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Limited farsightedness in network formation☆

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ABSTRACT

Pairwise stability (Jackson and Wolinsky, 1996) is the standard stability concept in network formation. It is a myopic notion in the sense that it only considers the immediate benefits of the players. A different perspective investigates perfect farsightedness, proposing related stability concepts. We design a simple network formation experiment to test these extreme theories, but find evidence against both of them: both myopically and farsightedly stable networks fail to emerge when they are not immune to limitedly farsighted deviations. The selection among multiple pairwise stable networks (and the performance of farsighted stability) crucially depends on the level of farsightedness needed to sustain them, and not on efficiency or cooperative considerations.

1. Introduction

The network structure of social interactions influences a variety of behaviors and economic outcomes, including the formation of opinions, decisions on which products to buy, investment in education, access to jobs, and informal borrowing and lending. A simple way to analyze the networks that one might expect to emerge in the long run is to examine the

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requirement that individuals do not benefit from altering the structure of the network. Any such requirement must answer the question of how individuals assess those benefits.

An extreme answer to this problem is to only look at myopic incentives, as in the notion of pairwise stability of Jackson and Wolinsky (1996). A network is pairwise stable if no individual benefits from severing a link and no two individuals benefit from adding a link between them, with at least one benefiting strictly. The notion is myopic, and not farsighted, in the sense that no future reaction to one's move is considered. Indeed, the adding or severing of one link might lead to subsequent addition or severing of another link, and so on. The von Neumann–Morgenstern pairwise farsightedly stable set (VNMFS) of networks (Herings et al., 2009) predicts the networks one might expect to emerge in the long run under farsightedness. In a VNMFS set there are no farsighted deviations among any two networks in the set, and there exists a farsighted deviation leading to the set from every network outside it. As the other approaches to farsighted stability,[1] it incorporates perfect farsightedness, in that sequences of reactions of any length are considered. As this constitutes the exact opposite of perfect myopia, there appears to be an unbridged gap between those extreme theories.[2]

The outcomes of real-life network formation are affected by the degree of farsightedness of the agents. Consider the cases where the worth of link creation turns nonnegative after some threshold in the connectedness of the network is reached, both for the individuals and on aggregate, but the individual benefits are negative below this threshold.[3] If network externalities take this form, myopic agents can be stuck in insufficiently dense networks. Farsightedness may take care of this problem and achieve efficiency. If agents have a limited degree of farsightedness their ability to pass the threshold will depend on its distance from the starting network.

In our paper we test the myopic and the (possibly limited) farsighted models of network formation, and compare the stability notions that are based on them. Network formation is hard to study in the field, as many potentially conflicting factors are at work. Consequently, we run lab experiments.

Stability concepts have their roots in cooperative game theory. They predict which network will emerge independently of the network formation process: but they are silent on how a network architecture is expected to emerge through the strategic decisions of the players. As such, myopia and farsightedness are not models of individual strategic behavior, because strategic behavior is cached in the stability approach. Acknowledging this we designed a network formation game where non-cooperative or behavioral approaches are silent, whereas stability notions provide clear predictions.

In the experiment, groups of four subjects had to form a network. More specifically, they were allowed to add or sever one link at a time: a link was chosen at random and the agents involved in the link had to decide if they wanted to form it (if it had not been formed yet) or to sever it (if it had been already formed). The process was repeated until all group members declared they did not want to modify the existing network, and the payoffs of the final networks were paid to subjects. In all treatments, payoffs were designed in such a way that a group consisting of myopic agents would never form any link. The treatments are characterized by slight manipulations of the payoffs, resulting in different VNMFS sets, featuring specific properties.

In treatment 1, the unique VNMFS network provides the players with equal payoffs, is strongly stable, in the sense that no coalition can improve upon it, and features no farsighted deviations. Thus, beyond being farsightedly stable, this network can be seen as attractive in many ways. In the other two treatments we vary those features to ascertain their contribution to the stability of an outcome. In both treatments 2 and 3 payoffs are unequal, with the disadvantaged players earning around half the payoffs of the others. We remove strong stability in treatment 2, as a coalition of three players can improve upon the networks in the VNMFS. In treatment 3 the networks in the VNMFS are strongly stable, but feature a farsighted deviation in two steps. We derive across-treatment hypotheses based on those properties.

In all treatments farsighted stability refines the set of pairwise stable networks (PWS) by selecting the (unique) Pareto dominant network within the set of PWS. Thus, we cannot test against PWS. Rather, we examine whether we can refine PWS using farsightedness.[4] However, the underlying notions – myopia and farsightedness – are at odds with each other, providing us with general within-treatment hypotheses.

On aggregate, 75% of the final networks are pairwise stable. In treatments 1 and 2 most of the groups (up to 70%) end in a VNMFS set, supporting farsighted network formation. In treatment 3, only one in five groups end in a VNMFS set, with half of the groups ending the game in the empty network. In this treatment, VNMFS sets are accessed almost as often as in the other treatments, but, after some time, most groups leave them. Given the properties of the VNMFS sets, this asymmetric result is inconsistent with strong stability (Jackson and van den Nouweland, 2005) – present in treatment 1 and 3, absent in treatment 2 – and cannot be attributed to the inequality in the payoffs – equal in treatment 1, unequal in treatments 2 and 3. Nor it can be explained by other refinements of pairwise stability, such as Nash stability, or Pareto dominance – both present in all treatments. It is, however, perfectly consistent with the hypothesis derived from limited farsightedness.

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[1] See the work of Chwe (1994), Herings et al. (2004, 2009), Mauleon and Vannetelbosch (2004), Page et al. (2005), and Page and Wooders (2009).

[2] Dutta et al. (2005) allows for different degrees of farsightedness in their equilibrium concept for a dynamic Markovian process of network formation. Farsightedness is captured by a discount factor on the stream of future payoffs, and is thus entangled with patience. Moreover, their dynamic equilibrium model is hardly comparable to the static stability notions which constitute the domain of our paper.

[3] Dutta et al. (2005) formally define this class of valuation structures that satisfy *increasing returns to link creation*.

[4] The experimental literature has generally found support for PWS networks, when they exist. It then looks reasonable to look for selection criteria within this set. Moreover, other definitions of farsightedness identify many farsightedly stable outcomes in our games, including some that are not PWS. The fact that those are virtually never played as final networks vindicates, *ex-post*, our approach.

We then analyze the relation between individual behavior and the length of available farsighted deviations. Subjects respond to myopic incentives as well as to farsighted improving paths of short length. As a consequence if a stable outcome features a farsighted deviation of limited length, the subjects are likely to follow it: they do not recognize the full chain of reactions that would guarantee stability under perfect farsightedness. Consequently, neither perfect myopia nor perfect farsightedness seem to be adequate models of network formation. A model of limited farsighted stability would be a valuable development.

Many context-specific factors may affect the degree of farsightedness in the field. In particular, real-life networks are generally larger than the one we implement. Perfect farsightedness becomes more demanding as the number of players grows, because it requires global knowledge of the network structures. The same does not hold for both myopia and limited farsightedness, because they both require only local knowledge of the network structures, independent of the dimension of the network. Thus, our design is likely to give perfect farsightedness its best chances to emerge, strengthening our case against it. On the other hand, while further investigation is needed to assess their robustness, there is no *ex-ante* reason why our results in favor of limited farsightedness should not hold in large field networks.

Relatively few experimental papers address pure network formation – i.e., a setting where no strategic interactions take place on the network once it has been formed. The majority of those investigate Bala and Goyal (2000)'s non-cooperative framework, with unilateral and simultaneous link formation (Callander and Plott, 2005; Goeree et al., 2009; Falk and Kosfeld, 2012). Despite the stark differences from our cooperative approach, one can still draw some parallels with their findings. For instance, the results in Callander and Plott (2005) are in line with ours in that stable network architectures emerge more often than not, and in excluding focalness and efficiency as guiding principles of network formation. On the other hand, their solution concept – strict Nash network – provides implausible predictions in the context of bilateral and sequential link formation [see Bloch and Jackson, 2006]. Also, simple decision rules as the Simple Strategic Behavior (Callander and Plott, 2005) or best response dynamics (Goeree et al., 2009) cannot be applied to our game. Closer to our design are the works of Ziegelmeyer and Pantz (2005) and Carrillo and Gaduh (2012). Their results support pairwise stability. In the former there is no tension between myopia and farsightedness.[5] In the latter, when multiple pairwise stable networks exist, subjects tend to coordinate on the high-payoff one. By finding a counterexample, we specify the conditions under which this result holds – that is, when the high-payoff network can be accessed, but not left, through limitedly farsighted deviations.

A number of experiments investigate myopic and forward-looking behavior, as well as other forms of limited reasoning, in contexts different from network formation. A large body of literature points at the relevance of limited steps of reasoning – e.g., level-*k* – in both static (Costa-Gomes et al., 2001), and dynamic (Ho and Su, 2013) games. Another is related to foresight in non-cooperative dynamic strategic interactions [e.g. Binmore et al., 2002; Johnson et al., 2002; Mantovani, 2014].[6] Limited farsightedness has much in common with the spirit of limited reasoning models. However, the latter explicitly model individuals' decision processes as best responses to beliefs.[7] Stability notions are silent on individuals' decision process, so that limited reasoning models can hardly be compared to limited farsightedness, nor they can be applied to our network formation game.[8]

The paper is organized as follows. In Section 2 we introduce the necessary notation and definitions. Section 3 presents the experimental design and procedures. Section 4 reports the experimental results. Section 5 concludes.

2. Networks: notation and definitions

Let $N=\{1, \ldots, n\}$ be the finite set of players who are connected in some network relationship. The network relationships are reciprocal and the network is thus modeled as a non-directed graph. Individuals are the nodes in the graph and links indicate bilateral relationships between individuals. Thus, a network g is simply a list of which pairs of individuals are linked to each other. We write $ij \in g$ to indicate that i and j are linked under the network g. Let g^N be the collection of all subsets of N with cardinality 2, so g^N is the complete network. The set of all possible networks or graphs on N is denoted by $\mathbb{G}$ and consists of all subsets of g^N. The network obtained by adding link ij to an existing network g is denoted $g+ij$ and the network that results from deleting link ij from an existing network g is denoted $g-ij$. We say that g' is adjacent to g if $g'=g+ij$ or $g'=g-ij$ for some ij. Let us denote with A_g the networks that are adjacent to g so that $A_g=\{g' \mid g'=g+ij \vee g'=g-ij$, for some $ij\}$, and let $\bar{A}_g$ be its complement.

The material payoffs associated to a network are represented by a function $x:\mathbb{G}\to\mathbb{R}^n$ where $x_i(g)$ represents the material payoff that player i obtains in network g. The overall benefit net of costs that a player enjoys from a network g is modeled by means of a utility function $u_i(g):\mathbb{R}^n\to\mathbb{R}$ that associates a value to the vector of material payoffs associated to network g. This might include all sorts of costs, benefits, and externalities.

[5] They observe relevant differences between the case in which the payoffs are considered as exogenously given, and the case in which players play a simultaneous game on the resulting network. This supports pure network formation as the cleanest setting to study network formation.

[6] Another set of papers deals with individual decision tasks [e.g. Cadsby and Frank, 1991; Gneezy and Potters, 1997], where myopia identifies a disproportional weight given, within a stream of payoffs, to the current-stage ones.

[7] For instance, a player's foresight regards his ability (i) to form expectations about future moves and (ii) to behave consistently with those.

[8] The limited forward-looking behavior addressed by Berninghaus et al. (2012) has also little in common with our conceptual framework. It regards the ability to forecast actions in a coordination game played on a network, when making the unilateral linking choices.

Let $N_i(g) = \{j \mid ij \in g\}$ be the set of nodes that i is linked to in network g. The *degree* of a node is the number of links that involve that node. Thus node i's degree in a network g, denoted $d_i(g)$, is $d_i(g) = \# N_i(g)$. Let $S_k(g)$ be the subset of nodes that have degree k in network g: $S_k(g) = \{i \in N \mid d_i(g) = k\}$ with $k \in \{0, 1, \ldots, n-1\}$. The *degree distribution* of a network g is a description of the relative frequencies of nodes that have different degrees. That is, $P(k)$ is the fraction of nodes that have degree k under a degree distribution P, i.e., $P(k) = (\#S_k(g))/n$. Given a degree distribution, $\bar{P}$, we define a *class of networks* as $C_{\bar{P}} = \{g \in \mathbb{G} \mid P(k) = \bar{P}(k), \forall k\}$. A class of networks is the subset of $\mathbb{G}$ with the same degree distribution.

Consider a network formation process under which mutual consent is needed to form a link and link deletion is unilateral. A network is pairwise stable if no player benefits from severing one of their links and no other two players benefit from adding a link between them, with one benefiting strictly and the other at least weakly. Formally, a network g is pairwise stable if

(i) for all $ij \in g$, $u_i(g) \geq u_i(g - ij)$ and $u_j(g) \geq u_j(g - ij)$, and
(ii) for all $ij \notin g$, if $u_i(g) < u_i(g + ij)$ then $u_j(g) > u_j(g + ij)$.

A network g' defeats g if either $g' = g - ij$ and $u_i(g') > u_i(g)$ or $u_j(g') > u_j(g)$, or if $g' = g + ij$ with $u_i(g') \geq u_i(g)$ and $u_j(g') \geq u_j(g)$ with at least one inequality holding strictly. Pairwise stability is equivalent to the statement of not being defeated by an adjacent network. Thus, PWS only considers myopic incentives.

Farsightedness captures the idea that agents will consider the chain of reactions that could follow when deviating from the current network, and evaluate the profitability of such deviation with reference to the final network of the chain of reactions. As a consequence, they will eventually choose against their myopic interest if they believe that the sequence of reactions that will follow could make them better off.

A *farsighted improving path* is a sequence of networks that can emerge when players form or sever links based on the improvement the end network offers relative to the current network. Each network in the sequence differs by one link from the previous one. If a link is added, then the two players involved must both prefer the end network to the current network, with at least one of the two strictly preferring the end network. If a link is deleted, then it must be that at least one of the two players involved in the link strictly prefers the end network. We now introduce the formal definition of a farsighted improving path.

Definition 1. A farsighted improving path from a network g to a network $g' \neq g$ is a finite sequence of graphs $g_1, \ldots, g_K$ with $g_1 = g$ and $g_K = g'$ such that for any $k \in \{1, \ldots, K-1\}$ either:

(i) $g_{k+1} = g_k - ij$ for some ij such that $u_i(g_K) > u_i(g_k)$ or $u_j(g_K) > u_j(g_k)$ or
(ii) $g_{k+1} = g_k + ij$ for some ij such that $u_i(g_K) > u_i(g_k)$ and $u_j(g_K) \geq u_j(g_k)$.

If there exists a farsighted improving path from g to g', then we write $g \to g'$. For a given network g, let $F(g) = \{g' \in \mathbb{G} \mid g \to g'\}$. This is the set of networks that can be reached by a farsighted improving path from g. The VNMFS set is obtained by introducing the notion of farsighted improving path into the standard definition of a von Neumann–Morgenstern stable set. In other words, we define a set of networks G to be VNMFS if there is no farsighted improving path connecting any two networks in G and if there exists a farsighted improving path from any network outside G leading to some network in G. Formally,

Definition 2. The set of networks G is a von Neumann–Morgenstern pairwise farsightedly stable set if

(i) $\forall g \in G$, $F(g) \cap G = \emptyset$ (*internal stability*) and
(ii) $\forall g' \in \mathbb{G} \setminus G$, $F(g') \cap G \neq \emptyset$ (*external stability*).

Although the existence of a VNMFS set is not guaranteed in general, when a VNMFS set exists it provides narrower predictions than other definitions of farsighted stability, a feature that is particularly welcome in experimental testing. For instance, a VNMFS set is always included within the pairwise farsightedly stable sets, as defined by Herings et al. (2009).[9] As it will be clear from our games, a network included in a VNMFS set may have farsighted deviations to some network outside the set. External stability guarantees, however, that a path from there leads back into the set; internal stability guarantees that the initial deviation is deterred, in the sense that the deviating agents are not better off once back into the set.

Another way to look at stability considers deviations by coalitions of players. We use the definition of strong stability by Jackson and van den Nouweland (2005), where a network is stable when any deviation by a coalition is blocked by some member of that coalition. That is, a network g is strongly stable if for any $S \subseteq N$, g' that is obtainable from g via deviations by S, and $i \in S$ such that $u_i(g') > u_i(g)$, there exists $j \in S$ such that $u_j(g') < u_j(g)$.

[9] A set of networks $G \subseteq \mathbb{G}$ is *pairwise farsightedly stable* if (i) all possible pairwise deviations from any network $g \in G$ to a network outside G are deterred by a credible threat of ending worse off or equally well off, (ii) there exists a farsighted improving path from any network outside the set leading to some network in the set, and (iii) there is no proper subset of G satisfying Conditions (i) and (ii).

Stability notions overlook the network formation process, and, thus, cache individual strategic behavior. Nevertheless, they build on the premise that players respond to the presence of myopic or farsighted deviations. We can evaluate the consistency of the players' actions with progressive levels of farsightedness. The following definition states that an action prescribing to form (break) a link that is not formed (has been formed) is consistent with farsightedness of level k, if building (breaking) the link lies on a farsighted improving path of length smaller or equal than k. An action prescribing not to form (keep) a link that is not formed (has been formed) is consistent with farsightedness of level k if forming (breaking) the link does not lie on a farsighted improving path of length smaller or equal than k. Let the length of a path be the number of steps in the sequence. Call $\mathcal{P}_g^k$ a generic farsighted improving path of length k, starting from network g, and $\{\mathcal{P}_g^k\}$ be the set containing all such paths. At stage t the link ij is selected, the action of agent i is $a_{it} \in \{0, 1\}$, where 0 means not to form (to break) the selected link ij, and 1 means to form (to keep) the link ij.

Definition 3. An action a_{it} is consistent with farsightedness of level k if either

(i) $ij \notin g_t$ and $((\exists l \leq k \text{ and a } \mathcal{P}_{g_t}^l \in \{\mathcal{P}_{g_t}^l\} \text{ s.t. } g_t + ij \in \mathcal{P}_{g_t}^l) \text{ and } a_{it} = 1) \vee ((\nexists l \leq k \text{ and a } \mathcal{P}_{g_t}^l \in \{\mathcal{P}_{g_t}^l\} \text{ s.t. } g_t + ij \in \mathcal{P}_{g_t}^l) \text{ and } a_{it} = 0)$, or

(ii) $ij \in g_t$ and $((\exists l \leq k \text{ and a } \mathcal{P}_{g_t}^l \in \{\mathcal{P}_{g_t}^l\} \text{ s.t. } g_t - ij \in \mathcal{P}_{g_t}^l) \text{ and } a_{it} = 0) \vee ((\nexists l \leq k \text{ and a } \mathcal{P}_{g_t}^l \in \{\mathcal{P}_{g_t}^l\} \text{ s.t. } g_t - ij \in \mathcal{P}_{g_t}^l) \text{ and } a_{it} = 1)$

As they are equivalent, we call myopic an action that is consistent with farsightedness of level one – i.e. one that looks at the profitability of adjacent networks.

3. Experimental design and procedures

3.1. The game

We consider a simple dynamic link formation game, almost identical to that proposed by Watts (2001). Stages are a countable infinite set: $T = 0, 1, \ldots, t, \ldots$; g_t denotes the network that exists at the end of stage t.[10] The process starts at $t = 0$ with $n = 4$ unconnected players (g_0 coincides with the empty network, $g^{\emptyset}$).[11] The players meet through stages and have the opportunity to form links with each other. Since $n = 4$, it follows that $\#g^N = 6$ and $\#\mathbb{G} = 64$.

At every stage $t > 0$, a link ij_t is randomly identified to be updated. At $t = 1$ each link from the set g^N is selected with uniform probability. At every $t > 1$, a link from the set $g^N \setminus ij_{t-1}$ is selected with uniform probability. Thus, a link cannot be selected twice in two consecutive stages. If $ij_t \in g_{t-1}$, then both i and j can decide unilaterally to sever the link; if $ij_t \notin g_{t-1}$, then i and j can form the link if they both agree. Once the individuals involved in the link have taken their decisions, g_{t-1} is updated accordingly, and g_t obtains. All group members are informed about both the decisions taken by the players involved in the selected link and the consequences on that link. They are informed through a graphical representation of the current network g_t and the associated payoffs.[12] After every stage all group members are asked whether they want to modify the current network or not. If they unanimously declare they do not want to, the game ends; otherwise, they move to the next stage.[13] To ensure that an end is reached, a random stopping rule is implemented after stage 25: at every $t \geq 26$ the game ends anyway with probability 0.2.

The design of the termination rule allows each individual to decide *unilaterally* to continue playing (at least for the first 25 stages). By providing the players with sufficient chances to explore the network space, this balances the choice of a fixed starting network. On the other hand, the individuals are not forced, *collectively*, to play any minimal number of stages: if they are satisfied, or they see they are unable to move, they can quit the game after any stage. This is meant to reduce the noise from players acting under different motives than those provided by the game (e.g. just because they are forced into it).

The game is repeated three times to allow for learning. Groups are kept the same throughout repetitions. Group members are identified through a capital letter (A, B, C or D). These identity letters are reassigned at every new repetition.

A vector of payoffs is associated to every network: it allocates a number of *points* to each player in the network. The subjects receive points depending only on the final network of each repetition. Thus, their total points are given by the sum of the points achieved in the final networks of the three repetitions. The subjects are informed about the payoffs associated to every possible network and know the whole structure of the game from the beginning.

3.2. Treatments and hypotheses

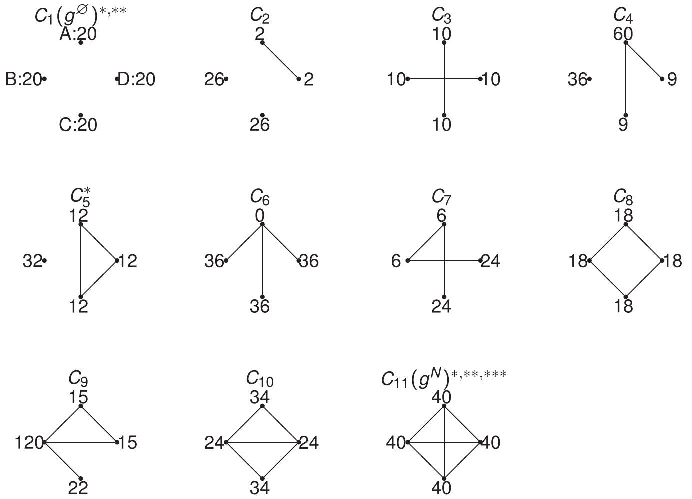
We run three treatments (T1, T2, T3) where we manipulate the payoffs in some networks to obtain VNMFS sets with different properties. Figs. 1–3 display the payoffs that were used in the three treatments for each class of networks, $C_{\bar{p}}$. Since

[10] By convention, the subscript t identifies the network or link that is active in stage t. Absent such subscript, the network or link is considered with no reference to a specific stage (i.e. abstracting from the link formation game).

[11] A fixed initial network allows for a cleaner design with respect to other feasible alternatives. With 64 possible initial networks, the starting network cannot be used as a treatment variable.

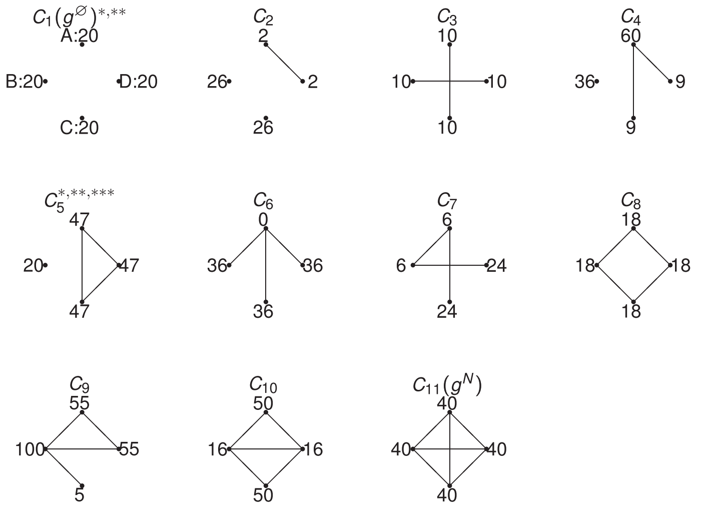
[12] Appendix C includes screenshots of the user's interface.

[13] Subjects are informed about the outcome of the *satisfaction* choices – i.e. end of the repetition or not – but not about individual choices.



* Pairwise Stable; ** Pairwise Nash Stable; *** Von Neumann-Morgenstern Farsightedly Stable.

Fig. 1. Payoffs for T1.



* Pairwise Stable; ** Pairwise Nash Stable; *** Von Neumann-Morgenstern Farsightedly Stable.

Fig. 2. Payoffs for T2.

Table 1
Summary of treatment properties and predictions.

	PWS	VNMFS	Myopic prediction	Farsighted prediction	Unequal payoffs	Strongly stable	Farsighted deviations
T1	$g^{\emptyset}$, C_5[a], g^N	$\{g^N\}$	$g^{\emptyset}$	g^N	No	g^N	–
T2	$g^{\emptyset}$, C_5	$\{g \mid g \in C_5\}$	$g^{\emptyset}$	C_5	Yes	–	Three steps[b]
T3	$g^{\emptyset}$, C_5[a], C_7	$\{g, g' \mid g, g' \in C_7$ and $d_i(g) = d_i(g'), \forall i \in N\}$	$g^{\emptyset}$	C_7	Yes	$g \in C_7$	Two steps

[a] Not nash stable.
[b] Weak deviation, based on indifference breaking rule.

the function of material payoffs satisfies anonymity,[14] this representation is sufficient to assign a payoff to each player in each possible network configuration. The numbers were chosen in order to provide the resulting predictions with a set of nice properties for each treatment that are described below and are summarized in Table 1. The payoffs are not meant to represent any real-life situation or a particular payoff function.

[14] Anonymity holds if payoffs in a network are assigned to each player independently of his or his partners' identity.

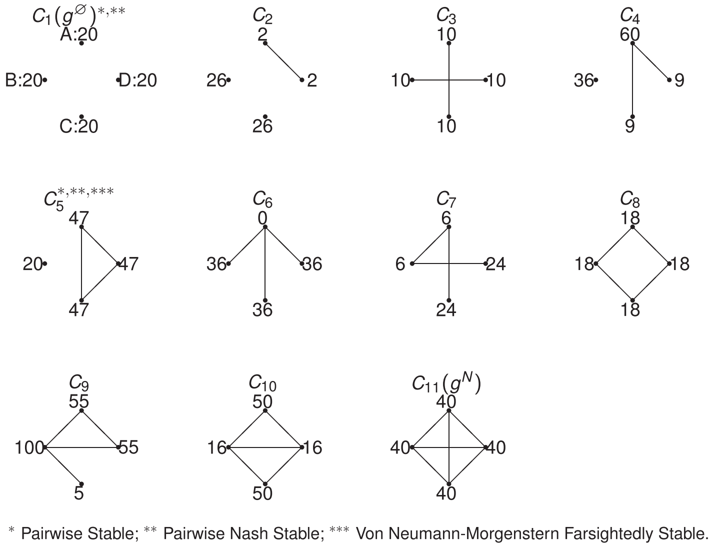


Fig. 3. Payoffs for T3.

The empty network, $g^{\emptyset}$, and the four networks in class C_5 are PWS in all treatments. These are the only PWS networks in T2, whereas g^N is also PWS under T1, and the networks in C_7 are also PWS in T3. Furthermore, in T1 and T3, in every network in C_5, the connected agents can improve their situation by cutting both of their links. These networks (contrary to the others PWS) are not Nash stable in the terminology of Bloch and Jackson (2006).[15]

In all treatments, groups start at $g^{\emptyset}$. Groups composed of myopic players are expected not to move from $g^{\emptyset}$. This prediction is robust to errors. A sequence of at least three (T1) or two (T2, T3) links added consecutively by error is needed in order to leave the basin of attraction of $g^{\emptyset}$. Indeed $g^{\emptyset}$ is the only stochastically stable network in all treatments.[16] To identify the VNMFS sets, we need to compute $F(g)$ for every g. We can prove the following results. The proofs can be found in Appendix A.

Proposition 1. *Consider a set of four self-regarding agents ($u_i(g) = x_i(g)$). Then,*

(i) *in T1 the set $G = \{g^N\}$ is the unique VNMFS set.*
(ii) *in T2 the set $G = \{g | g \in C_5\}$ is the unique VNMFS set.*
(iii) *in T3 a set G is a VNMFS set if and only if* $G = \{g \,|\, g \in C_7 \text{ and}, d_i(g) = d_i(g'), \forall i \in N, g' \in G\}$.

In T1 and T2 there is a unique VNMFS set: the complete network (i) and the set composed of the four networks in C_5 (ii), respectively. In T3 there are six VNMFS sets. Their union is C_7, i.e. it encompasses all line networks. Each set consists of a pair of line networks with identical degree distribution (iii).[17]

We expect a group composed by farsighted agents to end up in a network included in some VNMFS set. This prediction is robust to errors in the sense that the farsighted prediction does not depend on the starting point: from any other network, there is a farsighted improving path leading to a network in G. The payoffs guarantee that the predicted networks are essentially unique, in the sense that all the networks included in a VNMFS set are isomorphic.

Let $frac_{MYO}(T_i)$ and $frac_{FAR}(T_i)$ be the fraction of groups ending in the myopic and farsighted prediction, respectively, in treatment i. We state the following mutually exclusive hypotheses regarding perfect myopia and farsightedness.

Hypothesis 1. (Myopia) In all treatments, a relative majority of the groups end the game in $g^{\emptyset}$. This implies, in particular, that, for $i = 1, 2, 3$:

$$frac_{MYO}(T_i) > frac_{FAR}(T_i).$$

---

[15] Pairwise Nash stability is a refinement of both pairwise stability and Nash stability, where one requires that a network be immune to the formation of a new link by any two agents, and the deletion of any number of links by any individual agent. Nash stability implies the network can be sustained by Nash equilibrium strategies of a simultaneous linking game.

[16] When agents act myopically and make errors with some ϵ-probability, our linking game defines a Markov process. A network is stochastically stable if it is in the support of the limiting (for $\epsilon \to 0$) stationary distribution of this Markov process (Jackson and Watts, 2002).

[17] The pair of line networks in a VNMFS, are equal up to a single permutation of players with the same degree. For example, there are two networks in C_7 where A and B have 2 links each, call them g and g'. A and B are linked to one another in both networks, but A will be linked to C, and B to D, in g; vice versa in g'. The set $\{g, g'\}$ is a VNMFS.

Hypothesis 2. (Farsightedness) In all treatments, a relative majority of the groups end the game in a VNMFS set. This implies, in particular, that, for $i = 1, 2, 3$:

$$frac_{MYO}(T_i) < frac_{FAR}(T_i).$$

Because farsightedly stable networks are also PWS in our experiment, we cannot find direct experimental evidence against PWS, but rather against myopia as the guiding force behind network evolution and stability. On top of these within-treatment hypotheses, the different VNMFS sets differ on three important properties, providing us with testable across-treatment hypotheses (see Table 1).

First, the payoffs are equal in the VNMFS set in T1 (g^N) and unequal in T2 (C_5) and T3 (C_7). In the latter, the players gaining more obtain around twice as much as the least well off. Under both conditions, the disadvantaged players can lead the group to leave the VNMFS set, if they so wish, by severing a link in T3, by adding a link in T2.[18] If other-regarding preferences are sufficiently strong, the VNMFS sets could be less stable in T2 and in T3, with respect to T1. For instance, if players are inequity averse as in Fehr and Schmidt (1999) the VNMFS set would not be affected in T1, while it could be in T2 and T3.

Hypothesis 3. The fraction of groups ending the game in a VNMFS set is higher if the networks that are there included feature equal payoffs for the players. Thus:

(i) $frac_{FAR}(T_1) > frac_{FAR}(T_2)$, and
(ii) $frac_{FAR}(T_1) > frac_{FAR}(T_3)$.

Second, we also consider stability against changes in links by any coalition of individuals – i.e. look for strongly stable networks (immune to coalitional deviations). In T1 and T3 the networks included in VNMFS sets are also strongly stable. This is not true in T2, where strongly stable networks fail to exist.[19] In this view the VNMFS set are more robust in T1 and in T3 than in T2.

Hypothesis 4. The fraction of groups ending the game in a VNMFS set is higher if the networks that are there included are strongly stable. Thus:

(i) $frac_{FAR}(T_1) > frac_{FAR}(T_2)$, and
(ii) $frac_{FAR}(T_3) > frac_{FAR}(T_2)$.

Finally, the networks belonging to the VNMFS sets differ with respect to the presence and length of farsighted deviations leaving the set. Table 2 provides an overview and an example for each treatment. In T1, there are no farsighted improving paths leaving the complete network ($F(g^N) = \emptyset$).

In T2, $F(g \in C_5) = \{g' \mid g' \in C_9 \wedge g' \notin A_g\}$. This means that there are farsighted improving paths leaving the VNMFS set and leading to networks in C_9 that are not adjacent to the initial network g. The path is built as follows: from C_5 players move to C_9, then to C_{10} and finally back to another network in C_9. This path relies on the indifference-breaking convention stating that, in C_9, a player with two links is willing to build another one in order to (move to C_{10} and then) be exactly in the same situation in another network in C_9. Finally, $F(g \in C_9)$ includes, beyond the neighboring network in C_5 and the other networks in C_9, only the networks in C_4, reached with a four-step farsighted improving path. This implies that even groups that leave the VNMFS set for C_9 are somewhat stuck there. As such, this is a 'weak' deviation, that is unlikely to drive the subjects elsewhere from C_5 as a final outcome: the subjects are less likely to move, because the deviation is longer; in case they do, they are not likely to go beyond C_9, as moving from there implies either a move by an indifferent player or a very long and twisted deviation to C_4; finally, those that are stuck in C_9 are likely to move back to C_5. Thus, we do not expect this deviation to matter for the final outcomes.

In T3 there are two-step farsighted improving paths from any network in a VNMFS set to any network in another VNMFS set.[20] Namely, a player with two links cuts any of his existing links ($C_7 \to C_3$ or $C_7 \to C_4$). From there, another link is added leading back to C_7, but in a network where the initial deviator is better off (because he has only one link). After the first move away from C_7 is made, other deviations are feasible, driving the group away from the VNMFS set (and, most notably, toward $g^{\emptyset}$). Those differences bear little meaning in the context of perfect farsightedness. However, from the perspective of limited farsightedness, the VNMFS sets are more robust in T1 and in T2 than in T3.[21]

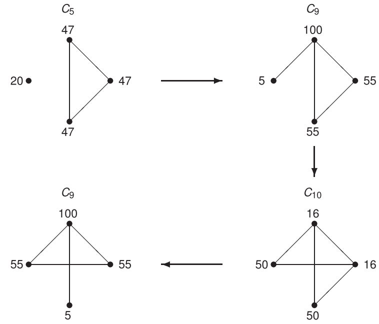
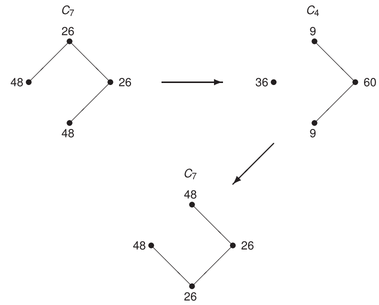
[18] Despite needing the agreement of his partner to add a link, adding a link in C_5 is highly beneficial to the already connected agents, so that they are likely to agree on that. The data confirm, *ex-post*, that the agent at disadvantage could add a link by unilateral decision, given the actual choices of the others (recall they observe these choices during the game).

[19] As shown by Jackson and van den Nouweland (2005) this is equivalent to an empty core in the derived cooperative game.

[20] There are other farsighted deviations, longer than four steps. See Appendix A for complete lists of farsighted improving paths.

[21] We focus on the comparison of VNMFS sets across treatments, and overlook two other potentially relevant aspects of limited farsightedness: the stability against farsighted deviations of other PWS networks, and the 'relative stability' of networks within a treatment. For instance, $g^{\emptyset}$ may seem 'more stable' in T1 than in T2 and T3. However, our experiment is not suited for studying these issues both because of design choices – e.g., $g^{\emptyset}$ is always the starting network – and because a proper theory of limitedly farsighted network formation, which would be needed to formulate clear hypotheses, is missing.

Table 2
Farsighted deviations from VNMFS sets.

	Origin	Destination	Length	Example
T1	g^N	–	–	–
T2	C_5	C_9	3	
T3	C_7	C_7	2	

Notes: The table identifies, for each treatment, the destination of the shortest farsighted improving path leaving the VNMFS set (Origin), and provides an example of such a path.

Hypothesis 5. The fraction of groups ending the game in a VNMFS set is higher if the networks that are there included are robust to short farsighted deviations. Thus:

(i) $frac_{FAR}(T_1) > frac_{FAR}(T_3)$, and
(ii) $frac_{FAR}(T_2) > frac_{FAR}(T_3)$.[22]

An ideal environment for testing each of these hypotheses would have the VNMFS sets identical except for the element that is under scrutiny. However, for an experiment to have something to say about network formation it must include a sufficient degree of complexity, and it appears that the ideal testing benchmark cannot be achieved in a design that satisfies this property. For instance, whether a network is or is not strongly stable also implies changes to the structure of farsighted improving paths and to the distribution of payoffs of some networks.

The design tries to strike a balance in this tradeoff between internal and external validity. For instance, while we keep the network formation environment credible, we opted for arbitrary payoffs, rather than specify a payoff function, to avoid potential confounds on treatment effects – e.g., that results are driven by simple decision rules that subjects can extract from real-life experiences or from the characteristics of the payoff function (e.g. link monotonicity etc.). While our results lend themselves to be qualified by future research, this partially explorative design allows us to draw a rich picture of the emergence and characteristics of stable networks.

3.3. Experimental procedures

The experiment took place at the EELAB of the University of Milan-Bicocca in June 2010 (T1) and April/May 2012 (T2, T3). The computerized program was developed using *Z*-tree (Fischbacher, 2007). We run 16 sessions for a total of 288 participants and 72 groups. Those corresponds to 36 independent observations for T1, and 18 independent observations for T2 and T3. Table 3 summarizes sessions' details. Participants were undergraduate students from various disciplines,[23] recruited through an announcement on the EELAB website. No subject participated in more than one session.

[22] An alternative, as expressed for instance by one anonymous referee, is to construct the hypothesis as a complete ordering, comparing the robustness of the VNMFS sets in T1 versus T2 based on the potential relevance of the farsighted deviations in T2. We note that the empirical strategy we adopt does not depend on the choice between our formulation of the hypothesis and this alternative.

[23] Sociology, economics, business, psychology, statistics, computer science, law, biology, medicine, mathematics, pedagogy and engineering.

Table 3
Sessions.

	Date	Participants	Groups (Ind. Obs.)	Treatment
1	Jun 2010	24	6	T1
2	Jun 2010	24	6	T1
3	Jun 2010	24	6	T1
4	Jun 2010	24	6	T1
5	Jun 2010	24	6	T1
6	Jun 2010	24	6	T1
7	Apr 2012	16	4	T2
8	Apr 2012	16	4	T2
9	Apr 2012	16	4	T2
10	May 2012	16	4	T3
11	May 2012	16	4	T3
12	May 2012	16	4	T3
13	May 2012	16	4	T3
14	May 2012	16	4	T2
15	May 2012	8	2	T2
16	May 2012	8	2	T3

Notes: Sessions 15 and 16 were run at the same time.

Subjects were randomly assigned to individual terminals and were not allowed to communicate during the experiment. Instructions were read aloud (see Appendix B for an English translation of the instructions). To ensure everybody had understood the game, participants were asked to fill in a control questionnaire. The experiment started only when all the subjects had correctly completed the task. After that, subjects were allowed to familiarize for three minutes with the network space. They could build and break links at their will through a dedicated interface and observe the corresponding payoff consequences. Before the real game started they also went through three trial stages to get used to the decision environment and the user's interface.

At the end of the experiment the points earned were converted into Euro at the exchange rate of 1 Euro = 6 points. Sessions took on average 90 minutes, including instructions, control test and final questionnaire phases. Average payment was 16.10 Euro (no show up fee was paid) with a minimum of 4.70 and a maximum of 32.40 Euro.

4. Results

We start by considering groups' final networks. Fig. 4 classifies groups with respect to their final network. Fig. 5 provides the same information for each repetition. In every treatment, around three in four groups end in a PWS network. This percentage increases consistently across repetitions within each single treatment, except between the second and third repetition of T3.

The distribution within PWS networks shows different patterns across treatments. In T1 and T2 the fraction of groups ending up in the VNMFS set is consistently higher than that ending up in $g^{\emptyset}$. This difference increases across repetitions with the farsighted and the myopic outcome accounting for around 70 and below 20% of the final networks, respectively, in the last repetition.

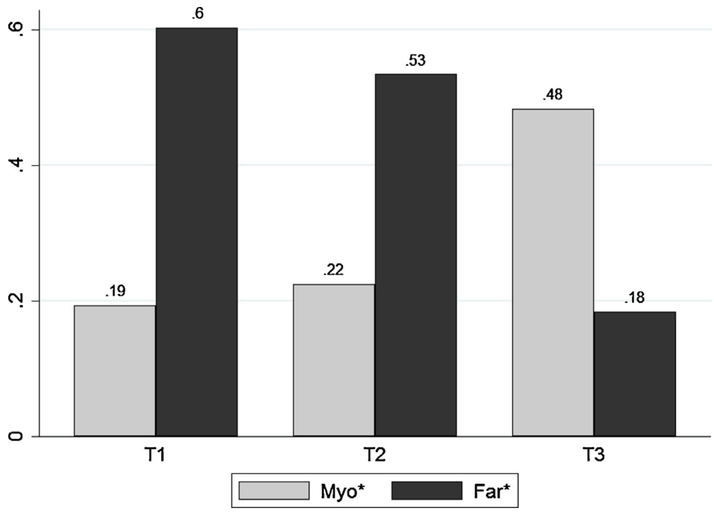


Fig. 4. Group final network, by type of outcome.

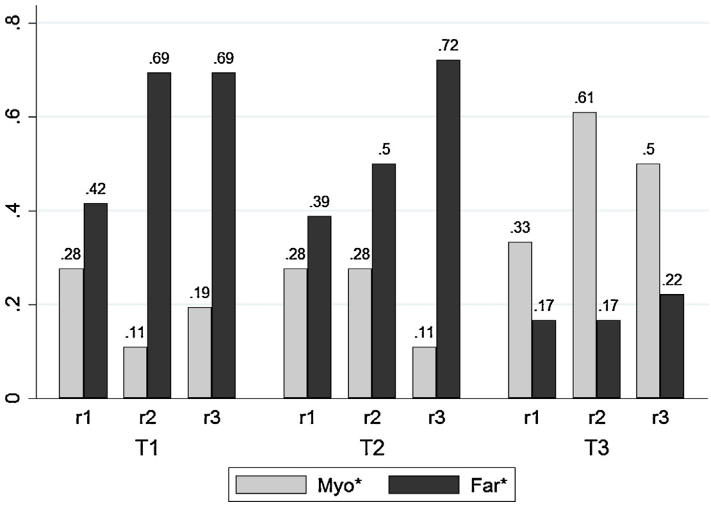


Fig. 5. Group final network, by type of outcome and repetition.

Table 4
Across-treatment tests.

	Chi-squared test							
	Whole sample				Randomly stopped excluded			
	Overall	T1 vs. T2	T1 vs. T3	T2 vs. T3	Overall	T1 vs. T2	T1 vs. T3	T2 vs. T3
Rep. 1	3.49 (.17)	0.04 (.84)	3.37 (.06)	2.21 (.13)	5.14 (.07)	0.84 (.36)	**5.02** **(.02)**	1.94 (.16)
Rep. 2	**13.39** **(.00)**	1.94 (.16)	**13.39** **(.00)**	**4.50** **(.03)**	**20.63** **(.00)**	1.75 (.19)	**20.66** **(.00)**	**8.57** **(.00)**
Rep. 3	**12.91** **(.00)**	0.04 (.83)	**10.76** **(.00)**	**9.02** **(.00)**	**17.19** **(.00)**	1.39 (.24)	**13.29** **(.00)**	**10.50** **(.00)**
All Rep.	**25.92** **(.00)**	0.62 (.43)	**25.13** **(.00)**	**14.48** **(.00)**	**36.41** **(.00)**	1.77 (.18)	**38.27** **(.00)**	**16.62** **(.00)**

Notes: This table reports the Pearson's Chi-squared statistic and its associated *P*-value (in parentheses). The test is performed on the fraction of farsighted outcomes in each treatment. Bold means significant at the.05 level. A battery of alternative tests are reported in Table 8.

This pattern is almost reversed in T3. The final network is $g^{\emptyset}$ for half of the groups, with this percentage peaking at 60% in the second repetition. About 20% of the groups end in a VNMFS set in all repetitions.

We use the Pearson's Chi-square and the Likelihood Ratio test to determine whether the relative frequencies of the myopic and the farsighted outcome differ or not within treatments and conclude that those differences are statistically significant at the.05 level in each single treatment.[24] Running the tests for each single repetition leads to significant differences in repetitions two and three of T1 and repetition three of T2.[25] Given that those differences go in opposite direction in T3 with respect to T1 and T2 those results imply a rejection of both Hypotheses 1 and 2.

Result 1. The networks predicted by myopia and farsightedness (see Table 1) account, on aggregate, for 75% of our groups' final outcomes. The VNMFS sets account for most of those observations in T1 and T2, but not in T3. The reverse holds for the myopic prediction, which shows some success only in T3. Thus, both perfect myopia (1) and farsightedness (2) fail to rationalize our results.

To test for the across-treatment hypotheses we employ a two-sample Chi-squared test on the dummy farsighted/not farsighted final network. Results are shown in Table 4. The overall test confirms that there are significant differences across treatments. In pairwise comparisons, we find that the overall fraction of farsighted outcomes in T1 and T2 are significantly different from that in T3. There is no significant difference when comparing T1 and T2. The same results hold when

[24] We run the tests on the distributions of outcomes (i.e. myopic, farsighted, other), for network classes and for single networks. We run them against different assumptions on the frequencies that are not being tested under the null hypothesis (H_0: equality of frequencies of myopic and farsighted outcomes): uniform distribution, uniform given the actual cumulative frequency of myopic and farsighted, actual frequencies. The results are identical across all specifications.

[25] Repetition two of T2 is significant at the 0.1 level. Recall we collected fewer observations for T2 and T3 than for T1.

Table 5
Group flows by treatment and repetition.

		T1 Rep. 2			T2 Rep. 2			T3 Rep. 2		
		Myopic	Farsighted	Other	Myopic	Farsighted	Other	Myopic	Farsighted	Other
Rep. 1	Myopic	0.20	0.50	0.30	0.60	0.20	0.20	0.67	0.17	0.17
	Farsighted	0.07	0.93	0.00	0.00	0.86	0.14	0.33	0.33	0.33
	Other	0.18	0.55	0.27	0.33	0.33	0.33	0.67	0.11	0.22
		T1 Rep. 3			T2 Rep. 3			T3 Rep. 3		
		Myopic	Farsighted	Other	Myopic	Farsighted	Other	Myopic	Farsighted	Other
Rep. 2	Myopic	0.60	0.00	0.40	0.20	0.40	0.40	0.64	0.09	0.27
	Farsighted	0.00	0.92	0.08	0.11	0.78	0.11	0.00	0.33	0.67
	Other	0.67	0.34	0.00	0.00	1.00	0.00	0.50	0.50	0.00

Notes: Each cell represents, of the groups that ended up in the row prediction in the row repetition, the fraction ending up in the column prediction in the column repetition (i.e. the row-wise sum of each triad equals one). The absolute numbers – the denominators of these fractions – are (Myopic, Farsighted, Other): T1, Rep. 1: 10, 15, 11; T1, Rep. 2: 4, 25, 7; T2, Rep. 1: 5, 7, 6; T2, Rep. 2: 5, 9, 4; T3, Rep. 1: 6, 3, 9; T3, Rep. 2: 11, 3, 4.

considering repetitions 2 and 3 in isolation.[26] Table 4 also reports the tests on the subset of groups that ended the game by deliberation. We detect the same significant differences that we found on the whole sample.[27]

This leads us to reject both Hypotheses 3 and 4, as we do not find the inequality of the payoffs nor strong stability to affect systematically the stability of the VNMFS sets. The results are, instead, well organized by limited farsightedness, and Hypothesis 5 cannot be rejected.

Result 2. The different performance of the VNMFS sets in T3, compared to T1 and T2, cannot be explained by payoff inequality or coalitional stability, leading to a rejection of both Hypotheses 3 and 4. Results are, instead, consistent with limited farsightedness (Hypothesis 5).[28]

Between one-fifth and one-third of the groups end neither in the myopic nor in the farsighted prediction; we generally refer to this category as "other". Remarkably, a vast majority of those, between 72 and 77%, end the game in networks that are direct neighbors of either of the two. The specific figures are as follows: in T1, 11 and 5 out of 22 groups end at one step from the empty and the complete network, respectively; in T2, 8 out 13 result in C_9; in T3, 7 out of 18 are in C_2, 6 are in C_4.

Table 5 reports the change in the outcome of individual groups from repetitions 1 to 2 and from repetitions 2 to 3, for all treatments. For example, the row "Farsighted" from the upper-left panel (T1, Rep. 1–Rep. 2) shows that in T1, among those groups who end in the complete network in repetition 1, only 7% switch to the empty network in repetition 2, whereas 93% of the groups also end in the complete network in repetition 2. Among those groups who end up in the empty network in repetition 1 (row "Myopic"), only 20% also end there in repetition 2, whereas 50% switch to the complete network, and 30% to an unstable network. Similarly, among the groups who end up in some other network in repetition 1 (row "Other"), 55% of them switch to the complete network in repetition 2, only 18% to the empty network.

Table 5 shows that groups that end in a VNMFS set in a previous repetition are able to replicate the result in T1 and T2: the Farsighted–Farsighted cell displays a fraction close or above 80% in the corresponding panels. The other categories display greater mobility across repetitions. Some of them end in a VNMFS set, others fluctuate among the empty network and the Other category. Again, a striking difference appears comparing those results with the right-hand side panels, corresponding to T3. Around two-thirds of the groups that end in the empty network in one repetition, replicate this outcome in the subsequent one. This is the only outcome showing some persistence; the farsighted outcome, in particular is much less stable across repetitions.

Moving beyond the analysis of the final outcomes, Table 6 displays, for each class of networks, a set of descriptive statistics regarding the groups' decision throughout the game. The first three columns give us for each treatment the number of times groups leave and access each class of networks, together with their ratio. It is not surprising, from the previous analysis, that most networks are always left. More interesting is that even the networks that account for a significant fraction of the final outcomes, with the exception of the complete network in T1, are often left once accessed. This happens 47% of the time (or 26 out of 55 times) for C_5 in T2, and 71 (66/91) and 76% (32/42) for C_1 and C_7, respectively, in T3. The columns labeled "Destinations" in Table 6 report the major receivers of the outflows from each class of network, and their share of those outflows. We are particularly interested in the results for C_7 in T3. It turns out that two-thirds of the groups that leave a

[26] We report a battery of alternative test in Appendix D. All of the results hold.
[27] Figures on final networks of these groups can be found in Appendix D.
[28] We cannot reject that the VNMFS set perform equally well in T1 and T2. The message for a theory of limited farsightedness seems to be that the simple presence and length of farsighted deviations are not sufficient metrics to assess stability under limited farsightedness (cf. Footnote 22). While this result supports the argument that the deviations in T2 should not be expected to matter for the long-run outcome of the process, it does not imply that they do not matter for play along the process, as documented in the following pages.

Table 6
Descriptive statistics, by treatment and class of networks.

	Outflow, inflow (ratio)			Destinations (share)			Average stay		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
C_1	115, 136 (.85)	60, 72 (.83)	65, 91 (.71)	C_2 (100%)	C_2 (100%)	C_2 (100%)	2.28	3.00	3.67
C_2	135, 146 (.92)	75, 77 (.97)	96, 103 (.93)	C_1 (21%), C_3 (12%), C_4 (67%)	C_1 (24%), C_3 (7%), C_4 (69%)	C_1 (39%), C_3 (10%), C_4 (51%)	2.60	2.90	3.24
C_3	18, 18 (1)	10, 10 (1)	21, 21 (1)	C_2 (18%), C_7 (82%)	C_2 (20%), C_7 (80%)	C_2 (76%), C_7 (24%)	1.61	1.10	1.43
C_4	129, 135 (.96)	66, 66 (1)	70, 76 (.92)	C_2 (26%), C_5 (30%), C_7 (24%)	C_2 (23%), C_5 (43%), C_7 (26%)	C_2 (31%), C_5 (30%), C_7 (33%)	2.12	1.99	1.84
C_5	46, 47 (.98)	26, 55 (.47)	24, 25 (.96)	C_4 (50%), C_9 (50%)	C_4 (8%), C_9 (92%)	C_4 (58%), C_9 (42%)	4.49	4.42	3.44
C_6	35, 35 (1)	8, 8 (1)	10, 10 (1)	C_4 (43%), C_9 (57%)	C_4 (37%), C_9 (62%)	C_4 (90%), C_9 (10%)	2.89	1.00	3.00
C_7	49, 50 (.98)	34, 36 (.94)	32, 42 (.76)	C_4 (10%), C_8 (22%), C_9 (61%)	C_3 (15%), C_4 (26%), C_9 (50%)	C_3 (41%), C_4 (25%), C_9 (31%)	1.54	1.28	5.05
C_8	16, 16 (1)	11, 11 (1)	13, 13 (1)	C_7 (19%), C_{10} (81%)	C_7 (82%), C_{10} (18%)	C_7 (69%), C_{10} (31%)	2.87	1.54	1.38
C_9	96, 96 (1)	51, 59 (.86)	31, 31 (1)	C_5 (12%), C_6 (12%), C_{10} (67%)	C_5 (53%), C_{10} (39%)	C_6 (19%), C_7 (16%), C_{10} (51%)	1.94	4.03	1.32
C_{10}	72, 77 (.93)	24, 24 (1)	19, 21 (.90)	C_9 (9%), C_{11} (90%)	C_8 (33%), C_9 (54%), C_{11} (12%)	C_8 (47%), C_9 (37%), C_{11} (17%)	4.06	2.96	3.05
C_{11}	0, 65 (0)	2, 3 (.66)	2, 3 (.66)	–	C_{10} (100%)	C_{10} (100%)	1.52	1.67	1.00

Notes: This table present a number of descriptive statistics for each class of networks. Outflow: number of groups that left the class; inflow: number of groups that entered the class; ratio: out/in; destinations: adjacent network class and corresponding share of the total outflows (in parentheses); average stay: average number of consecutive stages in the network class.

VNMFS set in T3 do so consistently with the short farsighted deviation described above (13/32 to C_3 and 8/32 to C_4). Note also that of the groups that leave the VNMFS set in T2 (C_5), more than 90% do so consistently with a farsighted deviation (24/26 to C_9).

The last three columns display the average number of consecutive stages the groups stayed in a network, which we consider as another marker of the absorbing power of a network. In T1, when groups access the complete network, they immediately decide to end the game. In T2 and T3 the players cannot decide to stop the game when they access a VNMFS set. Nevertheless they spend more consecutive stages there than in any other class. In T2 this results in a high percentage of groups ending the game in C_5. In T3 the players leave C_7 more often before the end of the game, despite staying there for more than five stages, on average.[29] Consistently, on average a game lasts longer in T3 (22.93 stages), followed by T2 (21.5) and T1 (17.73), and more games are ended by the random stopping rule in T2 and T3 (40 and 45%) with respect to T1 (19%).

Related to this, the behavior of disadvantaged players in C_5 in T2 is telling. When asked whether they would like to change the current network, 80% (202/242) declare they would. However, when given the opportunity to, 75% (82/110) refuse to form a new link.[30] One possible interpretation is that agents act out of frustration for the absence of a feasible way out that makes them better off, punishing the other group members by forcing new useless rounds. This shows that, while social preferences cannot account for the final outcomes, they might still play a role in the network formation process.[31]

All the results presented are in line with Hypothesis 5. Furthermore, they cannot be reconciled using traditional theoretical arguments. In T3, the VNMFS sets are Pareto efficient, Pareto dominant among the PWS networks and strongly stable (a condition not met in T2). Our interpretation is that the VNMFS sets are less robust to limitedly farsighted deviations in T3. An alternative interpretation would be that the multiplicity of networks that are in a VNMFS set generate coordination problems among the players. This problem is not present in T1 and has an obvious solution in T2, given the sequential nature of the game.[32] In T3, agents with two links are worse off than the agents with one link in network class C_7. Hence, agents have a strategic incentive to build only one link, and let the others build two. However, this interpretation is refuted by our

[29] C_5 features relatively high numbers in T1 and T3; those networks feature relatively low payoffs and are not Nash stable (the connected players can be better off by cutting two of their existing links). However they are PWS. C_9 shows a high number in T2. Those networks are often accessed when an unsatisfied player in a VNMFS set takes a non-myopic move. As expected, this deviation is generally unsuccessful, in the sense that the group is stuck in C_9 until a backward move is taken by the same player.

[30] In this situation their partners have a myopic incentive to form the new link even if they are in a VNMFS set. Perfect farsightedness would suggest they should not be willing to form this link (because of internal stability). Nevertheless 80 in 110 times they choose to form it. Similarly, at C_7 in T3, the subjects with two links are most often willing to form a third one.

[31] Since the payoff consequences of single decisions are not obvious, our game does not allow for a thorough analysis of players' motivations along the game.

[32] As the connected agents in a VNMFS set are better off, the first agents that are proposed a link on a path to C_5 should build them. In this sense, sequential link creation can substitute *ex-ante* heterogeneity as a way to sustain asymmetric outcomes [cf. Goeree et al., 2009].

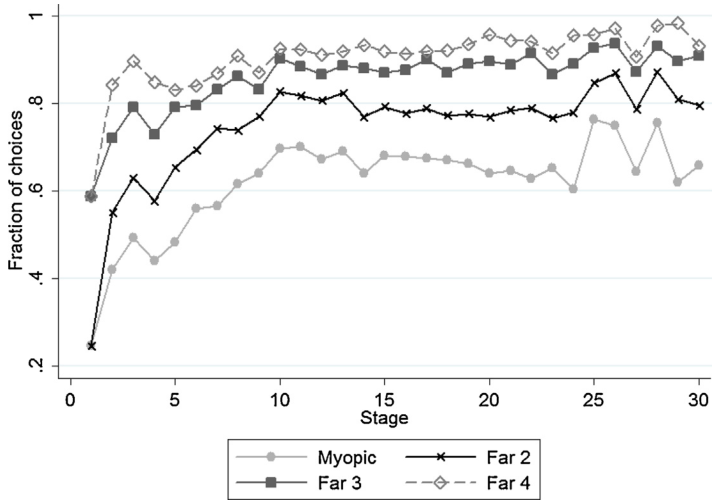


Fig. 6. Fraction of choices consistent with each level of farsightedness.

data. According to it, we would observe the agents having problems accessing C_7, and not moving away once they are there. We observe almost the opposite. As shown in Table 6, in T3 groups end the game in C_7 only in 10 out of the 42 times they access it. The same ratio (for C_5) is 29 out of 55 in T2. Thus, in T3 the groups have more problems staying in C_7 than accessing it.

We have already stressed that a proper model of individual strategic behavior does not descend from the stability notions we investigate. That is, one cannot interpret perfect or limited farsightedness as decision rules. With this caveat in mind, we can nevertheless use them *as if* they were decision rules, in order to assess the extent to which individuals respond to the presence of myopic and farsighted deviations. We build the vectors of choices of virtual players endowed with different levels of limited farsightedness, including myopia. Those are vectors of dummies, $f^{ij}_{i_k g_t}$, for $k = 1, 2, \ldots$ containing the actions of an individual i, with level of farsightedness k, choosing with respect to link ij in network g_t.

According to Definition 3, an action is consistent with farsightedness of level k if it lies on a farsighted improving path of length (weakly) shorter than k; $k = 1$ is identical to myopia. To lie on a farsighted improving path, an action must imply moving from the current network. In Fig. 6 we represent the fraction of choices that imply moving from the current network that are consistent with myopia and progressive levels of limited farsightedness over stages. Myopia explains approximately 60% of these choices in the central part of the game, a lower fraction in the first stages and a somewhat higher one in the last.[33] Including farsightedness of level two increases the fraction of consistent choices by about 15 percentage points. Another 10% is added by farsightedness of level three, whilst higher level of farsightedness result in improvements that are only marginal. This picture suggests, once more, that myopic incentives are a main guide for decision making in our framework; however agents often depart from those, following (short) farsighted deviations, with relevant consequences on the final outcomes.

Categorizing choices that imply inaction – i.e. staying in the current network – is more problematic. We classify them according to Definition 3: these actions are consistent with farsightedness of level k if moving would not be farsighted of level k, which equals assuming that a farsighted agent should always take any farsighted improving path. While the definition imposes a strong restriction on farsighted behavior,[34] it will provide conservative estimates on the relation between the actual choices, $a^{ij}_{ig_t}$, and the ideal benchmarks, $f^{ij}_{i_k g_t}$. We perform a regression analysis to explore this relation.[35] This exercise suffers from many statistical limitations. In particular, the number of choices each agent takes is endogenous, as groups can decide when to stop a game. We apply a two-step Heckman selection model (Heckman, 1979) to address this issue.

We estimate a (panel) linear probability model (LPM) with random effects, where the actions $a^{ij}_{ig_t}$ are regressed, conditional on being observed, over the benchmark choices, $F^{ij}_{ig_t} = \{f^{ij}_{i_k g_t}\}_{k=1}^{4}$, and a set of controls, $X^{ij}_{ig_t}$, including characteristics of the

[33] As the expected number of expected stages falls, lengthy paths are riskier, and myopic moves more appealing.

[34] For instance, a player that recognizes an improving path of some length may nevertheless choose not to take it, because he does not believe the other players to see that far, or he does not expect the appropriate links to be selected by the random link selection process, or simply thinks that taking a different path would be better.

[35] We include regressors up to a level of farsightedness of four. Adding further levels leaves all the main coefficients unaffected, but generates problems of collinearity. The estimates are available from the authors.

Table 7
LPM estimates of Eq. (1).

	(1)	(2)	(3)	(4)
T2	−.020	−.124***	.174***	.074*
	(.028)	(.031)	(.044)	(.039)
T3	−.093**	−.201***	.059	−.037
	(.037)	(.046)	(.052)	(.054)
Myopic	.152***	.146***	.292***	.283***
	(.024)	(.025)	(.027)	(.027)
Farsighted 2	.041**	.037**	−.050*	−.038
	(.019)	(.019)	(.033)	(.025)
Farsighted 3	.032	.042*	.108***	.105***
	(.025)	(.025)	(.039)	(.039)
Farsighted 4	−.051**	−.063***	−.023	−.037
	(.020)	(.019)	(.024)	(.024)
T2*Myopic			−.270***	−.261***
			(.039)	(.040)
T2*Fars2			.142***	.128***
			(.039)	(.040)
T2*Fars3			−.128**	−.105*
			(.052)	(.054)
T2*Fars4			−.114**	−.108**
			(.046)	(.046)
T3*Myopic			−.224***	−.219***
			(.040)	(.041)
T3*Fars2			.126***	.100**
			(.043)	(.043)
T3*Fars3			−.134*	−.117
			(.069)	(.072)
T3*Fars4			−.036	−.032
			(.059)	(.060)
Constant	.702***	1.12***	.596***	.995***
	(.177)	(.215)	(.166)	(.198)
Group effects	No	Yes	No	Yes
N. obs.	8632			
N. subj., groups	288, 72			

Notes: The dependent variable is always the individual choice, where 1 means 'form' or 'keep' the selected link, and 0 means 'do not form' or 'break' the link. In parentheses we report robust standard errors, clustered at the group level. Additional controls: stage, repetition dummies, age, gender, field of study, new link dummy (plus the inverse Mills ratio from the selection equation).

* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

choice problem and of the individual. The unobservable characteristics of the individual i, assumed independent from the attributes of the decision problem, are captured by ν_i, resulting in the LPM specification:

$$P(a^{ij}_{ig_t} = 1 \mid z^*_i > 0, F^{ij}_{ig_t}, X^{ij}_{ig_t}) = \beta_0 + F^{ij}_{ig_t}\beta + \hat{\lambda}_{it}\beta_\lambda + X^{ij}_{ig_t}\gamma + \nu_i \quad (1)$$

where $\hat{\lambda}_{it}$ is the estimate of the inverse Mills ratio from the selection equation:

$$z^*_{it} = \delta W_{it} + u_i$$

$$z_{it} = \begin{cases} 1 & \text{if } z^*_{it} > 0 \\ 0 & \text{if } z^*_{it} \le 0 \end{cases} \quad (2)$$

where z^*_{it} is the latent variable capturing the propensity of a choice to be selected, z_{it} is a dummy variable indicating whether we observe the choice or not, and u_i is a normal error term. W_{it} is the set of regressors that explain the selection of observations, including all controls $X^{ij}_{ig_t}$ that are applicable, plus a set of restrictions. We use as restrictions[36] in the selection equation dummies for each type of final outcome (myopic, farsighted, other). The restrictions are justified as the group final outcomes are relevant determinants of the stage when the agents stop the game, but should not impact single decisions.

We run different specifications with and without interactions of the main regressors with treatment dummies and group fixed effects. Results are shown in Table 7. Aggregating over treatments, myopic behavior and farsightedness of level two

[36] That is, we include those variables in W_{it}, but not in $X^{ij}_{ig_t}$.

have a positive and significant coefficient. For higher levels of farsightedness the coefficient is insignificant and eventually turns negative (and significant).

Some variation appears across treatments when we add interaction terms. In T1 subjects' choices are explained to a large extent by myopia, and, to a minor one, by farsightedness of level three. In T2 only farsightedness of level two shows a positive and significant effect.[37] In T3 both myopia and farsightedness of level 2 have a positive and significant coefficient. Indeed, in different treatments farsighted improving paths of different length are available to subjects, which explains the across-treatment differences.

On aggregate the analysis consistently shows that agents generally respond to the presence of myopic and farsighted deviations of limited length. This interpretation is consistent with the aggregate results.

Result 3. Individual behavior is best organized by low levels of farsightedness, including myopia. Despite the impact of myopic incentives, subjects often disregard them and take farsighted deviations, which consistently explains the differences across treatments, supporting Hypothesis 5 as a rationale for Result 1.

We are aware that the statistical approach suffers from important limitations. For instance, we do not properly take into account the effect of the past choices of the same individual and of the group, though it is likely that the path of a group has a huge influence on the behavior of the subjects. As a robustness check, in Appendix D we estimate the model separately for each treatment and for each repetition. Result 3 remains valid. We also estimate the level of farsightedness of individuals using the classification procedure of El-Gamal and Grether (1995).[38] This approach allows to assess the extent to which each single subject respond to deviations of different length, but has the disadvantage of interpreting myopia and farsightedness as prescriptive decision rules. The exercise confirms once more Result 3: most subjects are best classified as myopic, but many others are limitedly farsighted. However, the average deviation of subjects from each decision rule and the differences across treatments confirm the undesirability of strict type classifications based on myopia and farsightedness.

5. Conclusion

This paper reports an experimental test of the most used stability notions for network formation. In particular, by studying the performance of pairwise stability and of von Neumann–Morgenstern farsighted stability, we test whether the networks that emerge are best explained by myopic or farsighted notions of network formation. This is the first experimental investigation into this issue.

The results show that both of the extreme theories, perfect myopia and farsightedness, are inconsistent with our data, and suggest that only limitedly farsighted deviations are relevant for the subjects. Agents end in a stable network in 75% of the cases, and more so as the game is repeated. In two of the treatments, a vast majority end in a von Neumann–Morgenstern farsightedly stable set. In the third treatment, where the farsighted prediction is not robust to limitedly farsighted deviations, they fail to do so, and 50% of them end up in the myopic prediction. The properties of the treatments enable us to attribute this asymmetry to limited farsightedness, and individual behavior analysis confirms this interpretation: low levels of farsightedness, nesting myopia as the lowest level, best organize our data.

Our result opens the way to new interesting research questions. While the literature has concentrated on the extreme cases of perfect myopia and perfect farsightedness, our experimental results suggests that an intermediate approach could provide a valuable alternative and a promising refinement to pairwise stability.

Appendix A. Proofs

Proof of Proposition 1. To avoid reporting the farsighted improving path for each single network, let g^i be a generic network in class C_i and $c_i \subset C_i$ a generic proper subset of the corresponding class. We will write $g^i \to g$ with $g \in C_j$, and $g^i \to g$ with $g \in c_j$, when the generic network g^i in class C_i reaches with a farsighted improving path all the networks in class C_j or only a proper subset c_j of C_j, respectively.

(i) In T1 the list of farsighted improving paths among the networks in $\mathbb{G}$ is the following:

$F(g^{\emptyset}) = \{g \mid g \in C_{10} \cup C_{11}\}$
$F(g^2) = \{g \mid g \in C_1 \cup C_{10} \cup C_{11}\}$
$F(g^3) = \{g \mid g \in C_1 \cup c_2 \cup c_5 \cup C_{10} \cup C_{11}\}$
$F(g^4) = \{g \mid g \in C_1 \cup c_2 \cup c_5 \cup C_{10} \cup C_{11}\}$
$F(g^5) = \{g \mid g \in C_1 \cup c_2 \cup C_{10} \cup C_{11}\}$
$F(g^6) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup c_5 \cup C_{10} \cup C_{11}\}$
$F(g^7) = \{g \mid g \in C_1 \cup c_2 \cup c_3 \cup c_4 \cup C_5 \cup C_{10} \cup C_{11}\}$

[37] We here refer to the sum of the main effects plus the relevant interaction term, where significance is assessed at the.05 level using a Wald test.
[38] The approach has been widely used to classify experimental subjects according to a set a of decision rules. For instance, see Costa-Gomes et al. (2001) in the context of level-k models, and Callander and Plott (2005) for an application to network formation.

$F(g^8) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup C_5 \cup c_7 \cup C_{10} \cup C_{11}\}$
$F(g^9) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup c_5 \cup c_6 \cup c_7 \cup C_{10} \cup C_{11}\}$
$F(g^{10}) = \{g \mid g \in c_2 \cup c_4 \cup c_5 \cup c_6 \cup C_{11}\}$
$F(g^N) = \emptyset$.

It follows that $g^N \in F(g)$, for all g in $\mathbb{G} \backslash g^N$ and $F(g^N) = \emptyset$. Thus $\{g^N\}$ is the unique VNMFS set.

(ii) In T2 the list of farsighted improving paths among the networks in $\mathbb{G}$ is the following:

$F(g^{\emptyset}) = \{g \mid g \in C_5\}$
$F(g^2) = \{g \mid g \in C_1 \cup C_5 \cup c_9\}$
$F(g^3) = \{g \mid g \in C_1 \cup c_2 \cup C_5 \cup C_9\}$
$F(g^4) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup C_5 \cup c_9\}$
$F(g^5) = \{g \mid g \in C_9 \cap \bar{A}_{g^5}\}$
$F(g^6) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup C_5 \cup C_9\}$
$F(g^7) = \{g \mid g \in C_1 \cup c_2 \cup c_3 \cup c_4 \cup C_5 \cup C_9\}$
$F(g^8) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup C_5 \cup c_7 \cup C_9\}$
$F(g^9) = \{g \mid g \in c_4 \cup (C_5 \cap A_{g^9}) \cup (C_9 \backslash g^9)\}$
$F(g^{10}) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup C_5 \cup c_7 \cup c_8 \cup C_9\}$
$F(g^N) = \{g \mid g \in C_5 \cup C_9 \cup C_{10}\}$

The set $\{g \mid g \in C_5\}$ is a VNMFS set. It is reached by any network outside the set and there are no paths between any two networks in the set. Let us check that it is unique.

Consider first a candidate set that does not include any network in C_5. It must then be reached by each single network in C_5, which implies this set should include at least two networks that belong to C_9. Given that $\{g' \mid g' \in C_9 \setminus g\} \subset F(g)$ for every $g \in C_9$, a set including two networks in C_9 is not internally stable.

Now consider a candidate that includes at least one network $g \in C_5$. Then it should include at least one network $g' \in C_9$, such that $g' \notin F(g)$ and $g \notin F(g')$. This condition is impossible as all networks in C_9 that are not adjacent to a network in C_5 are reached by a farsighted improving path from this network, and all networks in C_9 that are adjacent to a network in C_5 reach this network with a farsighted improving path. We conclude that $\{g \mid g \in C_5\}$ is the unique VNMFS set.

(iii) In T3 the list of farsighted improving paths among the networks in $\mathbb{G}$ is the following:

$F(g^{\emptyset}) = \{g \mid g \in C_7\}$
$F(g^2) = \{g \mid g \in C_1 \cup C_7 \cup c_{10}\}$
$F(g^3) = \{g \mid g \in C_1 \cup c_2 \cup C_7 \cup C_{10}\}$
$F(g^4) = \{g \mid g \in C_1 \cup c_2 \cup c_5 \cup C_7 \cup c_{10}\}$
$F(g^5) = \{g \mid g \in C_1 \cup c_2 \cup C_7 \cup c_{10}\}$
$F(g^6) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup c_5 \cup C_7 \cup C_{10}\}$
$F(g^7) = \{g \mid (g \in C_7 \wedge \exists i \text{ s.t. } d_i(g) \neq d_i(g')) \vee g \in C_{10}\}$
$F(g^8) = \{g \mid g \in C_1 \cup c_4 \cup C_7 \cup C_{10}\}$
$F(g^9) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup c_5 \cup c_6) \cup C_7 \cup C_{10}\}$
$F(g^{10}) = \{g \mid g \in C_1 \cup c_2 \cup c_4 \cup c_5 \cup c_6 \cup C_7 \cup c_8 \cup C_{10} \setminus g^{10}\}$
$F(g^N) = \{g \mid g \in C_7 \cup C_{10}\}$

A network $g \in C_7$ is reached with a farsighted improving path from any other network except for the network $g' \in C_7$, where each single agent has the same degree as in g. By definition each dyad $\{g, g'\}$ is a VNMFS set. Let us check there is no other VNMFS set.

Given the previous argument, any set containing $g \in C_7$ and any other network $g'' \neq g'$ (as defined above) does not satisfy internal stability. Consider now a candidate set that does not include any network in C_7. As it must be reached by networks in C_7, it will necessarily include one and only one (for internal stability) network in C_{10}. Then it must necessarily include $g^{\emptyset}$, which violates internal stability.□

Appendix B. Experimental instructions

Welcome to this experiment in decision-making. In this experiment you can earn money. The amount of money you earn depends on the decisions you and other participants make. Please read these instructions carefully. In the experiment you will earn points. At the end of the experiment we will convert the points you have earned into euros according to the rate: 6 points equal 1 Euro. You will be paid your earnings privately and confidentially after the experiment. **Throughout the experiment you are not allowed to communicate with other participants in any way. If you have a question please raise your hand. One of us will come to your desk to answer it.**

Groups

- At the beginning of the experiment the computer will randomly assign you – and all other participants – to a group of 4 participants. Group compositions do not change during the experiment. Hence, you will be in the same group with the same people throughout the experiment.

- The composition of your group is anonymous. You will not get to know the identities of the other people in your group, neither during the experiment nor after the experiment. The other people in your group will also not get to know your identity.
- Each participant in the group will be assigned a letter, A, B, C, or D, that will identify him. On your computer screen, you will be marked 'YOU' as well as with your identifying letter (A, B, C or D). You will be marked with your identifying letter (A, B, C or D) on the computer screens of the other people in your group.
- Those identifying letters will be kept fixed within the same round, but will be randomly reassigned at the beginning of every new round.

Length and articulation of the experiment

- The experiment consists of 3 rounds, each divided into stages.
- The number of stages in each round will depend on the decisions you and the other people in your group make.
- After a round ends, the following will start, with the same rules as the previous: actions taken in one round do not affect the subsequent rounds.

General rules: rounds, stages, formation and break of links

- In each round the task is to form and break links with other members of the group.
- You will have the possibility to link with any other participant in your group. That is, you can end up with any number of links (0, 1, 2 or 3).
- Thus, the number of links that can be formed in your group will be a number between 0 and 6 (0, 1, 2, 3, 4, 5, 6). The set of links that exist in your group at the same time is called a network.
- Your group starts the first stage of every round with zero links.
- In every stage a network of links is formed, based on your and the other group participants decisions. This network is called the current network.
- Your group will enter a new stage with the links that exist in the network that is formed in the previous stage, according to the following linking rules:
  – *A link between you and another participant in your group is formed if you make a link to that person **AND** that person makes a link to you.*
  – *An existing link between you and another participant in your group is broken if you **OR** that participant decide to break that link.*

Stage rules

- In each stage the **computer** will select for each group a single link among the six possible at random. A link cannot be selected twice in two consecutive stages.
- The participants involved in that link will be asked to take a decision in that stage, the others will be informed about the selected link and will be asked to wait for others' decisions.
- If this link does not exist at the beginning of the stage, the decision will be whether to form that link or not. If this link exists at the beginning of the stage, the decision will be whether to keep or to break that link.
- Thus, in each stage at most **one** link can be formed or broken.

Stopping rules

- After every stage you and the other people in your group will be asked if you are willing to modify the current network. You can answer YES or NO.
- If ALL the people in your group answer NO the round ends and the points associated to the current network are considered to compute your earnings.
- If at least one person in your group answers YES, the group moves to the next stage.
- After stage 25 a random stopping rule is added. In this case, even if you or any of the other people in your group are willing to modify the current network, the round will end with probability 0.2.

Earnings

- To every participant in every network is associated a number of points.
- You will receive points according to the network that exists in your group at the end of each round.
- Your total earnings will be the sum of the earnings in each of the 3 rounds.
- Thus, the points associated to the networks you and the other people in your group form at every stage, except for the last of each round, are not considered for the computation of your earnings.

- You are always informed about the points associated to the current network on screen. On the top of your screen, you are always informed of the points you earned in the previous rounds.
- You can learn about the points associated to every other network through the points sheet you find attached to the instructions.[39] It displays the points associated to every class of networks:
  - In every network, the black dots are the participants in the group; the lines are the existing links.
  - Every class of network is characterized by the number of links each participant has.
  - The numbers close to every black dots indicate the number of points a person with that number of links is earning in that specific class of networks.
- An example will clarify the relation between network and points and the developing of the experiment. You will also practice through a training stage.

Concluding remarks

You have reached the end of the instructions. It is important that you understand them. If anything is unclear to you or if you have questions, please raise your hand. To ensure that you understood the instructions we ask you to answer a few control questions. After everyone has answered these control questions correctly the experiment will start.

Appendix C. User's interface screenshots

Figs. 7–11

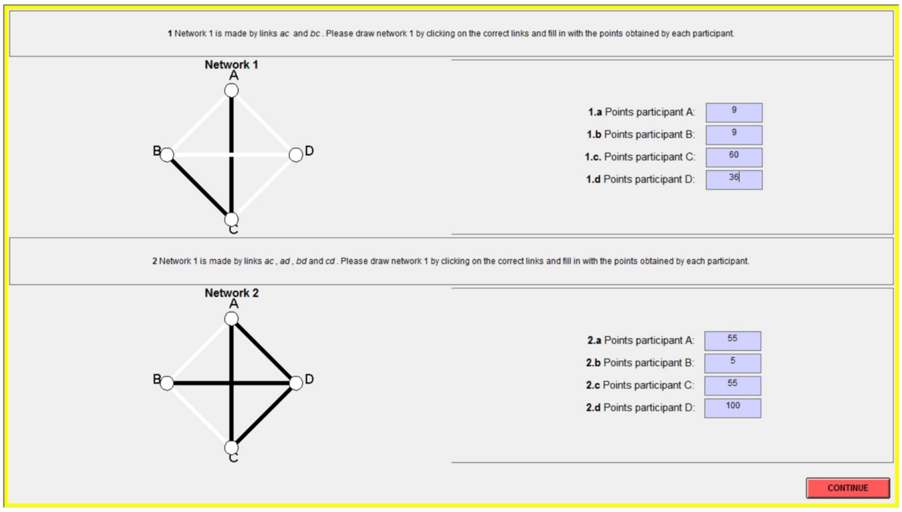


Fig. 7. Control questions 1.

[39] The points sheets used were identical to Figs. 1–3, except that they did not make reference to the solution concepts.

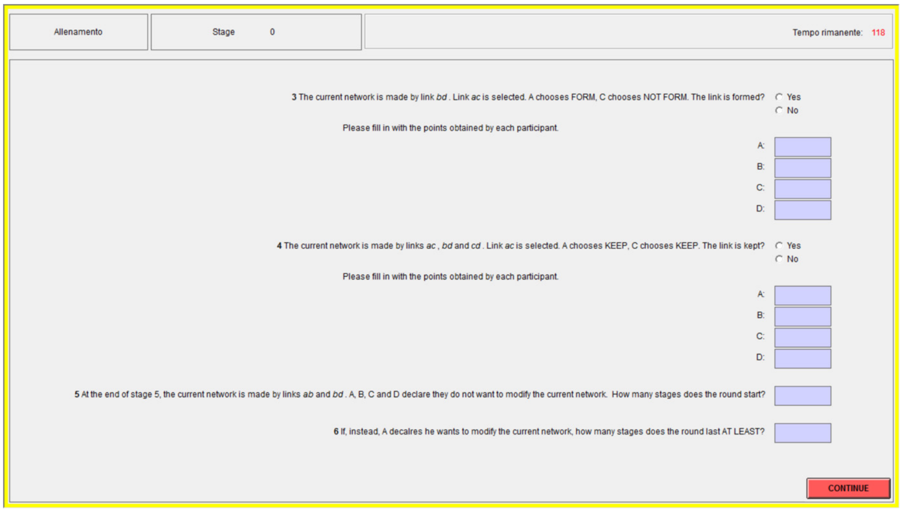


Fig. 8. Control questions 2.

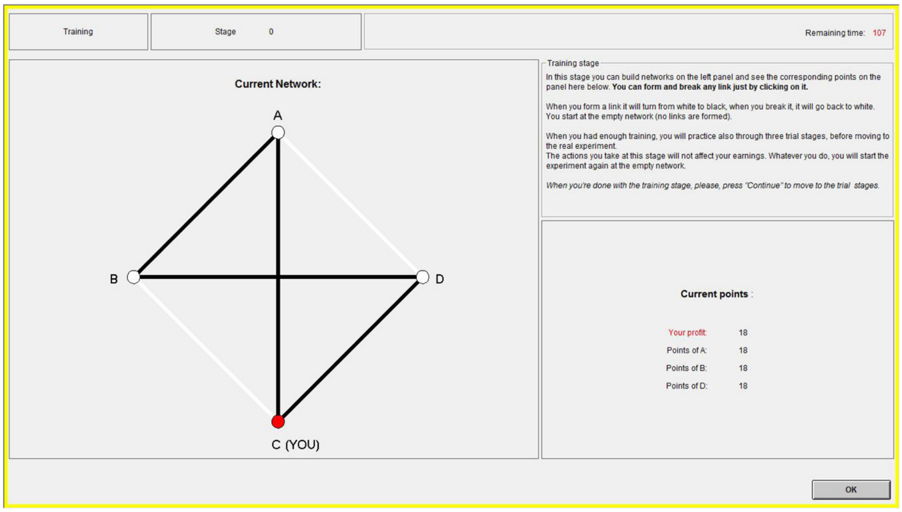


Fig. 9. Training screen.

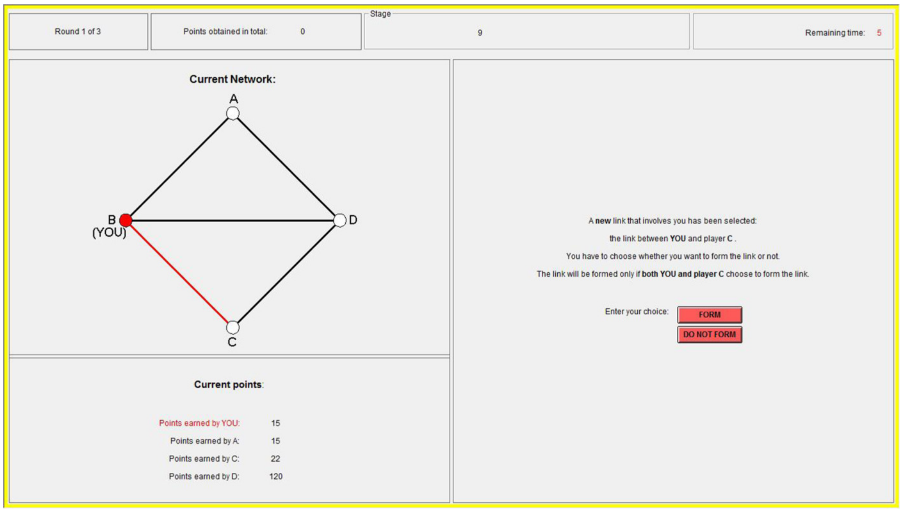


Fig. 10. Link formation screen.

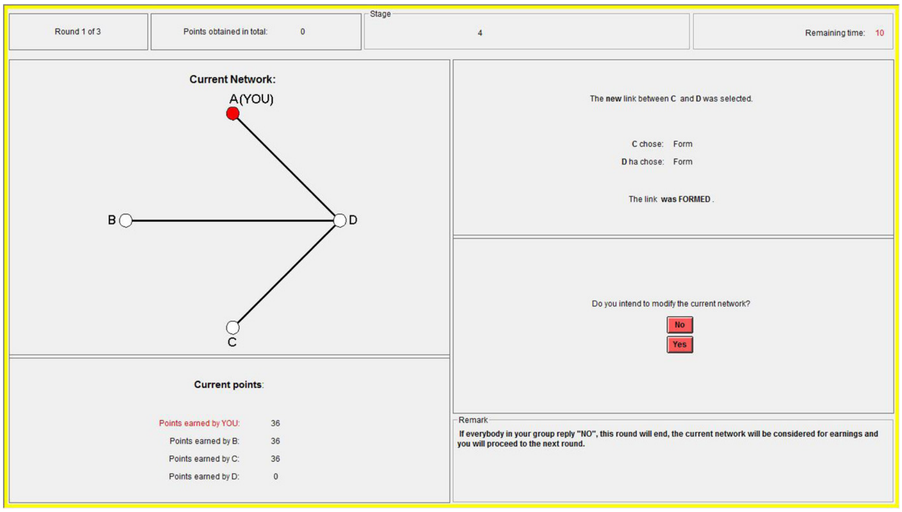


Fig. 11. Feedback screen.

Appendix D. Robustness checks

More games are ended by the random stopping rule in T2 and T3 (40 and 45%) than in T1 (19%). It is not obvious how one should consider the final networks of those groups. On the one hand, one would like to exclude groups that end in some network by chance. On the other, one does not want to exclude groups that could not leave a network, even if some players would have liked to.[40] Figs. 12 and 13 shows that excluding those group does not affect the aggregate picture, either within or across treatments. Tests are shown in Table 4.

Table 8 presents various test on the across-treatment hypotheses. All the tests detect the same significant differences.

We next run the Heckman selection model specified by Eqs. (1) and (2) separately for each treatment and repetition (Table 9). In all treatments subjects respond to farsighted deviations of limited length. We detect similar across-treatment differences as those reported in Table 7. When looking at single repetitions a similar picture emerges.

Finally, we apply the classification method of El-Gamal and Grether (1995). We start with a family of decision rules: myopic, farsighted of level 2, farsighted of level 3, etc. These rules are the benchmark behaviors described in Definition 3. The procedure aims at identifying the k rules that are active in the population and at classifying each individual as following one of these rules, by maximizing the likelihood of the observed sample.

[40] Other papers [e.g., Callander and Plott, 2005] define a network stable if the players do not change it for a number of consecutive stages, usually between three and five.

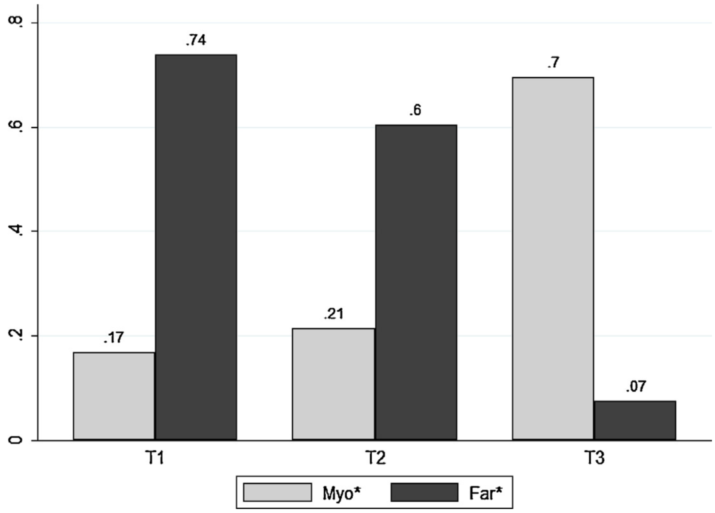


Fig. 12. Final networks, randomly stopped groups excluded.

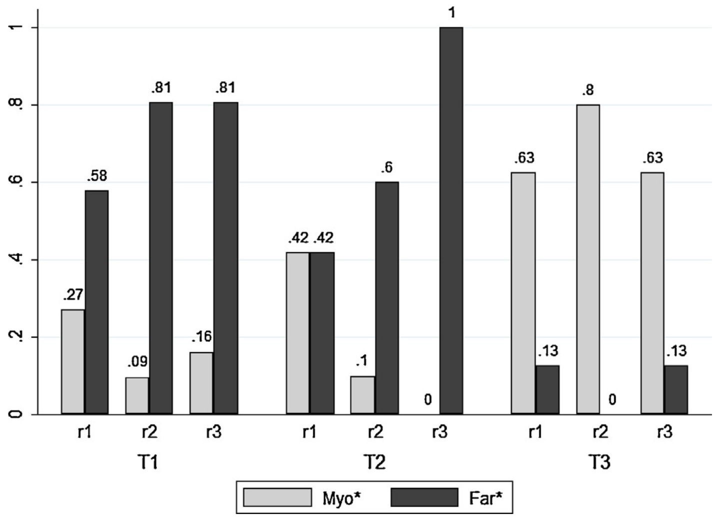


Fig. 13. Final network, by repetition, randomly stopped groups excluded.

Each subject follows one of k rules. He is not required to follow the rule perfectly, and is generally prone to error. By examining how frequently each rule is used by an individual, we can estimate the likelihood that a sequence of actions is produced by a subject following that rule for a given error rate. We then maximize, over the possible k-tuples of rules, and classification within each k-tuple, the likelihood of the observed sample.

The procedure goes as follows. For each given k-tuple, each subject is classified as following the rule that minimizes his deviations. The error rate is then estimated as the proportion of overall deviations, given the individual rules. The procedure then selects the k-tuple that maximizes the overall likelihood, given the estimate of the error rates. We run this procedure

Table 8
Comparison of various across-treatment tests.

	Overall		T1 vs. T2		T1 vs. T3		T2 vs. T3	
Chi^2	**25.92**	(**.00**)	0.62	(.43)	**25.13**	(**.00**)	**14.48**	(**.00**)
LR	**27.62**	(**.00**)	0.62	(.43)	**26.75**	(**.00**)	**14.48**	(**.00**)
FE		(**.00**)		(.50)		(**.00**)		(**.00**)
KS			0.17	(.83)	**.58**	(**.00**)	**.44**	(**.03**)
WRS			0.78	(.43)	**3.53**	(**.00**)	**2.82**	(**.00**)

Notes: The table reports a battery of tests and its associated P-value (in parentheses) on the fraction of farsighted outcomes in each treatment. Chi^2: Pearson's Chi-squared test (already shown in Table 4); LR: likelihood ratio tests; FE Fisher's exact test, provides identical results; KS: Kolmogorov–Smirnov test; WRS: Wilcoxon rank-sum test. Tests are based on 36 independent observations in T1, 18 in T2 and T3. Bold means significant at the.05 level.

Table 9
LPM estimates of Eq. (1), by treatment and round.

	T1	T2	T3	Rep. 1	Rep. 2	Rep. 3
Myopic	.297***	.002	.070**	.176***	.159***	.054**
	(.027)	(.032)	(.036)	(.035)	(.029)	(.027)
Farsighted 2	−.051**	.091***	.067**	.022	.048*	.011
	(.023)	(.033)	(.034)	(.026)	(.027)	(.022)
Farsighted 3	.102	−.015	−.033	.067*	.009	.067**
	(.039)	(.034)	(.056)	(.039)	(.038)	(.033)
Farsighted 4	−.024**	−.095**	−.079**	−.089**	−.073**	−.055**
	(.023)	(.043)	(.061)	(.038)	(.034)	(.025)
Constant	.646***	1.12***	1.58***	1.13***	1.16***	.641***
	(.157)	(.550)	(.478)	(.240)	(.128)	(.234)
N. obs.	3834	2322	2476	3012	2876	2744
N. subjects, groups	144, 36	72, 18	72, 18	288, 72	288, 72	288, 72

Notes: The dependent variable is always the individual choice, where 1 means 'form' or 'keep' the selected link, and 0 means 'do not form' or 'break' the link. In parentheses we report robust standard errors, clustered at the group level. Additional controls stage, age, gender, field of study, new link dummy, repetition dummies in T1–T3 and treatment dummies in Rep. 1–Rep. 3 (plus the inverse Mills ratio from the selection equation).
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 10
Estimated rules, error rates and classifications.

Sample	No. of rules	Rules chosen	Classification	Error rate
T1	1	M	144	.33
T2	1	M	72	.48
T3	1	M	72	.46
All	1	M	288	.41
T1	2	M,F4	107,37	.32
T2	2	M, F3	43, 29	.42
T3	2	M, F3	49, 23	.40
All	2	M, F3	211, 77	.37
T1	3	M, F3, F4	103, 16, 25	.32
T2	3	M, F2, F3	27, 23, 22	.41
T3	3	M, F2, F3	41, 11, 20	.40
All	3	M, F2, F3	190, 44, 54	.36
T1	4	M, F2, F3, F4	102, 1, 16, 25	.32
T2	4	M, F2, F3, F4	27, 22, 15, 8	.41
T3	4	M, F2, F3, F4	40, 11, 17, 4	.39
All	4	M, F2, F3, F4	173, 45, 40, 30	.36

Notes: The table reports the results of the classification procedure of El-Gamal and Grether (1995). 'M' stands for myopic, 'F2' for farsighted of level 2, and so on. Column 'Classification' reports the number of subjects classified in each corresponding rule. Bold lines identify the number of rules that maximizes Schwartz information criterion for each sample.

for $k = 1, 2, 3, 4$. The maximal likelihood obtained for each k can be used to assess the optimal number of decision rules using an appropriate information criterion. Results are reported in Table 10.

Both on aggregate and in each treatment, when we force the algorithm to select only one rule, it selects the myopic decision rule. When more rules are allowed a substantial fraction of subjects is classified as limitedly farsighted. The results vary across treatments. This variations are best appreciated by looking at the results for $k = 4$. Across-treatment differences go in the same direction as seen in the main text: in T1 myopia is more prevalent, followed by relative high levels of farsightedness; in T2 and T3 intermediate levels are relatively more important. Schwartz information criterion is maximized when k is equal to 2 in T2 and T3, where we allow for myopic and farsighted behavior of level 3. In T1 the information criterion is maximized when only myopic behavior is allowed. Finally, the estimated error rate is above.3 in all cases.

Overall this analysis confirms both the results we have reported in the main text and their limits. Subjects respond to farsighted deviations, and we can improve our understanding of network formation by including limited farsightedness in stability concepts. However, farsightedness and myopia are suboptimal proxies of individuals' decision rules, both in terms of goodness of fit and in terms of across-context stability of the estimates.

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