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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 becomes 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 are connected through a network, and each of them directly observes the actions of her neighbors as well as aggregated information. By manipulating both the type of information available and the structure of the network, we study the extent to which players are able to converge, and how convergence happens over time. 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.
JEL classification: C92, D81, D85.

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

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work by authors such as Azariadis (1981) and Cass and Shell (1983) established the theoretical basis for the literature that followed. In these macroeconomic 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, it did become readily apparent that in order for sunspot equilibria to obtain, certain parameters of the calibration needed to be outside the range of empirical plausibility. Hence, much subsequent work focused on producing variations of the 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.

More recently, another literature has emerged, one that more directly tests the hypothesis that sunspot equilibria can occur in the real world. This literature seeks 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 still is potentially useful as a coordination device. Marimon et al. (1993), and Duffy and Fisher (2005) are two early examples: both of these papers provide convincing evidence that, at least in some contexts, sunspot shocks do matter. Heinemann et al. (2012) also find evidence of sunspot equilibria in the presence of noisy sunspot signals. Agents are able to coordinate on an outcome when sunspot shocks occur in each of these games. 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. Compared to the existing experimental literature on sunspot equilibria, we consider a simplified and more general coordination game, and focus on the role of information in helping or hindering synchronization on the sunspot signal. 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). Put simply, each individual is a member of a network, and is able to observe her neighbors' behavior following a sunspot shock. Hence, every agent's imitation of her neighbors may aid in the coordination on a sunspot equilibrium. We put forth a model in which agents must decide between two symmetric assets. 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.

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 the sunspot signal (Duffy and Fisher, 2005) by referring to it as a potential coordination device.

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. Specifically, while mere information about other players' actions can crowd out the sunspot signal, more 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 the model that we have in mind; in Section 3, we describe the experimental design; in Section 4 we present results of our analysis; and Section 5 concludes.

2 The Model

We consider a model similar to that of Keser et al. (2012). Suppose that $N \geq 2$ investors choose between two assets, A and B.[1] The return for investor i in asset j is:

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

where $j \in \{A, B\}$, $N_j \in \{0, \dots, N-1\}$ is the number of agents besides i that choose asset j, and $k > 0$.

There are positive externalities, or complementarities, captured by the last term in the equation: each investor earns k times the number of other investors

[1] We limit our analysis to two assets for simplicity of exposition, but it can be trivially generalized to three or more symmetric assets, as long as the sunspot is also distributed uniformly over them.

who invest in the same asset. The term r_{ij} is 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.[2]

Heinemann et al. (2012) and Keser et al. (2012) also consider a context in which agents face a coordination problem in their decision between two assets A and B, with similarly defined complementarities. But in their work, the assets are differentiated by their risk profiles; in our case instead, they are perfectly symmetric, sharing the same k and with (r_{iA}, r_{iB}) being i.i.d. pairs of values from a common distribution. For simplicity, we assume that the sum of the base values is constant, and that the difference between them is uniformly distributed over the interval, $[-\gamma_M, \gamma_M]$, for $\gamma_M = \max(r_{iA} - r_{iB}) = \max(r_{iB} - r_{iA})$.[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: full coordination on each of the two assets. 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

So far we have seen that the two assets are differentiated by their base values, which are also independent across individuals. Now we introduce the a non-fundamental *sunspot* device S, taking value $S = A$ or $S = B$ with the same

[2]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.

[3]In our experiment, $r_{iA} + r_{iB} = 5$ and the difference between the base values follows a *discrete* probability distribution. We discuss the discrete case in the next subsection.

probability $\frac{1}{2}$. How does introduction of the sunspot affect the equilibrium properties of this game? We now examine the Nash equilibria of the repeated version of this game.

We enrich the model by allowing each agent to have expectations about the influence of the sunspot, $S \in \{A, B\}$, 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 $\alpha \in [0, 1]$, where $\mathbb{E}[N_S] = \alpha(N-1)$, so that

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

In particular, $\alpha = 1$ represents the belief that everybody follows the sunspot; $\alpha = 0$ represents the belief that everybody deviates from it; $\alpha = \frac{1}{2}$ (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:

$$\begin{aligned} x_i = S &\iff \mathbb{E}[R_{iS}] > \mathbb{E}[R_{iT}] \\ &\iff r_{iS} + k(N-1) \cdot \alpha > r_{iT} + k(N-1) \cdot (1-\alpha) \\ &\iff \gamma > k(N-1)(1-2\alpha) \end{aligned} \tag{6}$$

We are implicitly assuming that players pick T when indifferent: in fact, the following proof disregards this eventuality – since it happens with zero probability, it does not affect beliefs, and hence Nash equilibria. One can equivalently assume that when indifferent, agents randomize. Excepting this eventuality, 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:*

   For example, 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 $\alpha = \frac{1}{2}$*, 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.*

   For example, if $\alpha = 0$*, 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 strategies above, $\alpha \in \left\{0, \frac{1}{2}, 1\right\}$, each respectively an example of one of the forms of strategies, are also symmetric Nash equilibria.

In what follows, we analyze all possible values for α. In order to do so, 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 $\alpha \in \left\{0, \frac{1}{2}, 1\right\}$, guarantees that the possible values of α for which the best reply is to never play the sunspot (the never strategy) are an interval $[0, \underline{\alpha})$, 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 $\underline{\alpha} < \frac{1}{2} < \overline{\alpha}$.

Lemma 3. *No value of* $\alpha \in (0, \underline{\alpha}) \cup (\overline{\alpha}, 1)$ *results in a symmetric Nash equilibrium.*

Proof. If we take $\alpha \in (0, \underline{\alpha})$, the best reply is (by definition) to never play the sunspot, but this strategy *induces* a belief $\alpha_{BR} = 0 \neq \alpha$: hence, beliefs are not consistent. Analogously, if we take $\alpha \in (\overline{\alpha}, 1)$, then $\alpha_{BR} = 1 \neq \alpha$. □

To reiterate, the only symmetric Nash equilibria identified so far are $\alpha \in \left\{0, \frac{1}{2}, 1\right\}$.

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 threshold strategies. That is, they are strategies such that S is played whenever $\gamma > \bar{\gamma}$. This threshold is the value of γ for which Equation (6) is binding, that is, $\bar{\gamma} = k(N-1)(1-2\alpha)$.

In the following, we refer to symmetric Nash Equilibria with threshold strategies as Threshold Nash Equilibria (TNE). In a TNE each player uses a threshold strategy with the same $\bar{\gamma}$ that satisfies Equation (6).

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

Specifically, $\alpha_{BR} = \alpha_{\bar{\gamma}} = \mathbb{P}\{\gamma > \bar{\gamma}\}, = 1 - \mathbb{P}\{\gamma < \bar{\gamma}\}$. To pin down $\alpha_{\bar{\gamma}}$, we exploit the fact that γ is uniformly distributed. The CDF of the uniform distribution is, for $x \in [a, b]$, $F(x) = \frac{x-a}{b-a}$. In our case $a = -\gamma_M$ and $b = \gamma_M$. Hence,

$$\alpha_{\bar{\gamma}} = 1 - F(\bar{\gamma}) = 1 - \frac{\bar{\gamma} + \gamma_M}{2\gamma_M} = \frac{1}{2} - \frac{\bar{\gamma}}{2\gamma_M}.$$

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

Lemma 4. *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 $\alpha = \frac{1}{2}$.*

Proof. By definition,

$$\alpha_{\bar{\gamma}} = \frac{1}{2} - \frac{\bar{\gamma}}{2\gamma_M} = \frac{1}{2} - \frac{k(N-1)(1-2\alpha)}{2\gamma_M}.$$

Hence,

$$\alpha_{\bar{\gamma}} - \alpha = \frac{1}{2} - \frac{k(N-1)(1-2\alpha)}{2\gamma_M} - \alpha$$

which is seen to be equal to zero at $\alpha = \frac{1}{2}$. The gradient of this with respect to α is:

$$\frac{k(N-1)}{\gamma_M} - 1$$

which is guaranteed to be positive by Equation (3).

□

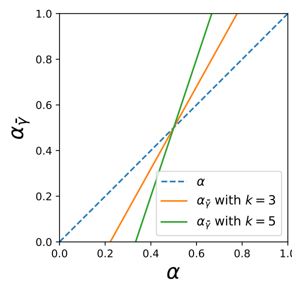
Hence, $\alpha = \frac{1}{2}$ is the only TNE. Figure 1 plots $\alpha_{\bar{\gamma}}$ against α for some example parameters.

The following result summarizes our analysis so far:

Result 1. *The coordination game with a sunspot signal, when base values follow a symmetric, uniform, continuous distribution and the benefits from coordination are not dominated by 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 $\alpha \in \{0, \frac{1}{2}, 1\}$ correspond to Nash equilibria. Lemma 3 guarantees that there are no other Nash equilibria in $(0, \underline{\alpha}) \cup (\overline{\alpha}, 1)$; Lemma 4 guarantees that there are no other Nash equilibria (TNE) in $[\underline{\alpha}, \overline{\alpha}]$. □

Figure 1: Comparison of α and $\alpha_{\bar{\gamma}}$



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

2.1.2 The discrete case

We now consider the case in which – as in our experiment, explained in detail in the next section – the difference between base values follows a *discrete* probability distribution. Let Γ be its support. We continue to assume that values in Γ are uniformly spaced in $[-\gamma_M, \gamma_M]$, and equiprobable. Hence, it should be easy to observe that the analysis of $\alpha \in [0, \underline{\alpha}) \cup (\overline{\alpha}, 1]$ remains valid. That is, the only Nash equilibria in these ranges occur at $\alpha = 0$ and $\alpha = 1$.

For what concerns threshold strategies ($\alpha \in (\underline{\alpha}, \overline{\alpha})$), now multiple values of α or of $\bar{\gamma}$ 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 which best replies to α is the same as that best replies to α_{BR}, this will also be a Threshold Nash Equilibrium.

Given the assumptions on the distribution of γ, the values of α which correspond to the elements of Γ are of the form $\alpha_h = \frac{h}{H}$ for $h \in \{0, \ldots, H\}$. That is, they partition $[0, 1]$ into H intervals of equal width $\frac{1}{H}$. The condition for the coincidence of a strategy with its best reply is hence

$$\begin{aligned} |\alpha_{\bar{\gamma}} - \alpha_h| < \frac{1}{H} &\iff \left| \frac{1}{2} - \frac{k(N-1)(1 - 2\frac{h}{H})}{2\gamma_M} - \frac{h}{H} \right| < \frac{1}{H} \\ &\iff \left| \left(\frac{1}{2} - \frac{h}{H} \right) \left(1 - \frac{k(N-1)}{\gamma_M} \right) \right| < \frac{1}{H} \\ &\iff \left| \underbrace{\left(\frac{H}{2} - h \right)}_{A} \underbrace{\left(1 - \frac{k(N-1)}{\gamma_M} \right)}_{B} \right| < 1. \end{aligned} \tag{7}$$

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.

Equation (7) also confirms 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).

We can hence conclude what follows.

Result 2. *The coordination game with a sunspot signal, when base values follow a symmetric, uniform, discrete distribution, can admit any strictly positive number of symmetric equilibria.*

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 $\alpha = \frac{1}{2}$.

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). $\square$

Figure 1 displays, for γ_M, N and H corresponding to our experimental design, the possible configurations of symmetric equilibria. In our experiment, $k = 5$, and hence only the three trivial symmetric equilibria are present. Equation (3) is binding for $5 = k \cdot 3 \implies k = \frac{5}{3}$, so the two corner solutions $\alpha = 0$ and $\alpha = 1$ exist if and only if $k > \frac{5}{3}$ (that is, in all panels of Figure 1 except the top left one).

2.1.3 Generalizing the continuous case

We conclude this analysis by considering the case in which the possible values of γ follow a continuous distribution over $[-\gamma_M, \gamma_M]$ which is symmetric but not uniform.

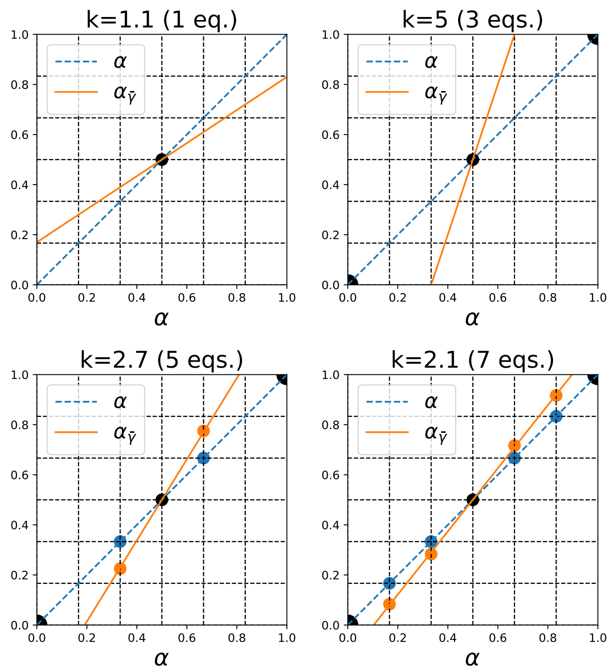
Result 3. *The coordination game with a sunspot signal, when base values follow a generic continuous distribution, can admit any number of symmetric equilibria.*

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 resulting CDF (the complement to 1 of α).

Now given any values of k, N, γ_M and H, consider the corresponding discrete game: let F_Γ be the resulting CDF, and F_U the CDF for the uniform distribution over $[-\gamma_M, \gamma_M]$. The CDF

$$F_\lambda(\gamma) = \lambda F_\Gamma + (1 - \lambda) F_U$$

Figure 2: 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 $\alpha_{\tilde{\gamma}}$ (orange dots) fall in the same interval.

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 $[-\gamma_M, \gamma_M]$. □

2.2 Testable hypotheses

The model naturally suggests some empirical hypotheses: first, that the sunspot does play a role.

> [HYPOTHESIS 1] $\alpha \neq \frac{1}{2}$: choices of individuals are affected by the sunspot signal.

We then know that for our parametrization, only the three trivial equilibria are available. It is hence natural to hypothesize that choices will converge towards one of the two corner solutions.

> [HYPOTHESIS 2] $\alpha \to \{0, 1\}$: if choices of individuals are affected by the sunspot, they eventually tend to one of the two "extreme" equilibria in which base values are entirely disregarded.

Finally, given that convergence on common strategies requires information on other players' actions (α) – an element which our experimental design allows us to manipulate – we can hypothesize that the speed of convergence will increase along with the amount of information received about other players' actions.

> [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 will describe the three alternative designs we implemented.

In each session, subjects were randomly and anonymously assigned to groups of four participants, in which they remained for the entire session. We divided each session into four phases, each of which was in turn composed of 20 periods, or rounds, for a total of 80 rounds in a session. At the beginning of each round, a sunspot shock was drawn: 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

Figure 3: Structure of local information

(a) Reference network (b) Unbalanced network

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 had invested in the same asset in that round. At 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).[4]

Each session was split into four phases; some groups of subjects 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 3a, where the arrow from B to A means for instance that A got to know B's previous choice. The network was shown to participants, who also knew that positions would remain unchanged throughout the entire session.

All information provided at any time was also repeated at the 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]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.

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

See Figure 8 in Appendix A.1 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 3b
2. **Aggregate information (AGG)**: participants did not receive information from the network, and were informed instead of the number of players in their group selecting RED in the previous period.
3. **No hint (NOH)**: each round was carried out exactly as in the base treatment, but the end-of-phase summaries did *not* contains 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 4, left, where each arrow represents an increase of information available to participants). 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 in the same way on the choices of all peers suggests that the available information set in **AGG** is richer for the purpose of coordination.

It is important to notice that information available to subjects in the experiment treatment takes two very different forms. Information concerning other players' actions (which is manipulated in the **UNB** and **AGG** dummies) does not involve in any way the sunspot signal, and in this sense we will refer to it as *generic* information.

Vice-versa, the "hint" provided at the end of phases mentions the sunspot signal, and the possibility to coordinate by exploiting it. Hence, we refer to it as *explicit* information. The difference is summarized in Figure 4, right.

Figure 4: Schema of experimental treatments

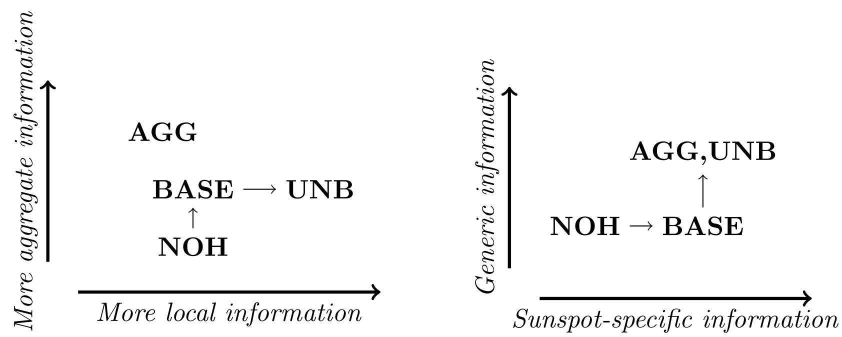


Table 1: Distribution of subjects across treatments

Treatment	**BASE**	**UNB**	**AGG**	**NOH**	*Total*
Subjects	36	40	24	20	120

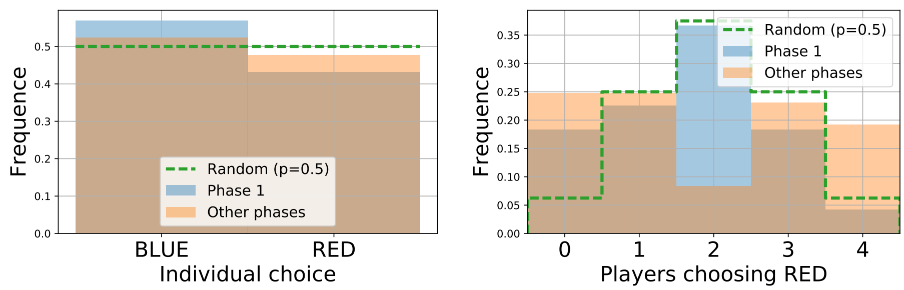
Treatments were assigned with a between-subjects design, with both local and aggregate information being released according to the alternating scheme over phases described for the **BASE** treatment. This will allow us in some cases to pool together observations from different treatments: for instance, under all treatments, half of the groups would play the first phase without any information, hence in the same exact conditions across all sessions.

4 Results

We ran the experiments between February 21st and February 28th, 2017 in the "Columbia Experimental Laboratory in the Social Sciences" (CELSS). 124 subjects participated in the experiment across six sessions, each counting between 16 and 24 participants. We exclude one group of four subjects because one participant left the experiment before its conclusion: our analysis is hence based on 24 groups of four subjects each, observed over 80 rounds, for a total of 9600 observations. See Table 1 for the distribution across treatments.

We start our analysis by looking at general evidence of coordination. Figure 5 (left) shows that there is a slight preference for BLUE overall (which is significant – $p = 0.000$ from a binomial test), but that such preference weakens after the first phase. Figure 5 (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

Figure 5: Frequency of RED



Note: Frequency of RED at the individual (left) and group (right) level.

observed configuration at the group level is with 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.

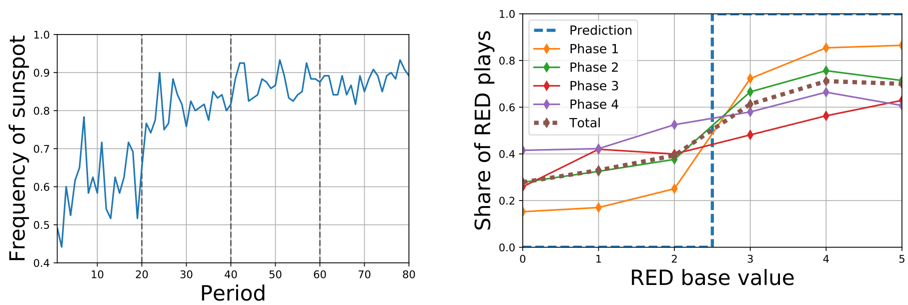
Figure 6 (left) shows that participants' choices are uncorrelated with the sunspot signal in the very first rounds (the probability of playing the sunspot being 0.5), but the correlation quickly increases and reaches 0.9 in the last rounds of play. Figure 6 (left) shows the other side of the coin: the decreasing importance, from phase to phase, of the individual base value.[5] For instance, having a base value of \$ 5 for RED results in playing RED 86.49 % of times in phase 1, and only 60.7 % of times in phase 4.

In order to pinpoint the specific determinants of the individual decision, we start by analyzing the **BASE** treatment. Consider the variable $rsuns_t$ defined as taking value 1 if the sunspot signal was RED at round t, 0 if it was BLUE, and the variable $red_{i,t}$ defined as 1 if participant i played RED at round t, 0 if participant played blue. Moreover, for $t > 1$ let $neigh_{i,t-1} = 1$ if subject i's neighbor chooses RED in period $t-1$, and $neigh_{i,t-1} = 0$ if she chooses BLUE.[6] 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

[5] In fact, this reflects the actual reason to introduce asymmetric – and private – base values, which was to slow down coordination by reducing the focus on the sunspot value.

[6] We consider a "neighbor" the subject whose action is observed by i; for instance, in Figure 3a, B is a neighbor of A.

Figure 6: 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.

following equation on periods from 2 onwards:

$$red_{i,t} = \beta_0 + \beta_1 rsuns_t + \beta_2 rbase_{i,t} + \beta_3 red_{i,t-1} + \beta_\tau t + \epsilon_{i,t} \quad (8)$$

which also controls for own lagged action $red_{i,t-1}$, and for a time trend (t is the period of play).

We then further restrict to periods in which local information was provided to subjects (i.e., excluding groups in "no information" phases), and estimate the following equation, which also accounts for the behavior of a subject's neighbor:

$$red_{i,t} = \beta_0 + \beta_1 rsuns_t + \beta_2 rbase_{i,t} + \beta_3 red_{i,t-1} + \beta_4 neigh_{i,t-1} + \beta_\tau t + \epsilon_{i,t} \quad (9)$$

Table 2 shows results from estimating equations 8 and 9 via probit. The preference for playing the asset with the highest base value is strongly significant (and intriguingly, own decision at previous round is significant only in presence of local information), 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.*

In order to better characterize the decision process – and to study which conditions affect the decision to play the sunspot value – we then adopt a different approach, and look at the determinants of the decision to *follow* the sunspot value. That is, we create a new dependent variable encoding whether the sunspot signal was followed or not:

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

Table 2: Main determinants of playing RED

	(1)	(2)
rsuns	0.817***	0.807***
	(0.031)	(0.058)
rbase	0.189***	0.162***
	(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)
Observations	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.

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 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 (9) looking at the choice to play the sunspot rather than to play RED:

$$follow_{i,t} = \beta_0 + \beta_1 rsuns_t + \beta_2 sbase_{i,t} + \beta_3 follow_{i,t-1} + \beta_4 fneigh_{i,t-1} + \beta_\tau t + \epsilon_{i,t}, \tag{10}$$

where $fneigh_{i,t-1}$, in analogy with $neigh_{i,t-1}$, denotes whether the neighbor followed the sunspot in the previous period. We still include $rsuns_t$ among the regressors in order to control for any idiosyncratic preference for following the sunspot when RED (we have seen in Figure 5 that the two assets are not perceived in a perfectly symmetric way).

Table 3 provides results from different formulations nested in Equation (10). 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.

Table 3: 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: $follow_{i,t}$. Qualitatively similar results are obtained when controlling also for group-fixed effects. ***p< 0.01, **p< 0.05, *p< 0.10.

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 6), 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 analysis above provides a conclusion concerning [HYPOTHESIS 2]:

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

The propensity to follow also features strong persistence, as evidenced by the positive and significant coefficient for one's lagged action ($follow_{i,t-1}$) in columns (4) and (5). 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 5).

While there is no obvious explanation for this preference, the fact itself that the coefficient is occasionally significant supports the decision to control for it.

4.2 Comparison of treatments

In this section we compare the results across the 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:

$$\begin{aligned} follow_{i,t} = \beta_0 + &\beta_1 rsuns_t + \beta_2 sbase_{i,t} + \beta_3 follow_{i,t-1} \\ &+ \beta_{UNB} UNB + \beta_{AGG} AGG + \beta_{NOH} NOH \\ &+ \beta_4 info\_start_i + \beta_\tau t + \beta_{\tau 2} t^2 + \epsilon_{i,t} \end{aligned} \tag{11}$$

where $info\_start_i$ denotes whether in the alternating scheme subject i was among those who received information in the first phase. See Table 4 for the estimation results. Again, the coefficient on *rsuns* is positive and significant: all else equal, subjects follow the sunspot more often when it is red. 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 sunspot-specific information (treatment **NOH**) also decreases the propensity to follow the sunspot signal. As a result, every treatment dummy has a negative coefficient[7] – 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. Information about other players' actions provided via the network or aggregate information does not per se provide proof that they are 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.

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

Table 4: Cross-treatments comparison

	All	All (t^2)	Ph. 1	Ph. 2	Ph. 3	Ph. 4
	(1)	(2)	(3)	(4)	(5)	(6)
rsuns	0.010*	0.012**	0.026	0.009	0.004	0.013*
	(0.006)	(0.006)	(0.026)	(0.009)	(0.006)	(0.007)
sbase	0.098***	0.098***	0.234***	0.099***	0.046***	0.047***
	(0.010)	(0.010)	(0.021)	(0.010)	(0.008)	(0.009)
follow_1	0.288***	0.281***	0.240***	0.240***	0.348***	0.387***
	(0.019)	(0.019)	(0.033)	(0.025)	(0.032)	(0.051)
UNB	−0.057*	−0.057*	−0.104**	−0.058	−0.029	−0.049
	(0.034)	(0.034)	(0.051)	(0.042)	(0.025)	(0.030)
AGG	−0.054	−0.054	−0.186***	−0.063*	−0.018	−0.021
	(0.034)	(0.034)	(0.060)	(0.035)	(0.024)	(0.046)
NOH	−0.048	−0.048	0.098	−0.068	−0.055	−0.061
	(0.045)	(0.046)	(0.060)	(0.046)	(0.039)	(0.043)
info_start	−0.036	−0.036	−0.080**	−0.043*	−0.006	−0.035
	(0.024)	(0.024)	(0.033)	(0.025)	(0.015)	(0.023)
t	0.003***	0.007***	−0.006	−0.011	−0.015**	0.020
	(0.0003)	(0.001)	(0.008)	(0.009)	(0.007)	(0.013)
t^2		−0.00005***	0.0004	0.0002	0.0001*	−0.0001
		(0.00001)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Observations	9,480	9,480	2,280	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 10 in Appendix D for interaction effects. ***p< 0.01, **p< 0.05, *p< 0.10.

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**,

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 still not exposed to *any* local or aggregate information.

Columns 1 to 3 of Table 5 provide the results from estimating the following equation:

$$follow_{i,t} = \beta_0+\beta_2 sbase_{i,t}+\beta_3 follow_{i,t-1}+\gamma_U U_i+\gamma_A A_i+\gamma_N N_i+\beta_\tau t+\epsilon_{i,t}. \quad (12)$$

(analogous to Equation (10)) 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 groupmates 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 emerges 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 5 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. *Adding* generic *information is detrimental to the decision to follow the sunspot signal and, hence, to coordination.*

4.4 Effect of sunspot specific nudging

Figure 7 presents suggestive evidence of the influence that the end of phase has on participants' actions. The effect of ends of phases is clearly identified by the concentration of non-sunspot plays just before, followed by a sharp decrease. This phenomenon is driven by subjects who start following the sunspot from the first round of the following phase, and before that, 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 "semantics of the language of sunspots matters": that is, inducing a "common understanding of the meaning of the sunspot realization" can influence the propensity to follow the sunspot.

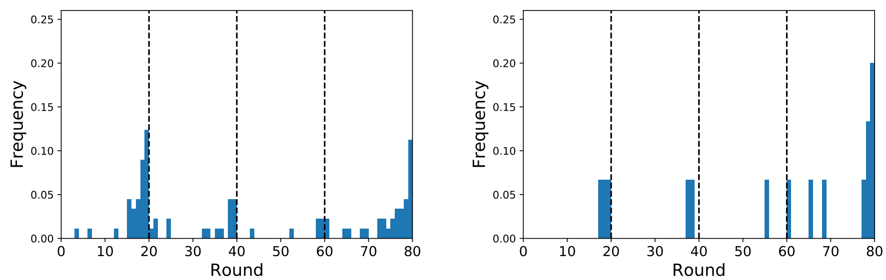
Recall that treatment **NOH** is perfectly comparable with treatment **BASE** except for the absence of two messages, on the screen at the end of each phase, reporting what (1) own gains and (2) average group gains, respectively, would

Table 5: 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	0.023	0.023	−0.006	-1.289^{***}	−0.246	-2.294^{***}
	(0.028)	(0.028)	(0.033)	(0.201)	(0.298)	(0.279)
sbase	0.231^{***}	0.231^{***}	0.232^{***}	0.747^{***}	0.821^{***}	0.631^{***}
	(0.020)	(0.020)	(0.021)	(0.058)	(0.085)	(0.079)
follow_1	0.254^{***}	0.254^{***}	0.282^{***}	0.055	0.084	0.072
	(0.033)	(0.033)	(0.037)	(0.197)	(0.283)	(0.271)
U)	-0.188^{***}	-0.188^{***}	-0.192^{***}	−0.499	−0.274	−0.626
	(0.063)	(0.063)	(0.073)	(0.372)	(0.533)	(0.508)
A)	-0.209^{***}	-0.209^{***}	-0.248^{***}	−0.554	−0.304	-1.012^{**}
	(0.080)	(0.080)	(0.079)	(0.373)	(0.539)	(0.509)
N)	−0.034	−0.034	−0.027	0.038	0.689^{*}	−0.498
	(0.062)	(0.062)	(0.065)	(0.247)	(0.353)	(0.338)
t	0.003	0.003	0.009^{*}	0.003	0.040	-0.218^{***}
	(0.002)	(0.002)	(0.005)	(0.017)	(0.056)	(0.046)
Observations	2,280	2,280	1,200	2,280	1,080	1,200
R^2				0.111	0.100	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.

Figure 7: 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).

have been, had everybody in the group followed the sunspot signal at every round of the phase:

$$hint_i^{(1)} = 5 \times 3 + \sum_{t=T+1}^{T+20} sbase_{i,t}$$

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

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 guide their actions. Indeed, no further information was available on other players' behavior, the average itself 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, while still including usual controls $rsuns_t$ and $sbase_{i,t}$:

Table 6: 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.

$$
\begin{aligned}
follow_{i,t} = \beta_0 + &\beta_1 rsuns_t + \beta_2 sbase_{i,t} \\
&+\beta_3 NOH_i + \beta_4 post_t + \beta_5 NOH_i \times post_t \\
&+\beta_6 info\_start_i + \epsilon_{i,t}
\end{aligned} \tag{13}
$$

Table 6 shows the estimation results for Equation 13. The positive and highly significant coefficient for *post* indicates that, as already observed in Figure 6 (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 ("post × NOH"). It proves that nudging has an important effect on the decision to follow the sunspot, and consequently on payoffs: it increases average payoffs by at least \$ 1.62.

In light of this, we can now better assert the importance of the hints:

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.

4.5 Network analysis

Next we examine more in depth the influence of the network structure on the actions of partipants. In order to do so, we focus on the **UNB** design, in which participants could be assigned to nodes in the network with more or fewer connections (corresponding respectively to A and C or B and D in Figure 3b). Specifically, we refer to nodes A and C, who have two incoming and two outgoing connections each, as *central* nodes, and to the two other nodes as *peripheral* nodes, borrowing from the social network literature (Hojman and Szeidl, 2008). Each central node has a central and a peripheral neighbor: each peripheral node only has a central neighbor.

In examining the **BASE** treatment, we included in Equation (10) a dummy variable for whether the neighbor played the sunspot in the previous period, and we had seen in Table 3, 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 a different behavior than peripheral nodes. Second, we can compare the importance attributed to central versus peripheral nodes.

We answer the first research question by just enriching Equation 10 with a dummy which is 1 if a node is central and 0 otherwise. The result is shown in column (1) of Table 7: the coefficient for *central* is positive but not significant.

As to the second question, in order 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 3b) and that coming from the other central node (e.g. A receiving information from C). The results are presented in Table 7 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 have a crucial role in pushing their group towards the adoption of the sunspot signal as a coordination device.

Table 7: Analysis of network position

	By network position	Restricted to central
	(1)	(2)
rsuns	0.027^{*}	-0.001
	(0.014)	(0.028)
sbase	0.132^{***}	0.075^{**}
	(0.036)	(0.032)
central	0.109	
	(0.080)	
follow_1		0.218^{**}
		(0.087)
fneigh^{P}_1		0.029
		(0.037)
fneigh^{C}_1		0.100^{**}
		(0.042)
t	0.010^{***}	0.005
	(0.002)	(0.003)
t^2	-0.0001^{***}	-0.00003
	(0.00001)	(0.00003)
info_start	-0.092	-0.029
	(0.101)	(0.070)
Observations	960	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.

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 – that is, 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 *asymmetric* and/or more than two assets, and their interaction with the network structure, are also important issues left to investigate.

References

Andreoni, J., N. Nikiforakis, and S. Siegenthaler (2017). Social change and the conformity trap. Technical report, Mimeo.

Arifovic, J., G. Evans, and O. Kostyshyna (2019). Are sunspots learnable? an experimental investigation in a simple macroeconomic model. *Journal of Economic Dynamics and Control*, 103775.

Arifovic, J. and J. H. Jiang (2019). Strategic uncertainty and the power of extrinsic signals– evidence from an experimental study of bank runs. *Journal of Economic Behavior & Organization*.

Azariadis, C. (1981). Self-fulfilling prophecies. *Journal of Economic theory 25*(3), 380–396.

Banks, J. S. and R. L. Calvert (1992). A battle-of-the-sexes game with incomplete information. *Games and Economic Behavior 4*(3), 347–372.

Battiston, P. and L. Stanca (2015). Boundedly rational opinion dynamics in social networks: Does indegree matter? *Journal of Economic Behavior & Organization 119*, 400–421.

Benhabib, J. and R. E. Farmer (1994). Indeterminacy and increasing returns. *Journal of Economic Theory 63*(1), 19–41.

Benhabib, J. and R. E. Farmer (1999). Indeterminacy and sunspots in macroeconomics. *Handbook of macroeconomics 1*, 387–448.

Carlsson, H. and E. Van Damme (1993). Global games and equilibrium selection. *Econometrica: Journal of the Econometric Society*, 989–1018.

Cass, D. and K. Shell (1983). Do sunspots matter? *Journal of political economy 91*(2), 193–227.

Cassar, A. (2007). Coordination and cooperation in local, random and small world networks: Experimental evidence. *Games and Economic Behavior 58*(2), 209–230.

Chwe, M. S.-Y. (2000). Communication and coordination in social networks. *The Review of Economic Studies 67*(1), 1–16.

Cooper, R., D. V. DeJong, R. Forsythe, and T. W. Ross (1992). Communication in coordination games. *The Quarterly Journal of Economics 107*(2), 739–771.

Corazzini, L., F. Pavesi, B. Petrovich, and L. Stanca (2012). Influential listeners: An experiment on persuasion bias in social networks. *European Economic Review 56*(6), 1276–1288.

Duffy, J. and E. O. Fisher (2005). Sunspots in the laboratory. *The American Economic Review 95*(3), 510–529.

Farmer, R. E. and J.-T. Guo (1994). Real business cycles and the animal spirits hypothesis. *Journal of Economic Theory 63*(1), 42–72.

Farrell, J. (1988). Communication, coordination and nash equilibrium. *Economics Letters 27*(3), 209–214.

Harrison, S. G. (2001). Indeterminacy in a model with sector-specific externalities. *Journal of Economic Dynamics and Control 25*(5), 747–764.

Heinemann, F., A. Llorente-Saguer, and D. Fehr (2012). The power of sunspots: An experimental analysis.

Hojman, D. A. and A. Szeidl (2008). Core and periphery in networks. *Journal of Economic Theory 139*(1), 295–309.

Jackson, M. O. (2010). *Social and economic networks.* Princeton university press.

Jackson, M. O. and L. Yariv (2011). Diffusion, strategic interaction, and social structure. In *Handbook of social Economics*, Volume 1, pp. 645–678. Elsevier.

Keser, C., I. Suleymanova, and C. Wey (2012). Technology adoption in markets with network effects: Theory and experimental evidence. *Information Economics and Policy 24*, 262–276.

Kydland, F. E. and E. C. Prescott (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society*, 1345–1370.

Marimon, R., S. E. Spear, and S. Sunder (1993). Expectationally driven market volatility: an experimental study. *Journal of Economic Theory 61*(1), 74–103.

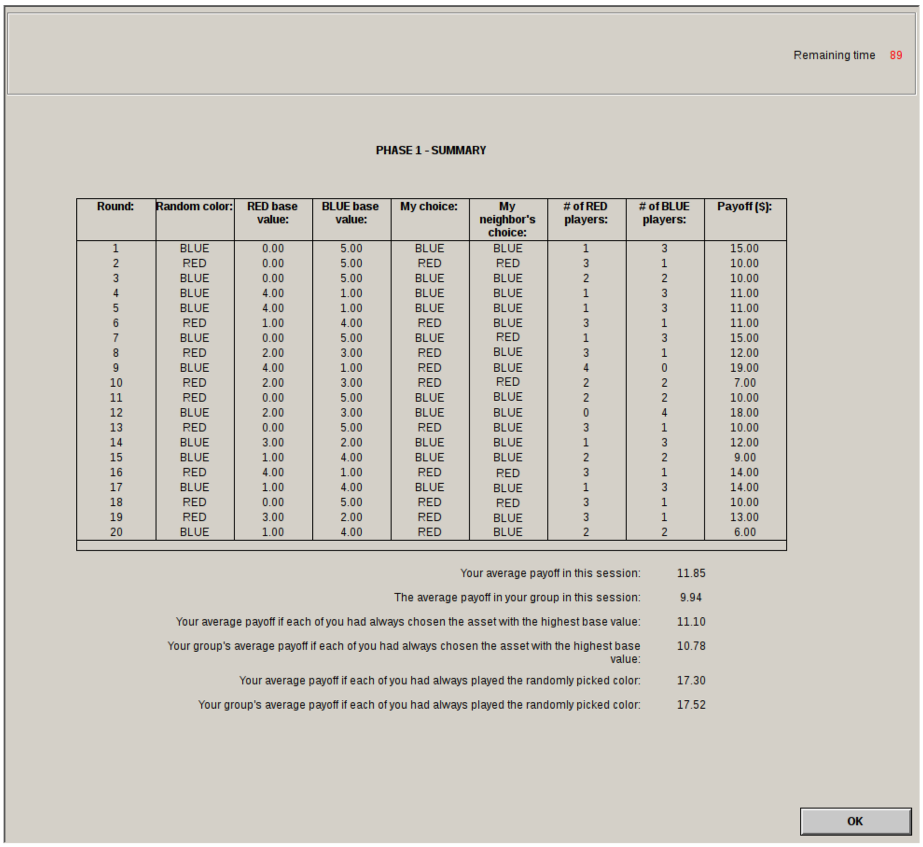
Morris, S. and H. S. Shin (2003). *Global Games: Theory and Applications*, Volume 1 of *Econometric Society Monographs*, pp. 56–114. Cambridge University Press.

Wen, Y. (1998). Capacity utilization under increasing returns to scale. *Journal of Economic theory 81*(1), 7–36.

A Additional material

A.1 Screenshots

Figure 8: End of phase 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

B Session design

Within each session, the phases with information and those without information were alternated, according to the scheme in Table 8

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 3a.

The decision to have sets of base values shared amoung pairs of groups – but vary across paris 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.

Table 8: 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

C Robustness tests

Table 9: 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 3). Dependent variable: $follow_{i,t}$. ***p< 0.01, **p< 0.05, *p< 0.10.

D Further results

Table 10: 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 4). 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.