetric equilibria. Blue dots denote nontrivial symmetric equilibria – cases in which α and $\alpha_{\bar{\gamma}}$ (orange dots) fall in the same interval.

Proof. If k is small enough so that equation (3) is not satisfied and H is even (so that $0 \notin \Gamma$), then the only resulting symmetric equilibrium will be $\alpha = 0$.

If $H = 0$, so that $\Gamma = \{0\}$, then clearly both playing the sunspot and not playing the sunspot are symmetric Nash equilibria, and there are no others.

To obtain a number of equilibria $p \geq 3$, it is sufficient to design a game with $H = p - 1$, and, for any choice of other parameters, pick k such that equation (3) is satisfied, and equation (7) is satisfied for $h = 1$ (and hence for all h). □

Figure 1 displays, for γ_M, N, and H corresponding to our experimental design, the possible configurations of symmetric equilibria, in terms of induced α. Equation (3) is binding for $5 = k \cdot 3 \implies k = \frac{5}{3}$, so the two corner solutions $\alpha = -1$ and $\alpha = 1$ exist if and only if $k > \frac{5}{3}$ (that is, in all panels of Figure 1 except the first one).

The equilibria identified in the two previous results differ systematically from the point of view of expected payoffs, as summarized by the following.

Lemma 4. *The larger $|\gamma_h|$, the higher the expected payoff from a symmetric equilibrium γ_h.*

Proof. See Appendix A.2 □

Given that the game is *ex–ante* symmetric, expected payoffs directly map into Pareto efficiency, hence allowing us to conclude what follows.

Result 3. *Any symmetric Nash equilibrium is Pareto dominated by any other symmetric Nash equilibrium where the sunspot is attributed more importance (larger $|\alpha|$).*

In particular, $\alpha \in \{-1, 1\}$ strictly dominate all other equilibria. Notice that such Pareto ranking refers to the choice of α *before* knowing the value of r_{ij}. Once such base values are drawn, an agent with $\gamma < 0$ might prefer a Nash equilibrium with $\alpha \in (-1, 0]$ to one with $\alpha = 1$, and vice–versa, an agent with $\gamma > 0$ might prefer $\alpha \in [0, 1)$ to $\alpha = -1$.

2.2 Testable hypotheses

In our experimental setting, with parameters $\gamma_M = 5$, $N = 4$, $H = 6$ and $k = 5$, equation (3) is satisfied, so trivial equilibria $\alpha \in \{-1, 0, 1\}$ exist. Instead, equation 7 is $|(3 - h)(-2)| \leq 1$: since it is not satisfied for $h = \lceil \frac{H}{2} \rceil - 1 = 2$, Result 1 guarantees that no non–trivial equilibria exist — as in the second panel of Figure 1. Hence, the model naturally suggests some hypotheses that can be tested empirically. First, that the sunspot does play a role, consistent with previous results in the literature (Marimon et al., 1993; Duffy and Fisher, 2005; Fehr et al., 2019):

> [HYPOTHESIS 1] $\alpha \neq 0$: the selection criterion that individuals adopt takes into account the sunspot realization.

Then, equilibria $\alpha = -1$ and $\alpha = 1$ are particularly relevant, as they Pareto dominate $\alpha = 0$ (Result 3). Moreover, if players start from any belief $\alpha > \frac{1}{15}$ and update their beliefs based on observed decisions, they converge to $\alpha = 1$ with probability > 0.5; if their initial belief is $\alpha > \frac{1}{3}$, they converge to $\alpha = 1$ with probability 1.[5] Similarly, convergence to $\alpha = -1$ happens with probability > 0.5 if initially $\alpha < \frac{1}{15}$, and is guaranteed if $\alpha < -\frac{1}{3}$. That is, the basins of attraction (Dal Bó and Fréchette, 2011; Ghidoni and Suetens, 2019) of these two corner equilibria cover most of the $[-1, 1]$ interval. It is hence natural to hypothesize that, in the repeated version of the game, choices will converge towards one of the two corner solutions.

> [HYPOTHESIS 2] $\alpha \to \{-1, 1\}$: individuals eventually converge to one of the two "extreme" equilibria in which they entirely disregard base values.

Finally, convergence on common strategies requires information about other players' actions (α). In other words, the basins of attraction defined above rely on such information: within each of them, evidence obtained on other players' actions allows for updating of the value of α towards that equilibrium. But

[5] These numbers are obtained by solving equation (6) with $\gamma = -1$ and $\gamma = -5$, the smallest and largest possible private incentives *against* the sunspot asset.

other players' actions do not transparently reveal their strategies and beliefs; they only represent incomplete and noisy (because other players' base values are unknown) signals. The literature on learning in social networks (Gale and Kariv, 2003; Golub and Jackson, 2008), shows that more connections lead to faster convergence. In our setup, variations in our experimental design allow us to manipulate information available about other subjects' decisions: it is natural to hypothesize that the speed of convergence will increase along with the amount of information provided.

> [HYPOTHESIS 3] Convergence to a symmetric equilibrium is faster if more information is available to each player about other players' choices.

Next, we test these hypotheses experimentally.

3 Experimental design

Our experiment brings this model into the lab, and inspired especially by Duffy and Fisher (2005), introduces sunspot shocks as a possible coordination device in a multiple equilibrium setting. In addition, we specifically look at the effect of *local* information (i.e. concerning specific individuals, and flowing over a predefined network structure) on individual decisions. We start by describing the reference design (**BASE**). Then we describe our three alternative designs.

In each session, subjects were randomly and anonymously assigned to groups of four participants, in which they remained for the entire session. Each session consisted of 80 rounds, split into 4 phases of 20 rounds each. At the beginning of each round, the experimenter drew a ball from an urn containing 2 red and 2 blue balls, and all screens in the room turned that color. This color was the sunspot signal, though we avoided any reference to this language in the experimental instructions, which only read:

"During each round, all screens will be colored the same color, either RED or BLUE, randomly selected in front of all participants. This color does not enter payoff computations."

For each subject, independently, the computer then randomly split \$5.00 between two assets RED and BLUE, assigning an integer "base value" to each (hence two numbers in $\{0, 1, 2, 3, 4, 5\}$, adding up to 5). Subsequently, each subject chose which asset to invest in: RED or BLUE. The return from the investment was the subject's base value for the chosen asset plus \$5 for every other member of her group who invested in the same asset in that round. At

Figure 2: Structure of local information

(a) Reference network (b) Unbalanced network

the end of each session, each subject was paid the return from a randomly chosen round of the session (plus a $5.00 show-up fee).[6]

During each session, some groups of four received *local* information in phases I and III, others in phases II and IV. We will refer to the other phases of the game as "no information" phases. Local information consisted in the decision of another member of one's group in the previous round (except for the very first round of the session), according to the cycle network depicted in Figure 2a, where the arrow from B to A means for instance that A got to know B's previous choice. We showed this network structure to the participants, and explicitly told them that each participant always receives information about the same other peer.

All information provided was also repeated in subsequent periods of the same phase. Moreover, after each phase, each participant saw a summary of her choices and of all information obtained during the phase, together with: (1) her average earnings in that phase (2) average earnings for her group in that phase (3) what her average earnings would have been if all members of her group had always chosen the asset with the higher base value in that phase (4) what average earnings in her group would have been if all members of her group had always chosen the asset with the higher base value in that phase (5) what her average earnings would have been if all members of her group had always followed the sunspot in that phase (6) what average earnings in her group would have been if all members of her group had always followed the sunspot in that phase.

Notice that having the same subjects receive both information on peers' past choices and the end–of–phase summary does not hinder our ability to independently study the effect of each. Indeed, choices in the first phase were unaffected by the summary; meanwhile, due to the alternating scheme

[6]This game is essentially a 4-players Battle of the Sexes (BoS) game, but with incomplete information (the base values of other players are unknown). See Banks and Calvert (1992) for a version of the 2-player BoS with incomplete information.

previously described, half of groups obtained no information on peers' past choices until the end of the first phase.

See Figure 8 in Appendix B.2 for a screenshot of this.

3.1 Alternative treatments

In order to unveil the mechanism by which sunspot shocks can emerge as coordination devices, we designed and implemented three variations of the **BASE** design.

1. **Unbalanced network (UNB)**: local information was allowed to flow according to the richer, and unbalanced, network shown in Figure 2b

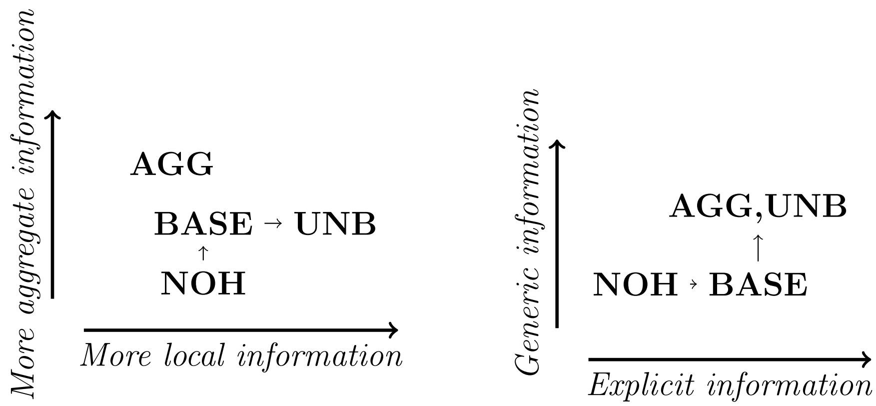
2. **Aggregate information (AGG)**: participants did not receive information from the network, and were instead informed of the number of players in their group selecting RED in the previous period.

3. **No hint (NOH)**: same as the base treatment, except the end-of-phase summaries did *not* contain the two statements about what average earnings would have been if everyone had played the sunspot throughout the phase.

Notice that treatment **NOH** provides subjects with strictly less information than **BASE**, **UNB** with strictly more (see Figure 3, left, where each arrow represents an increase of information available to participants). In particular, the literature on learning over social networks, both with fully rational agents (Gale and Kariv, 2003) and under limited rationality (Golub and Jackson, 2008), shows that more connections lead to faster convergence. Strictly speaking, treatment **AGG** is not directly comparable with any other treatment, since in comparison with **BASE** it brings a tradeoff between aggregate and local information (whereby the former does not allow for analysis of the behavior of any specific neighbor over time). The fact, however, that payoffs depend on the choices of all peers makes the available information set in **AGG** richer for the purpose of coordination.

Note also that information available to subjects in the experiment takes two very different forms. That concerning other players' actions (which is manipulated in the **UNB** and **AGG** treatments) does not involve the sunspot signal, and hence we refer to it as *generic* information. On the other hand, the "hint" provided at the end of phases mentions the sunspot signal, and therefore the possibility to coordinate by exploiting it. Hence, we refer to it as *explicit* information. The difference is summarized in Figure 3, right. Our experiment

Figure 3: Schema of experimental treatments



employed a between-subjects design; in each treatment, we released generic information every other phase, as described for the **BASE** treatment. One nice implication of this is that half of all subjects played the first phase with no information, allowing us to pool their results in some of the analysis below.

4 Results

We ran the experiments between February 21 and February 28, 2017 in the "Columbia Experimental Laboratory in the Social Sciences" (CELSS). 124 subjects, recruited via ORSEE (Greiner, 2015), participated in six sessions, each with between 16 and 24 participants. We excluded one group of four subjects because one participant left the experiment before its conclusion: our analysis is hence based on 30 groups of four subjects each, observed over 80 rounds, for a total of 9600 observations. 36 subjects played design **BASE**, 40 subjects played design **UNB**, 24 played design **AGG** and 20 played design **NOH**. Average payment (excluding the show-up fee) was \$14.38: \$ 15.78 for **BASE**, \$ 13.20 for **UNB**, \$ 14.50 for **AGG** and \$ 14.05 for **NOH**.

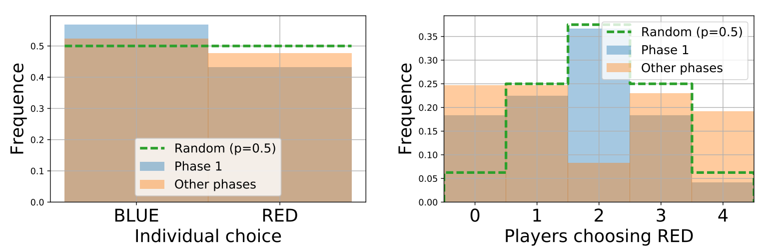
We begin with a look at the general evidence of coordination. Figure 4 (left) shows a slight preference for BLUE overall ($p = 0.000$ from a binomial test), but this preference weakens after the first phase. Figure 4 (right) shows that during the first phase the distribution of choices inside groups is qualitatively analogous to the expected one had players made their decision randomly (or according to their base signals, which were independently drawn). Coordination is very limited, and the most frequently observed outcome is two participants playing BLUE and two playing RED. In subsequent phases coordination increases, and this configuration becomes the *least* frequent.

4.1 Evidence of sunspot relevance

In principle, coordination could be reached by other means than via the sunspot: for instance, always playing RED would seem like a simpler symmetric strategy to guarantee perfect coordination. Hence, we now specifically check whether the color of the sunspot signal has any effect.

Figure 5 (left) shows that participants' choices are uncorrelated with the sunspot signal in the very first rounds (the probability of playing the sunspot being 0.5), but the correlation quickly increases and reaches 0.9 in the last rounds of play. In particular, adoption of the sunspot seems to get a strong boost in the transition to the second phase: we later analyze in detail the determinants of this shift. Figure 5 (right) shows the other side of the coin: the decreasing importance, from phase to phase, of the individual base value. For instance, having a base value of \$5 for RED results in playing RED 86.49 % of the time in phase 1, and only 60.7 % of the time in phase 4. Furthermore, in the last phase, when convergence was massive, no group played either BLUE or RED more than 76% of times; for comparison, in *all groups but four* the sunspot was being played more than 76% of the time.

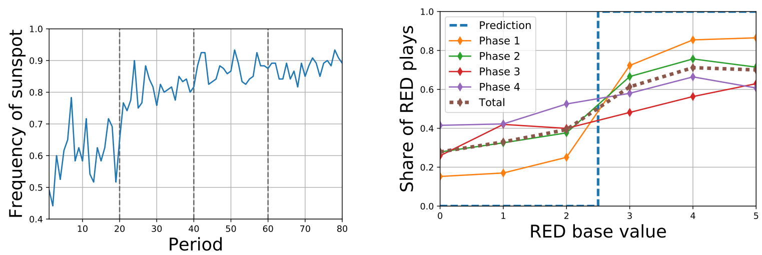
Figure 4: Frequency of RED



Note: Frequency of RED at the individual (left) and group (right) level. The dashed line denotes the expected distribution assuming players randomly selected each of the two assets with equal probability $\frac{1}{2}$.

Next, in order to pinpoint the specific determinants of the individual decision, we analyze the **BASE** treatment. We define $rsuns_t = 1$ if the sunspot signal was RED at round t, 0 if it was BLUE; and $red_{i,t} = 1$ if participant i

Figure 5: Influence of base value and sunspot signal



Note: Left: correlation between sunspot and chosen color, calculated for each round of play. Right: frequency of RED as a function of its base value.

played RED at round t, 0 if blue. Finally, let $rbase_{i,t}$ be the base value for the RED asset for participant i at period t (recall that the base value for the BLUE asset is just $5 - rbase_{i,t}$). We quantify the main determinants of the individual decision by estimating the following equation:

$$red_{i,t} = \beta_0 + \beta_1 rsuns_t + \beta_2 rbase_{i,t} + \beta_\tau t + \epsilon_{i,t} \tag{8}$$

where t, the round of play, controls for a time trend.

Table 1: Main determinants of playing RED

	(1)	(2)	(3)
rsuns	0.816***	0.817***	0.807***
	(0.031)	(0.031)	(0.058)
rbase	0.192***	0.189***	0.162***
	(0.021)	(0.021)	(0.037)
red_1		0.009	0.096*
		(0.032)	(0.056)
neigh_1			0.010
			(0.044)
t	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Observations	2,880	2,844	1,104

Note: Marginal effects from probit estimation with clustered standard errors at the group level. Dependent variable: $red_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.

Table 1 shows results from estimating equation 8 with probit,[7] also controlling for own ($red_{i,t-1}$) and own neighbor's ($neigh_{i,t-1}$) past choices, where applicable.[8] It is worth emphasizing that in columns (2) and (3), the same variable ("red") appears both as dependent variable and, lagged, as regressor. The interpretation of the lagged dependent variable is non-trivial;[9] however, typical panel data models (Arellano and Bond, 1991) are not appropriate to our case of a Boolean variable and a relatively large number of periods (as compared to the number of observations). In any case, this problem does not affect the crucial regressors for our analysis – "rsuns" and "rbase" – because these variables are randomly drawn round by round, uncorrelated with past realizations and choices.

The preference for playing the asset with the highest base value is strongly significant, but an overwhelming role is played by the value of the sunspot, leading us to confirm [HYPOTHESIS 1]:

Result 4. *The sunspot signal has a significant and substantial influence on individual choices.*

Next, in order to better understand the decision to *follow* the sunspot, we create a new dependent variable encoding whether the sunspot signal was followed or not:

$$follow_{i,t} = \begin{cases} 1 & \text{if } red_{i,t} = rsuns_t \\ 0 & \text{otherwise} \end{cases}.$$

Moreover, we transform $rbase_{i,t}$ into a new variable representing the base value *for the asset corresponding to the sunspot signal*:

$$sbase_{i,t} = \begin{cases} rbase_{i,t} & \text{if } rsuns_t = 1 \\ 5 - rbase_{i,t} & \text{otherwise} \end{cases}.$$

Notice that $sbase_{i,t}$, just like $rbase_{i,t}$, takes values in the set $\{0, 1, 2, 3, 4, 5\}$, and has expected mean 2.5. A value of 3 or more means that the sunspot signal

[7]All regressions in this study were also estimated via OLS, including by considering individual and group fixed effects, in all cases without qualitatively affecting the results (if anything, OLS resulted in more significant coefficients).

[8]We consider a "neighbor" the subject whose action is observed by i; for instance, in Figure 2a, B is a neighbor of A.

[9]Nickell (1981) shows why introducing fixed effects would still result in a biased coefficient.

and the base value are *aligned* (e.g. $sbase_{i,t} = 5$ if the sunspot is RED and the base value for RED is 5, or the sunspot is BLUE and the base value for BLUE is 5); a value of 2 or less implies a tension between following the sunspot and playing the asset with the largest base value.

We then estimate the analog of equation (8) looking at the choice to play the sunspot rather than to play RED:

$$follow_{i,t} = \beta_0 + \beta_1 rsuns_t + \beta_2 sbase_{i,t} + \epsilon_{i,t}. \tag{9}$$

We still include $rsuns_t$ in order to control for any idiosyncratic preference for following the sunspot when RED (we saw in Figure 4 that the two assets are not perceived in a perfectly symmetric way).

Table 2: Main determinants of choice

	(1)	(2)	(3)	(4)	(5)
rsuns	0.009	0.013*	0.010	0.014***	0.0001
	(0.008)	(0.007)	(0.008)	(0.005)	(0.010)
sbase	0.077***	0.070***	0.070***	0.060***	0.047***
	(0.013)	(0.014)	(0.014)	(0.012)	(0.014)
follow_1				0.220***	0.210***
				(0.036)	(0.077)
fneigh_1					0.001
					(0.016)
t		0.003***	0.005***	0.002***	0.002***
		(0.001)	(0.001)	(0.001)	(0.001)
t^2			−0.00003***		
			(0.00001)		
Observations	2,880	2,880	2,880	2,844	1,104

Note: Marginal effects from probit estimation with clustered standard errors at the group level. Dependent variable: $follow_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.

Table 2 provides results from equation (9), augmented with various controls ($fneigh\_1$, analogous to $neigh\_1$, denotes whether the neighbor followed the sunspot in the previous period). The coefficient on *sbase* is significant in every model: subjects again tend to follow the sunspot more when it has a higher base value, be it red or blue. Enriching the minimal model (column (1)) by controlling for the round of play and for its second power (given the curvature which clearly emerges from Figure 5), we see that subjects follow the sunspot more over time (positive coefficient on t) but the effect decreases over time (negative coefficient on t^2). This persistence in following the sunspot is also captured by the positive coefficient on $follow_{i,t-1}$. All of the previous coefficients are significant.

The above analysis provides a conclusion concerning [HYPOTHESIS 2]:

Result 5. *In the baseline treatment, propensity to follow the sunspot signal increases over time.*

The positive and strongly significant coefficient for one's lagged action ($follow_{i,t-1}$) in columns (4) and (5) suggests a strong persistence in the decision to follow the sunspot. However, we do not find significant evidence that subjects imitate their neighbor's behavior in the previous period (coefficient on $fneigh_{i,t-1}$ in column (5)). It is important to note that $fneigh_{i,t-1}$ is strongly correlated with $follow_{i,t-1}$. Hence, the latter's coefficient does not have an obvious interpretation. We defer the analysis of the effect of local information to later sections.

The coefficient on $rsuns_t$ is always positive, and significant in some of our models. This suggests that the sunspot is more salient when it is RED (possibly as a consequence of BLUE being considered a "default" choice – see Figure 436). While there is no obvious explanation for this preference, it can be argued that the fact that the coefficient is occasionally significant supports the decision to control for it.

4.2 Comparison of treatments

In this section, we compare results across different treatments. Hence, we expand the sample to include data from all treatments, and we include a dummy variable for each treatment, with the **BASE** treatment as the default:

$$\begin{aligned} follow_{i,t} = \beta_0 + & \beta_1 rsuns_t + \beta_2 sbase_{i,t} \\ & + \beta_{UNB} UNB + \beta_{AGG} AGG + \beta_{NOH} NOH \\ & + \beta_4 info\_start_i + \beta_\tau t + \beta_{\tau 2} t^2 + \epsilon_{i,t} \end{aligned} \quad (10)$$

where $info\_start_i$ denotes whether in the alternating scheme subject i was among those who received information in the first phase. See Table 3 for the results. Again, the coefficient on *rsuns* is positive and significant: all else equal, subjects follow the sunspot more often when it is RED. According with the analysis in the previous section, information on peers' past choices negatively affects the propensity to follow the sunspot (see coefficient "info_start_i" in columns (3)). When looking at coefficients for treatment dummies, the distinction, made in Section 3, between *generic* and *explicit* information becomes crucial. Increasing the availability of generic information (treatments **UNB** and **AGG**) results in the sunspot being played less. However, decreasing the availability of this sunspot-specific information (treatment **NOH**) also decreases the propensity to follow the sunspot signal. As a result, every treatment dummy has a negative coefficient[10] – subjects follow the sunspot less often in each of these treatments than in the **BASE** treatment.

Both the unbalanced and the aggregate information treatments provide more *generic* information than the **BASE** treatment. The fact that increasing communication opportunities decreases the ability to coordinate on the sunspot signal could seem surprising. But it in fact makes sense. With more generic information, subjects don't rely on a separate coordination device, i.e., the sunspot, as much. Aggregate or network information about the sunspot asset being chosen does not per se provide proof that other players are purposely following the sunspot; vice-versa, such information can crowd out attention devoted to the sunspot. On the other hand, the sunspot nudge has a clear interpretation. In the case of the **NOH** treatment, we intentionally did not give the subjects information about the sunspot itself. As a result, they are less likely to follow it. We interpret this as strong evidence reinforcing Duffy and Fisher (2005)'s assertion that the semantics of the sunspot matters.

4.3 More on the effect of information

Next, we investigate further, and more directly, the causal effect of generic information on the decision to follow the sunspot.

Recall that information was provided according to an alternating scheme (in phases I and III for some groups, II and IV for others). Hence, we can more carefully separate out the subjects that received information from those that did not. In particular, here, we restrict to the first phase, and run a between-subjects comparison, on four samples of participants:

B) those who receive local information according to the balanced network (reference category) – sourced from treatments **BASE** and **NOH**,

U) those who receive local information according to the unbalanced network – sourced from treatment **UNB**,

[10] **NOH** in the first phase is an exception (column (3)), but at that time the treatment was still identical to **BASE**.

Table 3: Cross-treatments comparison

	All	All (t^2)	Ph. 1	Ph. 2	Ph. 3	Ph. 4
	(1)	(2)	(3)	(4)	(5)	(6)
rsuns	0.015**	0.017***	0.041	0.008	0.006	0.016*
	(0.007)	(0.007)	(0.026)	(0.009)	(0.008)	(0.009)
sbase	0.101***	0.102***	0.226***	0.098***	0.060***	0.055***
	(0.012)	(0.012)	(0.022)	(0.011)	(0.011)	(0.012)
UNB	−0.082*	−0.083*	−0.142**	−0.075	−0.054	−0.074
	(0.046)	(0.046)	(0.059)	(0.052)	(0.048)	(0.054)
AGG	−0.078*	−0.078*	−0.212***	−0.080*	−0.043	−0.027
	(0.046)	(0.047)	(0.069)	(0.044)	(0.051)	(0.075)
NOH	−0.060	−0.058	0.098	−0.078	−0.093	−0.100
	(0.063)	(0.063)	(0.068)	(0.056)	(0.076)	(0.076)
info_start	−0.049	−0.049	−0.093**	−0.053*	−0.010	−0.057
	(0.033)	(0.033)	(0.038)	(0.030)	(0.030)	(0.044)
t	0.004***	0.009***	−0.005	−0.003	−0.015	0.003
	(0.0004)	(0.001)	(0.007)	(0.010)	(0.015)	(0.018)
t^2		−0.0001***	0.0004	0.0001	0.0001	−0.00002
		(0.00001)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Observations	9,600	9,600	2,400	2,400	2,400	2,400

Note: Marginal effects from probit estimation with clustered standard errors at the group level. Dependent variable: $follow_{i,t}$. See Table 9 in Appendix E for interaction effects. ***p< 0.01, **p< 0.05, *p< 0.10.

A) those who receive aggregate information – sourced from treatment **AGG**,

N) groups in a "no information" phase (recall Section 3), who receive neither local nor aggregated information – sourced from all four treatments.

Restricting to the first phase guarantees both that **NOH** is indistinguishable from **BASE** (since the hint was provided *at the end* of each phase), and that groups in sample N) were not exposed to *any* local or aggregate information.

Columns 1 to 3 of Table 4 provide the results from estimating the following equation:

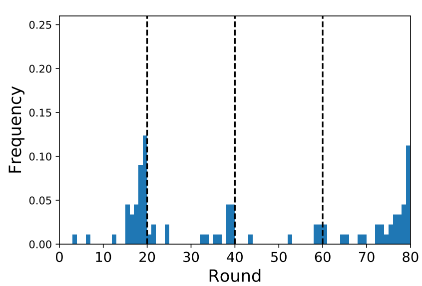
$$follow_{i,t} = \beta_0 + \beta_2 sbase_{i,t} + \gamma_U U_i + \gamma_A A_i + \gamma_N N_i + \beta_\tau t + \epsilon_{i,t}. \tag{11}$$

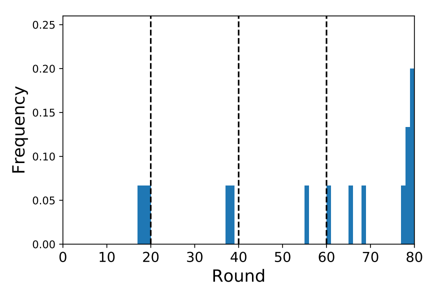
(analogous to equation (9)) on (parts of) phase I. Columns 4 to 6 reproduce the same model using the (round-specific) payoffs as dependent variable, i.e., estimating the determinants of welfare. We do this because, given that the sunspot does not directly affect fundamentals, payoffs could in principle be unrelated to the decision to follow the sunspot. The pattern identified in Section 4.2 is clearly confirmed: additional information about the actions of group-mates causes a significant *decrease* in the willingness to follow the sunspot signal (coefficients γ_A and γ_U), which results in a (albeit non-significant) decrease of average payoffs. More ambiguous results emerge from the analysis of group N), whose members seem to play the sunspot slightly less but initially gain comparatively high payoffs (higher base values are relatively important at the beginning, when coordination is very low). Summing up, Table 4 confirms the results in the previous section about the effect of generic and explicit information. We can summarize such results in the following, related to [HYPOTHESIS 3]:

Result 6. *Providing* generic *information about peers' past choices is detrimental to the decision to follow the sunspot signal and, hence, to coordination.*

4.4 Effect of sunspot specific nudging

Figure 6: Distribution of last round of non-sunspot play





Note: left: data from all treatments except NOH; right: data from NOH. Not shown: subjects who always played the sunspot (11 in the left sample, 5 in the right sample).

Figure 6 presents suggestive evidence of the influence that the end of phase has on participants' actions, identified by the concentration of non-sunspot plays just before, followed by a sharp decrease. This phenomenon is driven by

Table 4: Between-subject results on phase I

	follow			Payoffs		
	t=1-20	t=1-10	t=11-20	t=1-20	t=1-10	t=11-20
	(1)	(2)	(3)	(4)	(5)	(6)
rsuns	0.039	0.039	0.014	-1.231^{***}	-0.175	-2.290^{***}
	(0.029)	(0.029)	(0.032)	(0.195)	(0.279)	(0.278)
sbase	0.222^{***}	0.222^{***}	0.216^{***}	0.713^{***}	0.732^{***}	0.631^{***}
	(0.022)	(0.022)	(0.023)	(0.057)	(0.080)	(0.079)
U)	-0.212^{***}	-0.212^{***}	-0.207^{**}	-0.414	-0.127	-0.636
	(0.070)	(0.070)	(0.082)	(0.360)	(0.499)	(0.506)
A)	-0.227^{***}	-0.227^{***}	-0.270^{***}	-0.502	-0.283	-1.025^{**}
	(0.085)	(0.085)	(0.084)	(0.360)	(0.505)	(0.506)
N)	-0.034	-0.034	-0.019	0.085	0.730^{**}	-0.500
	(0.071)	(0.071)	(0.078)	(0.240)	(0.332)	(0.338)
t	0.003	0.003	0.008	0.013	0.068	-0.217^{***}
	(0.002)	(0.002)	(0.005)	(0.016)	(0.047)	(0.046)
Observations	2,400	2,400	1,200	2,400	1,200	1,200
R^2				0.104	0.087	0.159

Note: Dependent variable: $follow_{i,t}$ for columns 1 to 3 (probit marginal effects), payoffs for columns 4 to 6 (OLS coefficient estimates). Standard errors are clustered at the group level. Each column provides the result of the estimation on a subset of periods of Phase I. ***p< 0.01, **p< 0.05, *p< 0.10.

subjects who start following the sunspot from the first round of the following phase, and before that, seem to play it by mere chance. Since the probability of playing the sunspot by chance is $\frac{1}{2}$, the number of consecutive chance non-sunspot plays is distributed as 2^{-n}.

We now further examine the effect of our end-of-phase hints or sunspot nudges, motivated by Duffy and Fisher (2005), who state that inducing a "common understanding of the meaning of the sunspot realization" can influence the propensity to follow the sunspot.

Recall that treatment **NOH** is perfectly comparable with treatment **BASE** except for the absence of two messages, on the screen at the end of each phase, reporting what (1) own gains and (2) average group gains, respectively, would have been, had everybody in the group followed the sunspot signal at every round of the phase:

$$hint_i^{(1)} = 5 \times 3 + \sum_{t=T+1}^{T+20} sbase_{i,t} \qquad hint_i^{(2)} = 5 \times 3 + \frac{1}{4} \sum_{t=T+1}^{T+20} \sum_{j \in G(i)} sbase_{j,t}$$

where the first term of each, 5×3, is the outcome of perfect coordination, $T \in \{0, 20, 40, 60\}$, and $G(i)$ denotes the group of i.

It is important to recognize that these hints provided no actual information which could be used for future play: they can hence be interpreted as a pure nudging mechanism. $hint^{(1)}$ could have been entirely reconstructed by subjects based on information they already possessed (their base values and the value of the sunspot at each round). $hint^{(2)}$ in principle allowed them to reconstruct the average of the 60 base values of other group members – which were unknown to the subject. But in addition to the complexity of the operation – which subjects had little time to execute – its result would have been of little importance to them: its average was strongly concentrated around 2.5 (the average base value), and most importantly it was unrelated to *future* base values (which were to be independently drawn).

In order to specifically analyze the effect of nudging, we construct and estimate a difference-in-differences model, interacting the variable *post*, indicating rounds from 21 onwards (i.e., when subjects in **BASE** have been nudged at least once) with the **NOH** treatment, including control variables $rsuns_t$ and $sbase_{i,t}$:

$$\begin{aligned} follow_{i,t} = \beta_0 + &\beta_1 rsuns_t + \beta_2 sbase_{i,t} + \beta_3 NOH_i + \beta_4 post_t + \beta_5 NOH_i \times post_t \\ &+ \beta_6 info\_start_i + \epsilon_{i,t} \end{aligned} \tag{12}$$

The results are in Table 5. The positive and highly significant coefficient for *post* indicates that, as already observed in Figure 5 (left), the sunspot is played more frequently as the game progresses. The *differential* effect of transitioning to the second phase is captured by the negative and significant sign of the interaction coefficient ("NOH × post"). It proves that nudging has an important effect on the decision to follow the sunspot, and consequently on payoffs. The effect is sizeable: given that synchronization increases overall from around 50% to around 90% (see Figure 5, left), the coefficient of 17.9% for "NOH × post" means that the message is responsible for more than one third of this increase – and for an increase in average payoffs of at least \$ 1.62. In light of this, we can now better assert the importance of the hints:

Table 5: Difference-in-differences results for **BASE** and **NOH**.

		follow			Payoffs	
	t=1-40	t=1-60	t=1-80	t=1-40	t=1-60	t=1-80
	(1)	(2)	(3)	(4)	(5)	(6)
rsuns	0.006	−0.008	0.002	−0.856***	−0.877***	−0.714***
	(0.010)	(0.008)	(0.006)	(0.188)	(0.145)	(0.123)
sbase	0.127***	0.096***	0.084***	1.450***	1.488***	1.455***
	(0.017)	(0.014)	(0.013)	(0.053)	(0.042)	(0.036)
info_start	−0.035	0.007	0.018	−0.783***	0.004	0.324***
	(0.040)	(0.035)	(0.032)	(0.184)	(0.146)	(0.124)
NOH	0.053	0.034	0.026	0.506*	0.306	0.189
	(0.040)	(0.032)	(0.030)	(0.266)	(0.255)	(0.250)
post	0.191***	0.220***	0.251***	2.165***	2.692***	2.934***
	(0.027)	(0.038)	(0.048)	(0.222)	(0.184)	(0.171)
NOH × post	−0.179***	−0.158***	−0.151***	−1.723***	−1.625***	−1.895***
	(0.047)	(0.059)	(0.054)	(0.376)	(0.311)	(0.287)
Observations	2,240	3,360	4,480	2,240	3,360	4,480
R^2				0.316	0.346	0.340

Note: Dependent variable: decision to follow ($follow_{i,t}$) for columns 1 to 3 (probit marginal effects), payoffs for columns 4 to 6 (OLS coefficient estimates). Standard errors are clustered at the group level. Each column provides the result of the estimation on a subset of phases. Treatments **UNB** and **AGG** are excluded. ***p< 0.01, **p< 0.05, *p< 0.10.

Result 7. *Sunspot specific nudging results in more subjects starting to follow the sunspot, and hence in a positive welfare effect.*

This result once more emphasizes the difference between generic information on other players' actions – which we have seen, in Result 3, actually hinders coordination – and sunspot specific hints. This is consistent with Figure 5, left, where a main shift from a low to a high level of coordination seems to happen from the first to the second phase. Indeed, adoption of the sunspot seems to increase in the very first couple of rounds, but then it lags at a value of around 60% to 70% until round 20.

By focusing our analysis on the **NOH** design (see Table 10 in Appendix E), we find that synchronization on the sunspot is still significant, and significantly increasing over time, although at a slower pace than in the **BASE** design (Table 2).

The sunspot nudge could affect players' actions in two different ways.[11] On one hand, it could function as a shared focal point (Mehta et al., 1994; Bacharach and Bernasconi, 1997) to solve the problem of strategic uncertainty (also discriminating between $\alpha = -1$ and $\alpha = 1$, which are perfectly symmetric, and hence indistinguishable in our model). On the other hand, it could simply reveal that the sunspot strategy performed well in the past, something which a large empirical literature shows is important in investment decisions (Ippolito, 1989; Chevalier and Ellison, 1997; Karceski, 2002; Del Guercio and Tkac, 2002). The latter channel can be expected to be less relevant in the first rounds (when the sunspot strategy was less played, and hence less effective), including in the transition from the first to the second phase. Cleanly disentangling the two channels is outside of the scope of our experiment.

4.5 Network analysis

Next we examine more in depth the influence of the network structure on the actions of partipants. We focus on the **UNB** design depicted in Figure 2b. Specifically, borrowing from the social network literature (Hojman and Szeidl, 2008), we refer to nodes A and C, who each have two incoming and two outgoing connections, as *central* nodes, and to nodes B and D as *peripheral* nodes. Each central node has a central and a peripheral neighbor; each peripheral node only has a central neighbor.

In examining the **BASE** treatment, in equation (9), we included a dummy variable for whether the neighbor played the sunspot in the previous period,

[11] We thank an anonymous referee for this observation.

and we saw in Table 2, column (5), that it was not significant. The **UNB** treatment allows us to improve our analysis in two directions. First, we can check whether central nodes exhibit different behavior than peripheral nodes. Second, we can compare the importance attributed to central versus peripheral nodes.

Table 6: Analysis of network position

	By network position	Restricted to central	
	(1)	(2)	(3)
sunspot	0.027*	0.004	−0.001
	(0.014)	(0.025)	(0.028)
v_suns	0.132***	0.077**	0.075**
	(0.036)	(0.034)	(0.032)
central	0.109		
	(0.080)		
follow_1			0.218**
			(0.087)
info1_follow_1		0.039	0.029
		(0.049)	(0.037)
info2_follow_1		0.090*	0.100**
		(0.054)	(0.042)
Period	0.010***	0.008*	0.005
	(0.002)	(0.004)	(0.003)
Period2	−0.0001***	−0.00005	−0.00003
	(0.00001)	(0.00004)	(0.00003)
info_start	−0.092	−0.029	−0.029
	(0.101)	(0.099)	(0.070)
Observations	960	456	456

Note: Marginal effects from probit estimation with clustered standard errors at the group level. Dependent variable: decision to follow the sunspot. ***p< 0.01, **p< 0.05, *p< 0.10.

We answer the first question by adding a dummy variable equal to 1 if a node is central and 0 otherwise in equation (9). The result is shown in column (1) of Table 6: the coefficient for *central* is positive but not significant.

As to the second question, to answer it we need to restrict our analysis to those nodes which have two neighbors – that is, to central nodes. We can then discriminate between information coming from the peripheral node (e.g.

A receiving information from B in Figure 2b) and that coming from the other central node (e.g. A receiving information from C). The results are presented in Table 6 column (2). Similarly to the balanced network, subjects don't seem to imitate their peripheral neighbor. But, they do pay attention to their central neighbor: the coefficient on $fneigh^C_{i,t-1}$ is positive and statistically significant. Two interpretations of this result are possible. The first is that, as observed by Corazzini et al. (2012), subjects fail to account for repeated information – i.e., for the fact that their "second" neighbor in turn receives information from themselves. A complementary explanation is that, as observed by Battiston and Stanca (2015), subjects tend to attribute more importance to neighbors who are themselves better connected in the network. Whatever the case, central nodes seem to play a crucial role in pushing their group towards the adoption of the sunspot signal as a coordination device.

5 Conclusions

The study of sunspot equilibria has long been a topic of interest for economists. It then becomes an interesting empirical question to ask whether there is support for their existence. A limited stream of literature has approached the issue through experimental studies. Inspired by it, we designed an experiment in which information flows over a social network. By manipulating the amount and type of information obtained by subjects, we are able to better analyze the factors behind the birth of a sunspot equilibrium.

Several aspects of interaction over social networks have been studied experimentally in the literature. In particular, some studies (Farrell, 1988; Cooper et al., 1992) have looked at coordination games, and at how the availability of communication devices allows nodes to reach efficient equilibria. Meanwhile, the literature on opinion formation has studied experimentally network games in which the only available communication device is the ability to observe one's neighbors' past actions (Corazzini et al., 2012; Battiston and Stanca, 2015). In this paper, we bridge the two streams by analyzing a game of coordination in which imitation can possibly affect choices. We then analyze the interplay between such local information – obtained from the network – and the alternative coordination device represented by the sunspot signal.

This is, to the best of our knowledge, the first study showing evidence of the importance of local interaction in sunspot equilibria. It does so by bridging the experimental literature on sunspots with the literature on social networks. Our design allows us to manipulate the amount and type of messages that subjects receive, and hence determine their importance in the realization of sunspot equilibria.

Our results confirm that the sunspot signal is an effective coordination device, and that subjects spontaneously rely on it increasingly over time. However, we also find out that generic information on other players' actions can *crowd out* the sunspot signal, reducing the propensity of subjects to rely on it, and hence reducing payoffs. Vice-versa, messages which explicitly refer to the sunspot significantly increase the salience of the sunspot, and thus enhance coordination. We also find that the way in which people are connected matters for their ability to exploit sunspot equilibria: in particular, more connected subjects emerge as "endogenous leaders" (in the spirit of Andreoni et al., 2017), and play a stronger role in driving the adoption of the sunspot signal as a coordination device.

This study opens new avenues for future research. The importance of nodes' centrality in explaining coordination is an insight with important implications, and calls for a more in depth exploration of how the network topology influences coordination when individuals can observe their neighbors' behavior. In addition, for simplicity, our study analyzed two perfectly identical assets, but the determinants of sunspot equilibria in the presence of correlated base values, resulting in *asymmetric* and/or more than two assets, and their interaction with the network structure, are also important issues left to investigate.

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A Theoretical appendix

A.1 The continuous model

In what follows, we show that the possibility of non-trivial TNE equilibria showcased in Section 2 does not arise, whatever the choice of parameters, if γ follows a *continuous* uniform distribution over $\Gamma = [-\gamma_M, \gamma_M]$.

We first observe that the analysis of $\alpha \in [-1, \underline{\alpha}] \cup [\overline{\alpha}, 1]$ does not rely on Γ being discrete, and it remains valid. That is, the only Nash equilibria in these ranges occur at $\alpha = -1$ and $\alpha = 1$.

For what concerns threshold strategies, the value of α induced by a given $\bar{\gamma}$ is $\alpha_{BR} = \alpha_{\bar{\gamma}} = \mathbb{P}\{\gamma > \bar{\gamma}\}, = 1 - \mathbb{P}\{\gamma < \bar{\gamma}\}$. To pin down $\alpha_{\bar{\gamma}}$, we exploit the fact that γ is uniformly distributed, and hence its CDF is, for $x \in [a, b]$, $F(x) = \frac{x-a}{b-a}$. In our case $a = -\gamma_M$ and $b = \gamma_M$, hence $\alpha_{\bar{\gamma}} = 2(1 - F(\bar{\gamma})) - 1 = -\frac{\bar{\gamma}+\gamma_M}{\gamma_M} - 1 = -\frac{\bar{\gamma}}{\gamma_M}$.

One last intermediate result will help us characterize $\alpha_{\bar{\gamma}}$:

Lemma 5. *For $\alpha \in [\underline{\alpha}, \overline{\alpha}]$, if $\bar{\gamma}$ is the threshold for the best reply to beliefs α, then $\alpha_{\bar{\gamma}} - \alpha$ is strictly increasing in α, and it is 0 for $\alpha = 0$.*

Proof. By definition,

$$\alpha_{\bar{\gamma}} = -\frac{\bar{\gamma}}{\gamma_M} = \frac{k(N-1)\alpha}{\gamma_M}.$$

Hence, $\alpha_{\bar{\gamma}} - \alpha = \frac{k(N-1)\alpha}{\gamma_M} - \alpha$,which is seen to be equal to zero at $\alpha = \frac{1}{2}$. Its gradient with respect to α is $\frac{k(N-1)}{\gamma_M} - 1$, which is guaranteed to be positive by equation (3).

□

Hence, $\alpha = 0$ is the only TNE, leading us to formulate the following result.

Result 8. *The coordination game with a sunspot signal, when base values follow a symmetric, uniform, continuous distribution and the benefits from coordination dominate differences in base values, admits exactly three symmetric Nash equilibria: always follow the sunspot, always deviate from the sunspot, and always play the asset with the highest base value.*

Proof. We already know that when equation (3) is satisfied, all values of $\alpha \in \{-1, 0, 1\}$ correspond to Nash equilibria. Lemma 3 guarantees that there are no other Nash equilibria in $(-1, \underline{\alpha}] \cup [\overline{\alpha}, 1)$; Lemma 5 guarantees that there are no other Nash equilibria (TNE) in $(\underline{\alpha}, \overline{\alpha})$. □

Figure 7: Comparison of α and $\alpha_{\bar{\gamma}}$ in the continuous case

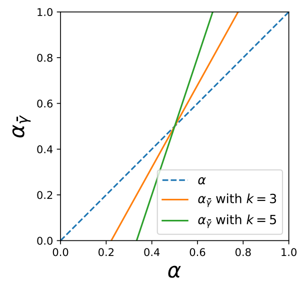


Figure 7 plots $\alpha_{\bar{\gamma}}$ against α for some example parameters.

Note: $\gamma_M = 5$, $N = 4$, k as specified.

We conclude this analysis by showing that however Γ being discrete is not a necessary condition for the existence of non-trivial equilibria.

Result 9. *The coordination game with a sunspot signal, when base values follow a generic continuous distribution, can admit any number of symmetric equilibria.*

Proof. Equation (6) – and hence the determination of $\bar{\gamma}$ from a given α – is unchanged from the uniform case. For its part, Result 2 does not depend on the actual numerosity of Γ, but only on the CDF for α – that is, the correspondence γ_h and α_h.

Now consider the discrete game defined by any combination of values of k, N, γ_M and H: let F_Γ be the resulting CDF, and F_U the CDF for the uniform distribution over $[-\gamma_M, \gamma_M]$. The CDF $F_\lambda(\gamma) = \lambda F_\Gamma + (1 - \lambda)F_U$ defines a probability distribution that, for $\lambda \to 1$ is arbitrarily close to that of the discrete case, while still assigning a strictly positive probability to any interval in $[-\gamma_M, \gamma_M]$. $\square$

In other terms, the existence of non-trivial TNEs does depend on the probability distribution of γ being heterogeneously distributed over $[-\gamma_M, \gamma_M]$, but it needs not being concentrated in a finite number of points.

A.2 Proofs

Proof of Lemma 4. We can write the expected payoff for any equilibrium strategy γ as

$$\bar{\pi}_\gamma = \underbrace{\bar{r}_\gamma}_{\mathbb{E}[r_{ij}]} + \underbrace{\bar{c}_\gamma}_{k\mathbb{E}[N_{i\hat{j}}]}$$

with $\bar{r}_\gamma$ decreasing, and $\bar{c}_\gamma$ increasing, as $|\gamma|$ increases. Moreover, given any two equilibrium strategies γ and γ', let us denote as $\bar{\pi}_{\gamma|\gamma'} = \bar{r}_{\gamma|\gamma'} + \bar{c}_{\gamma|\gamma'}$ the expected payoff for a player who plays strategy γ while all other players are playing strategy γ'. Given that the expected base value only depends on one's strategy, $\bar{r}_{\gamma|\gamma'} = \bar{r}_\gamma$.

Now let us consider an equilibrium strategy γ_h with $h \geq \frac{H}{2}$. The expected complementarity term for strategy γ_h is given by the probability of any two players playing the same strategy, which in turn depends on the expected share of players choosing each strategy:

$$\begin{aligned}
\bar{c}_{\gamma_h} =& k(N-1)\left(\left(\frac{1+\alpha_h}{2}\right)^2 + \left(1 - \frac{1+\alpha_h}{2}\right)^2\right) \\
=& k(N-1)\left(\left(\frac{1+\alpha_h}{2}\right)^2 + \left(\frac{1-\alpha_h}{2}\right)^2\right) \\
=& k(N-1)\left(1 - 2\frac{h}{H} + 2\frac{h^2}{H^2}\right).
\end{aligned}$$

Similarly,

$$\begin{aligned}
\bar{c}_{\gamma_h|\gamma_{h+1}} =& k(N-1)\left(\frac{1+\alpha_h}{2}\frac{1+\alpha_{h+1}}{2} + \left(1 - \frac{1+\alpha_h}{2}\right)\left(1 - \frac{1+\alpha_{h+1}}{2}\right)\right) \\
=& k(N-1)\left(\frac{1+\alpha_h}{2}\frac{1+\alpha_{h+1}}{2} + \frac{1-\alpha_h}{2}\frac{1-\alpha_{h+1}}{2}\right) \\
=& k(N-1)\left(\frac{h(h+1)}{H^2} + \left(1 - \frac{h}{H}\right)\left(1 - \frac{h+1}{H}\right)\right) \\
=& k(N-1)\left(1 - \frac{2h+1}{H} + \frac{2h^2+2h}{H^2}\right).
\end{aligned}$$

Hence, we can take the difference between the expected values of the two complementarity terms:

$$\bar{c}_{\gamma_h|\gamma_{h+1}} - \bar{c}_{\gamma_h} = k(N-1)\frac{2h-H}{H^2}$$

which is positive because of the initial assumption $h \geq \frac{H}{2}$. Moreover, from γ_{h+1} being a TNE, and hence a best reply to itself, it follows that

$$\begin{aligned}\bar{\pi}_{\gamma_{h+1}} \geq \bar{\pi}_{\gamma_h|\gamma_{h+1}} &\implies \bar{r}_{\gamma_{h+1}} + \bar{c}_{\gamma_{h+1}} \geq \underbrace{\bar{r}_{\gamma_h|\gamma_{h+1}}}_{=\bar{r}_{\gamma_h}} + \underbrace{\bar{c}_{\gamma_h|\gamma_{h+1}}}_{\geq c_{\gamma_h}} \\ &\implies \bar{\pi}_{\gamma_{h+1}} \geq \bar{\pi}_{\gamma_h}.\end{aligned}$$

By replacing h with $H - h$ and comparing γ_h to γ_{h-1} in the steps above, the result is also proven for the symmetric case $h \leq \frac{H}{2}$. □

It can be observed that while this proof results in a weak dominance only, it becomes strict if either of the two following conditions holds: (i) γ_{h+1} is a strict Nash equilibrium; (ii) $h \neq \frac{H}{2}$. In other words, the only possible case in which the dominance is weak is for $h = \frac{H}{2}$ and k such that equation (7) is binding (with γ'_h, the best reply to γ_h, coinciding with γ_{h+1}) – which means that weak dominance can happen only when γ_{h+1} and γ_{h-1} are the *only* non-trivial TNE.

B Additional material

B.1 Experimental instructions

Below are the instructions for the **BASE** and **NOH** designs.

Welcome, and thanks for your participation in this experiment. During the experiment, talking or communicating with other participants is not allowed in any way. If you have a question at any time, please raise your hand and one of the experimenters will come to answer your question.

General instructions

- At the beginning of the experiment, you will be randomly assigned to a group of 4 people: during the entire experiment, you will interact only with the other three members of your group, and the composition of your group will never be revealed.
- All members in your group are subject to the same rules, and your earnings are not influenced in any way by members of other groups.

Structure of the task

- The experiment will take place in four phases: each phase is in turn composed of 20 rounds.
- In each round, you will be asked to perform a choice between two "assets": RED and BLUE.
- Before each round, the computer will assign a *base value* to each of the assets, RED and BLUE, by randomly subdividing a sum of \$ 5.00 between them. Each asset yields a payoff equal to its base value, plus \$5.00 for each other member in your group (*excluding* you) who chooses the same asset.
- These values will always be summarized on the screen.

Example
If, in a given round, the computer assigned to you \$ 4.00 as the base value for the RED asset and \$ 1.00 for the BLUE asset, you will see the following sentence written on the screen:

In this round,
the RED asset yields \$4.00 plus \$5.00 for every other participant in your group who chooses RED;
the BLUE asset yields \$1.00 plus \$5.00 for every other participant in your group who chooses BLUE.
See the following tables:

Other RED players	Payoff from RED (\$)
0	\$4.00
1	\$9.00
2	\$14.00
3	\$19.00

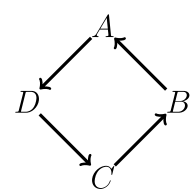
Other BLUE players	Payoff from BLUE (\$)
0	\$1.00
1	\$6.00
2	\$11.00
3	\$16.00

Information

- During each round, all screens will be colored the same color, either RED or BLUE, randomly selected in front of all participants. This color does not enter payoff computations.

- Starting from the second round, you *might* (depending on your group and on the phase of play) also receive information about the decision of another member of your group in the previous round.

  In this case, each member in your group gets to observe the choice of a different member, as in the following figure, where the arrow from B to A means for instance that A gets to know B's previous choice:



For your convenience, all information revealed to you at any round will also be provided at later rounds of the same phase.

In addition, at the end of each phase you will be provided with a summary of the phase, including your payoffs.

Earnings

- In each round of the game, a payoff is determined, as explained above.

- At the end of the session, one round will be randomly drawn by the computer. *Your earnings from this experiment will correspond to your payoff in this round.*

- To these earnings, we will add the $5 show-up fee, which you will receive in any case.

Instructions for the other designs differed in the second bullet point of "Information" (from "Starting from the second round" to the network representation). It was replaced with the following:

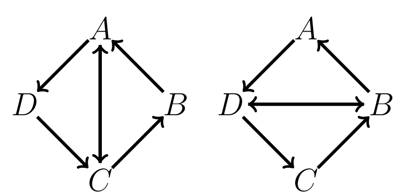
- **AGG** design:

Starting from the second round, you *might* (depending on your group and on the phase of play) also receive information about the number of members of your group who chose each asset in the previous round (in this case, each member in your group receives exactly the same information), and also your payoff from the previous round.

- **UNB** design:

Starting from the second round, you *might* (depending on your group and on the phase of play) also receive information about the decision of another member of your group in the previous round.

In this case, each member in your group gets to observe the choice of a different member, as in one of the two following figures, where the arrow from B to A means for instance that A gets to know B's previous choice:



Note that each participant always keeps the same position across rounds.

B.2 Screenshots

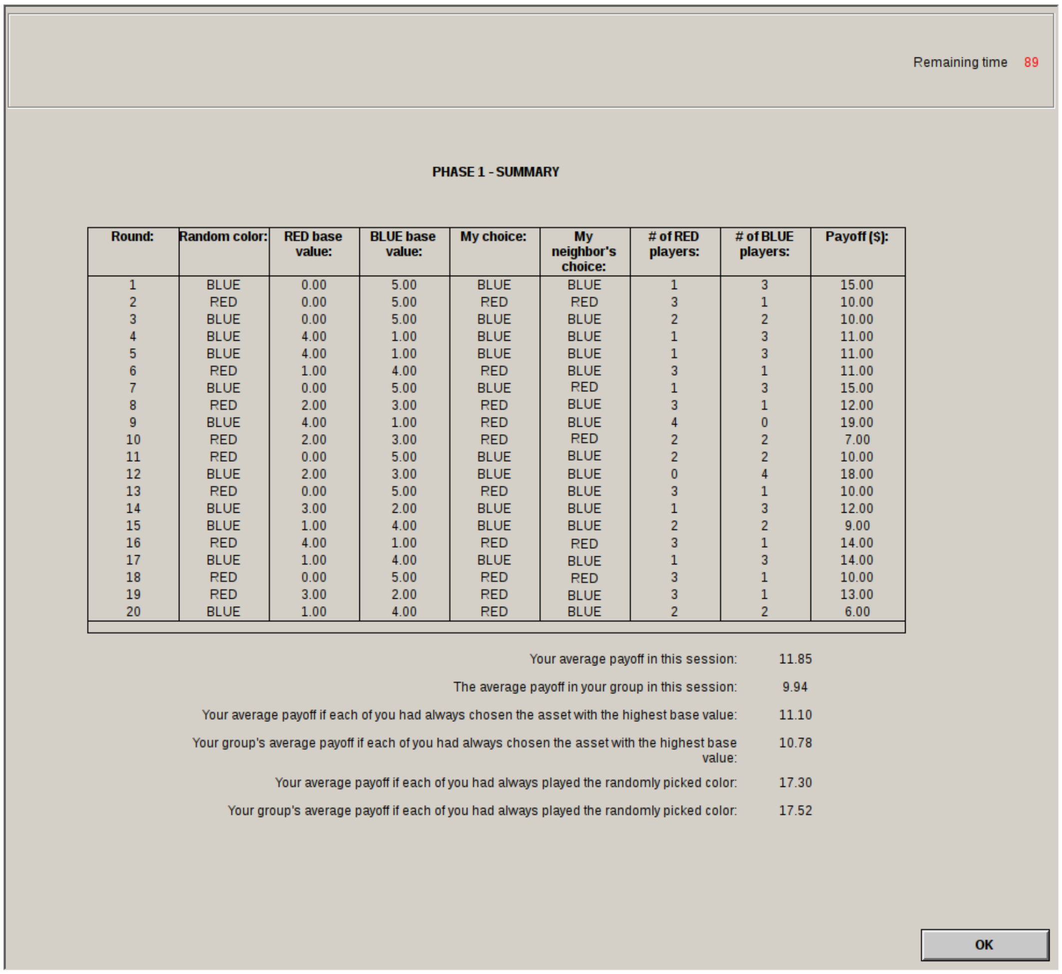
C Session design

Within each session, the phases with information and those without information were alternated, according to the scheme in Table 7

The specific kind of information depended on the treatment: for instance in the **BASE** design it was local information, based on the network in Figure 2a.

The decision to have sets of base values shared amoung pairs of groups – but vary across pairs of groups – represented a tradeoff between maximizing comparability in the between-subjects design, and increasing variability of the base values themselves. Notice that some sessions only had 4 or 5 groups; in the latter case, one group was actually unpaired.

Figure 8: End of phase summary



Remaining time 89

PHASE 1 - SUMMARY

Round:	Random color:	RED base value:	BLUE base value:	My choice:	My neighbor's choice:	# of RED players:	# of BLUE players:	Payoff ($):
1	BLUE	0.00	5.00	BLUE	BLUE	1	3	15.00
2	RED	0.00	5.00	RED	RED	3	1	10.00
3	BLUE	0.00	5.00	BLUE	BLUE	2	2	10.00
4	BLUE	4.00	1.00	BLUE	BLUE	1	3	11.00
5	BLUE	4.00	1.00	BLUE	BLUE	1	3	11.00
6	RED	1.00	4.00	RED	BLUE	3	1	11.00
7	BLUE	0.00	5.00	BLUE	RED	1	3	15.00
8	RED	2.00	3.00	RED	BLUE	3	1	12.00
9	BLUE	4.00	1.00	RED	BLUE	4	0	19.00
10	RED	2.00	3.00	RED	RED	2	2	7.00
11	RED	0.00	5.00	BLUE	BLUE	2	2	10.00
12	BLUE	2.00	3.00	BLUE	BLUE	0	4	18.00
13	RED	0.00	5.00	RED	BLUE	3	1	10.00
14	BLUE	3.00	2.00	BLUE	BLUE	1	3	12.00
15	BLUE	1.00	4.00	BLUE	BLUE	2	2	9.00
16	RED	4.00	1.00	RED	RED	3	1	14.00
17	BLUE	1.00	4.00	BLUE	BLUE	1	3	14.00
18	RED	0.00	5.00	RED	RED	3	1	10.00
19	RED	3.00	2.00	RED	BLUE	3	1	13.00
20	BLUE	1.00	4.00	RED	BLUE	2	2	6.00

Your average payoff in this session: 11.85

The average payoff in your group in this session: 9.94

Your average payoff if each of you had always chosen the asset with the highest base value: 11.10

Your group's average payoff if each of you had always chosen the asset with the highest base value: 10.78

Your average payoff if each of you had always played the randomly picked color: 17.30

Your group's average payoff if each of you had always played the randomly picked color: 17.52

OK

Table 7: General structure of sessions

	Group					
	1	2	3	4	5	6
	Random base values					
	A		B		C	
Phase	Condition					
1	Info		Info		Info	
2		Info		Info		Info
3	Info		Info		Info	
4		Info		Info		Info

D Robustness tests

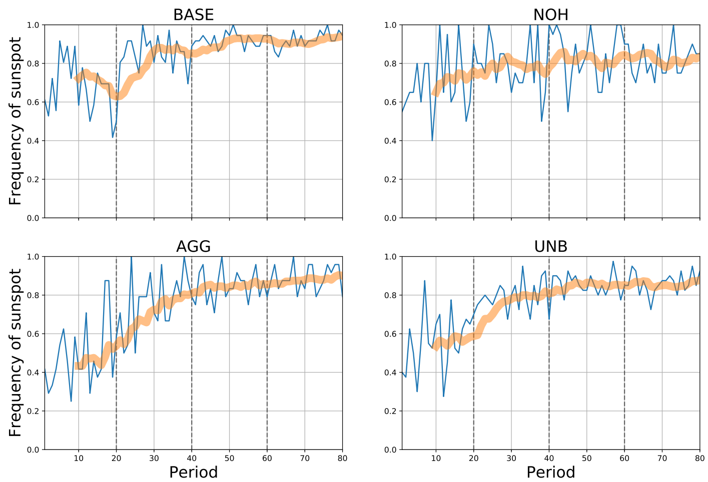
Table 8: Main determinants of choice - OLS estimation

	(1)	(2)	(3)	(4)	(5)
Constant	0.619***	0.445***	0.381***	0.280***	0.248***
	(0.014)	(0.017)	(0.021)	(0.020)	(0.035)
rsuns	0.009	0.020	0.013	0.020*	0.010
	(0.013)	(0.012)	(0.012)	(0.012)	(0.018)
sbase	0.087***	0.090***	0.090***	0.086***	0.077***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)
follow_1				0.254***	0.283***
				(0.016)	(0.026)
fneigh_1					0.006
					(0.026)
t		0.004***	0.009***	0.003***	0.004***
		(0.0003)	(0.001)	(0.0003)	(0.0004)
t^2			−0.0001***		
			(0.00001)		
Observations	2,880	2,880	2,880	2,844	1,104
R^2	0.170	0.235	0.242	0.291	0.324

Note: OLS estimation with clustered standard errors at group level (equivalent of Table 2). Dependent variable: $follow_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.

E Further results

Figure 9: Convergence to sunspot by treatment



Note: equivalent of Figure 5 disaggregated by treatment. Thick lines denote a 10 periods moving average.

Table 9: Cross-treatments comparison: interactions

	(1)	(2)	(3)
rsuns	0.010*	0.012**	0.010*
	(0.006)	(0.006)	(0.006)
sbase	0.098***	0.098***	0.098***
	(0.010)	(0.010)	(0.011)
follow_1	0.274***	0.290***	0.279***
	(0.019)	(0.048)	(0.048)
t	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)
t^2	−0.00005***	−0.00005***	−0.00005***
	(0.00001)	(0.00001)	(0.00001)
info_start	−0.037	−0.037	−0.039
	(0.024)	(0.024)	(0.024)
UNB	−0.024	−0.042*	−0.016
	(0.027)	(0.023)	(0.020)
AGG	−0.083**	−0.046**	−0.068**
	(0.040)	(0.019)	(0.033)
NOH	0.041*	−0.072**	0.021
	(0.025)	(0.033)	(0.018)
t × UNB	−0.001		−0.001
	(0.001)		(0.001)
t × AGG	0.001		0.001
	(0.001)		(0.001)
t × NOH	−0.002***		−0.002***
	(0.001)		(0.001)
follow_1 × UNB		−0.020	−0.013
		(0.039)	(0.038)
follow_1 × AGG		−0.010	−0.022
		(0.039)	(0.037)
follow_1 × NOH		0.025	0.032
		(0.031)	(0.030)
Observations	9,480	9,480	9,480

Note: Additional specifications of cross-treatment comparisons (see Table 3). Marginal effects from probit estimation with clustered standard errors at group level. Dependent variable: $follow_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.

Table 10: Analysis of **NOH**

	(1)	(2)	(3)	(4)	(5)	(6)
rsuns	-0.014	-0.008	-0.010	-0.021	-0.003	-0.005
	(0.012)	(0.014)	(0.016)	(0.015)	(0.014)	(0.014)
sbase	0.113***	0.112***	0.107***	0.106***	0.111***	0.112***
	(0.028)	(0.028)	(0.024)	(0.025)	(0.025)	(0.025)
follow_1			0.369***	0.324***		
			(0.019)	(0.044)		
fneigh_1				-0.040		
				(0.067)		
t		0.002***	0.001***	0.001		0.001*
		(0.0004)	(0.0002)	(0.001)		(0.001)
info_start					0.096	0.097
					(0.065)	(0.066)
post					0.086**	0.038
					(0.037)	(0.044)
Observations	1,600	1,600	1,580	792	1,600	1,600

Note: Selection of specifications from tables 2 and 5, estimated only on subjects playing the **NOH** design. Marginal effects from probit estimation with clustered standard errors at group level. Dependent variable: $follow_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.