Dynamics and Stability of Social and Economic Networks: Experimental Evidence *

Juan D. Carrillo†
University of Southern California and CEPR

Arya Gaduh‡
University of Arkansas

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Abstract

We use a laboratory experiment to test the dynamic formation of networks in a six-subject game where link formation requires mutual consent. First, the game tends to converge to the pairwise-Nash stable (PNS) network when it exists, and to not converge but remain in the closed cycle when no PNS network exists. When two Pareto-rankable PNS networks exist, subjects often coordinate on the high-payoff one. Second, the analysis of single decisions indicates the predominance of myopic rational choices, but it also highlights interesting systematic deviations, especially when actions are more easily reversible and when they involve smaller marginal losses. Third, behavior is heterogeneous across subjects, with varying degrees of sophistication.

Keywords: social networks, stable networks, myopic rationality, laboratory experiments.
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†University of Southern California, Department of Economics, Kaprielian Hall 120, Los Angeles, CA 90089, Email: juandc@usc.edu

‡University of Arkansas, Walton College of Business, Department of Economics, Business Building 402, Fayetteville, AR 72701-1201. Email: agaduh@walton.uark.edu.

1 Introduction

Networks shape a variety of social and economic interactions and their importance has been increasingly recognized in economics (Jackson, 2008, 2014). Among economists, a key question of interest is on how incentives shape networks that are formed by self-interested agents. Studies of stable forms of cooperation have a deep root in economics, particularly in the context of decentralized matching (Gale and Shapley, 1962). More recently, theorists tackle a similar question in the context of network formation, with the introduction of solution concepts that predict the kind of stable networks that will emerge under different assumptions about individual behavior.

Two stability notions commonly used in the theoretical literature are *Nash stability* (Myerson, 1991) and *Pairwise stability* (Jackson and Wolinsky, 1996). They formally describe the networks that emerge under certain interactions by self-interested individuals. The theoretical literature has also analyzed the network evolution process. For example, Jackson and Watts (2002) study the dynamics of social and economic networks when the actions of all subjects are *myopic rational*, that is, when each link is decided solely based on its current net benefit without strategically thinking ahead.

Despite significant theoretical advances, there is only a small experimental literature examining pairwise stability in dynamic linking games with mutual consent (Pantz, 2006; Kirchsteiger et al., 2016; Teteryatnikova and Tremewan, 2019).[1] Empirical evidence can help researchers understand the relevance of the theoretical notions of stability and the circumstances conducive to deviations. Since testing stability using observational data is difficult,[2] we build a controlled laboratory experiment with three objectives. First, we study the likelihood that participants in our network formation game converge to a stable network as a function of the existence and number of such stable networks, as well as their characteristics (payoff structures, difficulty to reach them, etc.). Second, since individuals sometimes deviate from myopic rational choices either as a means to reach some stable network or simply as an exploration strategy, we analyze the circumstances conducive to such deviations (opportunity cost, reversibility, etc.). Third, we investigate heterogeneity in behavior across subjects and how this variability impacts both the individual payoffs and the final outcomes.

[1] In contrast, experimental analyses of stability in decentralized matching settings have received more attention (see, e.g., Chen and Sönmez, 2006; Echenique and Yariv, 2013; Echenique et al., 2016; Agranov et al., 2020). There is also a recent literature that explores from a theoretical and experimental viewpoint the stability in the dynamics of vote trading (Casella and Palfrey, 2019, 2020).

[2] Methodological papers that analyze peer effects in endogenously-formed social networks have assumed that the observed networks are pairwise stable (see e.g., Boucher and Mourifié (2017) and Sheng (2020)).

Our experimental game slightly modifies the dynamic linking game developed by Watts (2001). Each game is played with six subjects. This expands significantly the complexity of the network formation process relative to the previous literature (as complexity grows exponentially with the number of players). It introduces a rich game structure, where we can vary the existence and number of stable networks. It also allows us to avoid networks such as the empty and full network. Such networks can often become "focal" in the sense of Schelling (1960) — namely, networks whose salience allow players to coordinate on by default in the absence of communication. Our study analyzes the data in three (complementary) ways: network outcomes, single decisions, and choices of individuals.

The analysis of final networks suggests that outcomes can, to some extent, be predicted by the notion of "Pairwise Nash Stable" networks (PNS, which combines Pairwise stability and Nash stability). We show that if the game has no PNS network, behavior does not converge. However, and in accordance to the theoretical prediction, it stays within a closed cycle in 66% of the games. When a unique PNS network exists, we find some evidence of convergence to it (31% and 47% of the games depending on the treatment) and little evidence of convergence elsewhere. We argue that the observed differences in PNS convergence across treatments may be linked to the characteristics of the PNS network and, in particular, symmetry/asymmetry of payoffs across subjects. Finally, with multiple PNS networks, the process reaches the Pareto-Superior PNS network in 44% of the games while it never stays in the Pareto-Inferior PNS.

Our study of single decisions empirically qualifies a key behavioral assumption of Jackson and Watts (2002)'s theory of social network evolution. Their predictions rely on having agents that (almost) always make myopic rational choices. Although a large fraction of decisions in our experiment are myopic rational (74% to 91% depending on the treatment), we also find evidence of *systematic* deviations. We therefore develop an empirical strategy to test for correlates of deviations from myopic rationality.

We find four *intuitive* situations that affect the probability of deviations. First, deviations are more common in early turns. This is natural because, in our design, subjects are guaranteed 12 turns before they enter a probabilistic match-ending phase. Second, deviations are more frequent when they imply keeping an excessive number of links, presumably because future link removals do not require mutual consent. These two deviations suggest that subjects are more likely to "experiment" with decisions that are not myopic rational if they feel that such actions can be more easily reversed later on. Third, subjects deviate more often when the marginal payoff losses are small. This is consistent with a theory of "imperfect choice", where mistakes are inversely related to their cost. Fourth, deviations are also more frequent in the treatment with multiple PNS, where non-myopic rational choices are necessary in order to escape the low payoff stable network. This final deviation provides some evidence of farsightedness, that is, the ability to think beyond the current cost and benefit of actions.

A cluster analysis performed at the subject level reveals substantial heterogeneity in behavior across individuals. We find about 48% of subjects who, while understanding the strategic nature of the game, are highly myopic rational. Two clusters, comprising 44% of subjects, exhibit more strategic behaviors by adjusting their actions in different stages of the game. These more strategic subjects are more willing to experiment by deviating from myopic rationality in early turns. Finally, the remaining 8% of subjects significantly deviate from myopic rationality in all stages of the game — a behavior that is difficult to rationalize as an optimizing strategy of this game.

Our paper contributes to the growing number of experimental studies on network formation.[3] The bulk of the literature focuses on examining stability in the unilateral link formation framework of Bala and Goyal (2000) or the bilateral link announcements game of Myerson (1991).[4] Closer to our setting is the experimental literature on dynamic linking games with mutual consent. Pantz (2006) and Kirchsteiger et al. (2016) examine outcome selection given multiple PNS networks. Of these, Kirchsteiger et al. (2016) also implement the dynamic linking model of Watts (2001) in a smaller, four-person network. The authors find that subjects deviate from myopic rationality to reach the Pareto superior payoff, but only when reaching that network requires a limited degree of farsightedness. Our focus is different in that we design our experiment to systematically study myopic rationality as a function of the existence and number of equilibria. We are also interested in determining the circumstances conducive to deviations (turn, action type and marginal payoff) in a more complex setting. There is also a literature that studies interesting variants of the bilateral linking game. In Teteryatnikova and Tremewan (2019), payoffs are received at each turn. In Comola and Fafchamps (2018), payoffs are pair-specific. In Caldara and McBride (2015), subjects have limited observation of the network structure. In Candelo et al. (2014), networks face threats of disruption. Finally, in Neligh (2020), the timing of entry affects the individual payoffs.

The paper is organized as follows. In Section 2, we present the conceptual framework and the theoretical literature pertinent to our experiment. Section 3 describes the experimental design and introduces our treatments. Then, in the following three sections, we

[3]There is also a related experimental literature on equilibrium selection in network games (see e.g. Fatas et al., 2010; Charness et al., 2014).

[4]See e.g., Callander and Plott (2005), Berninghaus et al. (2006), Berninghaus et al. (2007), Falk and Kosfeld (2012) and Goeree et al. (2009) for the first line of investigation and Conte et al. (2015), Di Cagno and Sciubba (2008) and Burger and Buskens (2009) for the second one.

present our analysis at the final network level (Section 4), single decision level (Section 5) and subject level (Section 6). Section 7 concludes.

2 Network environment and basic definitions

A network is a collection of links that connect a set of agents. A link between two agents forms if and only if both decide that it is worth forming. Each link is costly for both agents and this cost is non-transferable. Meanwhile, the benefit depends on and is a strictly increasing function of the size of the network component that an agent belongs to. We distinguish between a *network* and a *component*. A network describes the link configuration that includes the full graph (all agents) while a component is a sub-graph in which there exists a path linking any two agents. In our setup, all agents in a component receive the same benefit. Payoffs are computed as the difference between benefits and costs. A number of theoretical approaches analyze endogenous network formation among rational, self-interested agents when link formation requires mutual consent (Bloch and Jackson, 2006). We provide an informal and brief summary of the concepts most relevant for our experiment.

Myerson (1991) explicitly considers a linking game and uses Nash equilibrium to define the stability of a network. In his game, agent i's strategy set is an n-tuple of binary variables indicating his willingness to link with each of the other agents in the game. A link between i and j forms if both agents mutually agree to link. A strategy profile is a Nash equilibrium of the game if and only if no subject can benefit from a unilateral deviation from their strategy. A network is *Nash stable* if it is induced by a (pure strategy) Nash equilibrium of the linking game.

Nash stability does not allow the coordination of agents to improve their payoffs. Jackson and Wolinsky (1996) relaxed this restriction with their notion of pairwise stability. Pairwise stability allows for pairwise deviations and rules out networks that are "intuitively unstable" when formed by strategic actors. A network is *Pairwise stable* if: (i) all existing links are weakly preferred by both agents in the link; and (ii) if an agent of a non-existing link would strictly prefer to be in the link, then the other agent of that link strictly prefers not to be in it (see Jackson and Wolinsky, 1996, p.48).

Finally, Pairwise Nash stability combines both notions: a network is *Pairwise Nash stable* (PNS) if and only if it is both Nash stable and Pairwise stable (Bloch and Jackson, 2006). It is worth noting that Nash stability and Pairwise stability are two related but distinct concepts. The simplest example to illustrate the distinction is to consider a network with two agents where linking would increase the payoff of both agents. Here, a network of two singletons is Nash stable since a strategy profile where both agents expect the other not to reciprocate is a Nash equilibrium. However, this network is not Pairwise stable since both agents strictly prefer to form a link. Bloch and Jackson (2006, Example 1) offers an elaborate example to show that the sets of Nash stable and Pairwise stable networks may not intersect and both be non-empty.

In a dynamic linking game where pairs of agents randomly meet and make linking decisions, Jackson and Watts (2002) show how pairwise stability can help predict the network outcome. Suppose that each linking action is *myopic rational* – to wit, it optimizes the marginal payoff from the link under consideration (and not on the option value of forming or severing links in the future). Hence, a link forms if both agents are weakly better-off with it and at least one is strictly better-off. Conversely, an existing link breaks if at least one agent is strictly better-off without it. If all actions are myopic rational, then the network evolves following an *improving path*. Starting from any network, Jackson and Watts (2002, Lemma 1) show that improving paths lead to either a Pairwise stable network or, when none exists, a *closed cycle*. A set of networks forms a closed cycle if no network in the set lies on an improving path leading to a network that is not in the set. In the experiment, we will also refer as a benchmark to the networks that arise when agents maximize the sum of payoffs received by all agents. Following Jackson and Wolinsky (1996), we call them the *Efficient* networks.

Notice that there might be multiple Pairwise stable networks, some more attractive than others. Under multiplicity, agents who follow myopic rational choices will be stuck in the Pairwise stable network they reach via the improving path. However, if they realize the long run benefits of myopically suboptimal choices, they may move away from one Pairwise stable network into a *Pareto-Superior Pairwise stable* network, where the payoffs are weakly higher for all agents (and strictly higher for at least one agent).[5]

Finally, but crucial for our experiment, agents in a component often have different payoffs (they all obtain the same benefits but they are subject to a different number of direct links). This poses a different multiplicity problem. Even after reaching a PNS network, a forward-looking agent may have incentives to make or break links in order to move away and then go back to the same PNS network but in a different position within the component (e.g., in the same component but with other agents bearing the largest number of links). If all agents anticipate this possibility, the process may never stop.

[5]This approach is different from the notion of *pairwise farsightedly stable* network developed by Herings et al. (2009), which explicitly considers the possibility of farsighted improving paths. The experiment by Kirchsteiger et al. (2016) provides evidence of farsighted network formation in a more compact, four-agent setting.

3 Experimental setting and procedures

3.1 The basic configuration

We are interested in environments with a *large number of network configurations* where links are costly and mutual pairwise consent is needed to form a link but not to break it. To this end, we implement a stochastic dynamic linking game that slightly modifies the procedure proposed by Jackson and Watts (2002). We consider the largest network we could manage, namely $n = 6$ subjects. This implies $n(n-1)/2 = 15$ possible bilateral undirected links between different subjects, and therefore $2^{n(n-1)/2} = 32,768$ possible networks. Many networks differ from each other only by the identity of subjects in the different positions. We say that two networks have the same *network structure* if they are identical up to a permutation of the identity of subjects.

We consider a particular payoff structure. Every subject in a component receives the same benefit, which is a strictly increasing function of its size, while the cost of links is borne solely by their owners. This setup matches, for example, the endogenous formation of risk-sharing networks. In a repeated interaction setting, Bramoullé and Kranton (2007) shows that an arrangement where individuals commit to share monetary holdings equally with linked partners amounts to equal sharing within network components. Another example would be the case of club goods offered by religious or social groups without centralized coordination (see e.g. Berman, 2000) where all members benefit from having an additional recruit, but participation requires individuals to maintain costly direct links.

This design choice serves two objectives. First, we want to maintain tractability given the large number of possible networks. This payoff structure limits the set of stable and efficient networks to be a subset of networks where all components are *minimally connected*. We say that a component is non-minimally connected if there exists at least one (redundant) link that can be removed without affecting the size of the component. Conversely, a component is minimally connected if there does not exist any such redundant link. When the benefit is only a function of the component size, removing a link that does not reduce the component size is always Pareto improving. With 6 subjects, there are 20 network structures where all components are minimally connected. Second, we also want to simplify the game enough to minimize the likelihood of participants' computing mistakes. As such, the allocation of benefits deviates from the usual connections model where links have indirect benefits that decay with distance at a rate δ (Jackson and Wolinsky, 1996). We further simplify the structure by maintaining a constant unit cost of a direct link both within and across treatments.

3.2 Experimental design

Each match consists of multiple turns and starts with an empty network. At each turn, the computer randomly pairs the six subjects. Subjects then choose their actions with respect to their partner in the pair. A new turn begins after all subjects have taken their actions. If all subjects are satisfied with the network outcome, they can collectively end the game. We implement a match-ending rule that provides very extensive opportunities for subjects to converge. At the same time, it allows decisions to be meaningful and the experiment to be time manageable. Subjects play for 12 turns unless all subjects are satisfied with the network. Afterwards, each turn is the last one with probability $p = 0.2$, providing an additional $1/p = 5$ turns on average. With this probabilistic match-end rule, we hope to mitigate the last-round effects. It also allows for an interesting comparison of behavior before and after Turn 12. Finally, since each turn is composed of six decisions, one for each subject, 12 turns provide a fairly large number of individual decisions per match ($17 \times 6 = 102$ on average, unless subjects decide to stop before).

Figure 1 shows the user interface. At each turn, subjects make decisions with respect to their current partner by clicking on one of the action buttons displayed on the lower left section of the screen. If a subject (he) is not linked to his partner, he chooses whether to "Propose" a link or "Pass Turn". If he is linked, he chooses whether to "Remove" a link or "Pass Turn". We impose no time limit for making a choice. Once both partners in a pair have taken their actions, the result is immediately displayed on the screen. Hence, when each subject makes his decision, he observes the latest state of the network. Showing the latest network configuration *within a turn* allows us to cleanly determine whether each individual decision reflects a myopic rational behavior or otherwise.[6] If a subject is not only satisfied with the relationship with his partner but also with the overall network, he can choose "Network OK" instead of choosing "Pass Turn".[7] As mentioned above, the match immediately ends if all subjects within a turn choose "Network OK".

There are two reasons why we matched individuals in pairs within each turn instead of allowing them to simultaneously make decisions with all other participants. First, with one decision at a time, participants face well-defined, payoff-relevant choice problems at all times without overwhelming them with information and multi-dimensional trade-offs. Second, this setting matches Jackson and Watts (2002)'s stochastic dynamic linking pro-

[6]On the other hand, it could encourage a war of attrition, where subjects wait to see what others do in a turn before choosing their own action. There is no evidence in our data of individuals systematically waiting for others to move within a turn.

[7]Once a subject chooses "Network OK", he does not need to choose further actions until the network changes. To avoid mistakes, all of his action buttons become inactive. These buttons are immediately reactivated following a change in the network.

cedure (except for the simultaneous choice of all pairs within a turn as discussed above). It therefore allows us to study the empirical relevance of the concepts developed in that theory, namely myopic rationality, improving paths and pairwise stability.

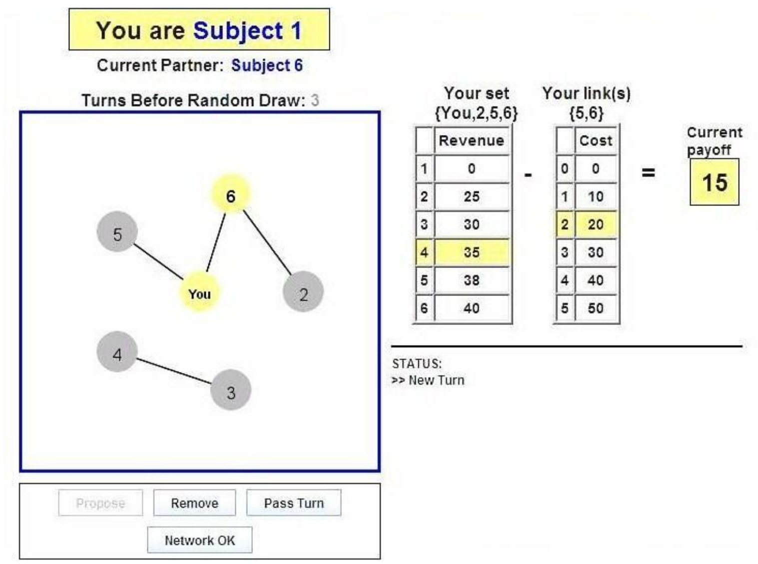


Figure 1: User interface for the linking game.

We carefully designed an interface that balances clarity and amount of information. On the left side of the screen, it displays all the pertinent information: the subject's role, the role of the person he is currently matched with, whether the current turn is a potential terminal turn and, naturally, the current network configuration. On the right side of the screen, it displays the benefit of the subject as a function of the size of the component he is in, the cost as a function of his number of direct links, and his net payoff given the current network configuration. This succinct but comprehensive visual display allows the subject to compute with reasonable ease not only the net value of adding or removing an existing link (i.e., the improving path) but also his payoff in any other network configuration. Finally but crucially, the node representing the subject is always located at the center and labeled “You”. The nodes representing the other subjects in a match are labeled by their roles and surround the subject's node in clockwise order at an equal distance from it. By always putting the subject's node at the center, each subject sees a different graphical representation even though the underlying connections between subjects in a match are identical. We therefore avoid leading participants towards visually attractive configurations such as the star or wheel network.

3.3 Treatments

The experiment consists of four treatments illustrated in Figures 4–7 at the end of the paper. Treatments vary in the presence and uniqueness of the PNS network and share a common representation. First, we construct a “supernetwork” that contains the 20 network structures with minimally connected components (labeled $\{A\}$ to $\{T\}$). Network structures are vertically ordered based on the total number of links, from zero (top row) to five (bottom row). Network structures with the same number of links are presented in the same row. Each network is then connected by a directed arc to one or more networks in the row above and the row below it. The connections represents the network(s) that can be reached from the original one either by adding one new link (connection to row below) or severing one existing link (connection to row above). The direction of the arc captures the improving path. If forming a new link is on the improving path, then the arrow points to the row below. If severing an existing link is on the improving path, then the arrow points to the row above. Network structures with one or more non-minimally connected components are necessarily off the improving paths. They are omitted unless a match ends in one of them.

Differences across treatments come exclusively from differences in payoffs (benefits of component size and cost per link). Naturally, the improving path depends on these values. We construct payoff functions that do not follow a simple functional form. Instead, our payoffs obey two simple restrictions: the benefits are strictly increasing in component size and the unit cost of a link is constant. We use this flexibility to devise treatments: (i) with no PNS network, a unique PNS network, and multiple PNS networks; and (ii) do not have focal PNS networks (the empty or the full network). For a given network configuration, a subject can receive either a positive or a negative payoff, which is represented in the figures by a black and a red dot, respectively.

Table 1 summarizes the payoff structure and outcome predictions of the four treatments, whose properties are illustrated in Figures 4–7. Treatment **N**, has *no* PNS network and a closed cycle of networks $\{B, C, D, F, G, H, N\}$ (the blue shaded area). Treatments $\mathbf{U_A}$ and $\mathbf{U_S}$ have each a *unique* PNS network (blue shade). The main difference between the two treatments lies in the asymmetry (PNS network $\{L\}$ in Treatment $\mathbf{U_A}$) v. symmetry (PNS network $\{H\}$ in Treatment $\mathbf{U_S}$) of payoffs across subjects. We conjecture that asymmetry is conducive to instability: the individual bearing the highest number of links has incentives to deviate with the intention of going back to the same network structure but in a more advantageous position.[8] Treatment **M** has *multiple* PNS networks. PNS network $\{A\}$

[8]Both $\{L\}$ in Treatment $\mathbf{U_A}$ and $\{H\}$ in Treatment $\mathbf{U_S}$ are strongly stable (robust to coalition devi-

(blue shade) is stochastically stable in the sense of Jackson and Watts (2002), therefore most robust to random perturbations to the improving paths. PNS network $\{K\}$ (yellow shade) is Pareto Superior, with strictly higher payoff for five players and the same payoff for the singleton.[9] A computation error (which we realized after running the experiment) led to the inclusion of two other Pairwise stable networks, $\{I\}$ and $\{J\}$, which are not Nash stable (pink shade). However, we show in Section 4 (Footnote 13) that the impact of their inclusion on network outcomes is small.

Table 1: Treatment Design

Treatment	Benefit (size of component)						Link Cost	PNS	Efficient
	1	2	3	4	5	6			
$\mathbf{N}^{\dagger}$	0	20	30	39	42	43	15	None	$\{O,P,Q,R,S,T\}_{[6]}$
$\mathbf{U_A}$	0	19	36	42	44	45	15	$\{L\}_{[3\text{-}3]}$	$\{O,P,Q,R,S,T\}_{[6]}$
$\mathbf{U_S}$	0	29	36	41	43	44	15	$\{H\}_{[2\text{-}2\text{-}2]}$	$\{O,P,Q,R,S,T\}_{[6]}$
$\mathbf{M}^{\S}$	0	10	17	22	38	44	15	$\{A\}_{[1\text{-}1\text{-}1\text{-}1\text{-}1\text{-}1]}$	$\{O,P,Q,R,S,T\}_{[6]}$
								$\{K\}_{[5\text{-}1]}$	

Notes: Numbers in brackets refer to the size of each component. † Networks $\{B,C,D,F,G,H,N\}$ are in the closed cycle; § Networks $\{I\}$ and $\{J\}$ are Pairwise stable.

The PNS networks can potentially be reached after zero ($\{A\}$ in Treatment $\mathbf{M}$), one ($\{H\}$ in Treatment $\mathbf{U_S}$) or two turns ($\{K\}$ in Treatment $\mathbf{M}$ and $\{L\}$ in Treatment $\mathbf{U_A}$). Therefore, while 12 turns may not seem an excessively long horizon, it provides adequate opportunities for participants to reach any PNS network. Naturally, the empirical minimum will depend on the realization of the random pairing and the behavior of participants (myopic rationality vs. forward looking).

ations) in the sense of Dutta and Mutuswami (1997) and neither of them is strongly stable in the sense of Jackson and van den Nouweland (2005). In any case, given the structure of our game with dynamic pairwise meetings, coalition deviations does not seem the most natural concept to apply.

[9]Network $\{K\}$ is also the unique von Neumann-Morgenstern pairwise farsightedly stable (VNMFS) network (Kirchsteiger et al., 2016, Definition 2). VNMFS are networks (i) from which there is no *farsighted improving path* to and from any network in the set; and (ii) to which there exists a farsighted improving path from any network outside this set. A farsighted improving path is defined as the sequence of networks that emerge when pairs of agents that decide on the linking decision consider payoffs that they will receive at an end network. Each network in this sequence differs from its predecessor by one link. A link is formed if the payoffs at this end network are beneficial to both agents. A link is removed if the payoffs at this end network are strictly beneficial for at least one agent.

To facilitate the comparison of final outcomes, in all treatments: (i) subjects always start in the empty network $\{A\}$; and (ii) the efficient networks are all the networks with one component where all six subjects are connected, that is, $\{O, P, Q, R, S, T\}$. The presence of multiple efficient networks and, in particular, network $\{T\}$ (the line that comprises all agents) should give a fair chance for the efficient outcome. Although initial and efficient networks are not next to each other, the latter can be reached after only two rounds so that, once again, agents have ample opportunities to reach any desired location in the supernetwork. Moreover, in the case of Treatment **M** and given that subjects always start at $\{A\}$, at least three non-myopic rational choices are necessary to reach the improving path leading to the Pareto Superior PNS network $\{K\}$ (see Figure 7).

3.4 Implementation

We conducted 8 sessions with 12 subjects in each session at CASSEL with UCLA students. With 12 subjects, there were always 2 groups of 6 subjects in each session, playing 2 matches simultaneously. Each subject played each of the four treatments twice. We shuffled the order of the treatments to neutralize the possible effects from the ordering within a session.[10] The analysis utilizes a total of 128 match observations (32 matches per treatment) from 96 subjects (12 subjects in 8 sessions).

To introduce anonymity, after each match we reshuffled subjects into new groups and assigned a new role (1 to 6) to each subject. Sessions lasted between 90 and 120 minutes. No subject took part in more than one session. Participants interacted exclusively through computer terminals without knowing the identity of the subjects they played with. Before the paid matches, instructions were read aloud and two practice matches were played to familiarize participants with the computer interface and procedure. Participants also had to complete a quiz to ensure they understood the rules of the experiment.

At the end of each match, subjects obtained a payoff based on the size of the component they were in (benefit) and the number of direct links (cost). Participants were endowed with experimental tokens and they could earn or lose tokens. At the end of the session, the payoffs in tokens accumulated from all experimental games were converted into cash, at the exchange rate of 4 tokens = \$1. Participants received a show-up fee of \$5, plus the amount they accumulated during the paid matches. Payments were made in cash and in private. Matches lasted between 13 and 36 turns, with an average of 16.8 turns. There was a significant spread in winnings: including the show-up fee, participants earned between

[10] Specifically: (i) the orders of the treatments in the first half and the second half of each session were different; (ii) no two sessions had identical treatment sequences; and (iii) each treatment was implemented in exactly two (out of eight) sessions for each order in the sequence.

\$11 and \$43 with an average of \$29. A copy of the instructions is included in Appendix B.

4 Network outcomes

This section reports the results on *network outcomes*, most notably convergence and stability of the final configuration. The results of our analysis are based on the final network outcomes and those conditional on convergence. We employ the operational definition of convergence suggested by Callander and Plott (2005), as the absence of change in the network configuration for the last $T = 3$ turns.[11]

Before describing the main results, we first study whether our subjects understand the basic tenets of the game. Table 2 (column 2) shows that subjects consistently avoid networks with non-minimally connected components. As discussed above, removing a link that does not change the component size strictly increases the payoffs of both agents involved, without affecting any other. Subjects understand this principle, as only 5 out of 128 matches end up in a network with a non-minimally connected component.

4.1 Pairwise Nash stability and network convergence

Hypothesis 1 *The dynamic link formation process:*

(a) *remains in the closed cycle when no PNS network exists;*

(b) *leads to a PNS network when it exists; and*

(c) *leads either to the stochastically stable PNS or the Pareto superior PNS when multiple PNS networks exist.*

The theory presented in Section 2 states that if agents follow improving paths, the linking game will lead to either the unique PNS network or, when a PNS network does not exist, a network in the closed cycle. In the latter case, we should not observe convergence. When multiple PNS network exist, it is reasonable to think that some groups will follow the myopic improving path while others will have farsighted agents who engage in transitory deviations that lead to a Pareto superior stable outcome. With these premises in mind, we begin with an analysis of the realized network outcomes.

Result 1 *Our results show that:*

[11] $T = 3$ is arbitrary. It corresponds to $6 \times 3 = 18$ individual decisions, which seems reasonably large. With a larger T, convergence decreases but the qualitative conclusions are similar ($T = 5$ is not presented for brevity but it is available from the authors).

Table 2: Network Outcomes

Treatment	Not Min. Conn. (1)	Closed cycle (2)	PNS (3)	Efficient (4)	N (5)
	Panel A. **All games**				
$\mathbf{N}$	2	21		3	32
	(0.06)	(0.66)		(0.09)	
$\mathbf{U_A}$	2	-	10	2	32
	(0.06)		(0.31)	(0.06)	
$\mathbf{U_S}$	0	-	15	0	32
	(0)		(0.47)	(0)	
$\mathbf{M}^{\dagger}$	1	-	14	5	32
	(0.03)		(0.44)	(0.16)	
	Panel B. **Conditional on convergence**§				
$\mathbf{N}$	1	1		2	5
	(0.20)	(0.20)		(0.40)	
$\mathbf{U_A}$	1	-	4	1	15
	(0.07)		(0.27)	(0.07)	
$\mathbf{U_S}$	0	-	9	0	16
	(0)		(0.56)	(0)	
$\mathbf{M}^{\dagger}$	0	-	9	4	15
	(0)		(0.60)	(0.27)	

Notes: Share with respect to N in parentheses. †All PNS network in $\{K\}$.
§Convergence is defined as maintaining the same network in final 3 turns.

(a) *when a PNS network does not exist (Treatment* $\mathbf{N}$*), most matches end in a network within the closed cycle;*

(b) *when a unique PNS network exists (Treatments* $\mathbf{U_A}$ *and* $\mathbf{U_S}$*), behavior is dispersed but the most likely outcome is the (unique) PNS;*

(c) *when multiple PNS networks exist (Treatment* $\mathbf{M}$*), behavior is also dispersed but the most likely outcome is the Pareto superior PNS and no group remains in the stochastically stable PNS; and*

(d) *no evidence of convergence to the Efficient network exists except in Treatment* $\mathbf{M}$.

Table 2 summarized the frequency (and proportion) of the final outcomes by network type in each of the treatments.[12] The results provide evidence (albeit limited) in favor of Hypothesis 1. Panel A shows that in the absence of a PNS network (Treatment **N**), 66% of matches end in a network within the closed cycle. Using turn-level data, we find that matches stay within the closed cycle most of the time: in 58% of all turns, subjects chose to be in a network within the closed cycle. Furthermore, once a turn ended in the closed cycle, subjects chose to stay in the closed cycle 76% of the time. In treatments with a unique PNS network ($\mathbf{U_A}$ and $\mathbf{U_S}$) and multiple PNS networks (**M**), subjects end up in a PNS network a significant (though not overwhelming) amount of time: 31%, 47% and 44% of matches, respectively. In addition, matches rarely end in an efficient network (except for 16% of matches in Treatment **M**) or in any other specific network of the game. Overall, PNS is an imperfect but valuable predictor of behavior in the network formation game.

Panel B shows that, as predicted by theory, convergence is least frequent in Treatment **N** where no PNS exists (5 out of 32 matches) compared to Treatments $\mathbf{U_A}$, $\mathbf{U_S}$ and **M** where more than half of the matches converge. Indeed, in Treatment **N**, myopic rational subjects are expected to move indefinitely within the closed cycle and along the improving path, which they often do.

While those results provide support for myopic rational behavior, Treatment **M** also highlights some interesting evidence of farsightedness that will be further discussed in section 5. Indeed, 44% of games ended in the Pareto superior PNS while none ended in the stochastically stable PNS.[13] This result is all the more surprising that, in order to escape the initial PNS, individuals must incur significant deviations from myopic rationality.[14] It is consistent with the findings of Kirchsteiger et al. (2016), which show higher shares of groups converging to the farsighted (VNMFS) network compared to the myopic Pairwise stable networks when the VNMFS network is unique.

In Appendix A.2 we provide a complementary analysis based on the shortest (or geodesic) distance between the observed and predicted networks (efficient, PNS, closed cycle), both conditional and unconditional on convergence. The conclusions are similar. The distance between the observed outcome and any of the efficient networks is longer than the distance between the observed outcome and the networks in the closed cycle (Treatment **N**), the unique PNS network (Treatment $\mathbf{U_S}$) or the Pareto superior PNS network

[12]Figures 4–7 provide a detailed report on number and proportion of final outcomes in each network, both conditional on no change in final 3 turns (labeled C) and unconditional on convergence (labeled U).

[13]Also, only 9% ended in one of the other two Pairwise stable networks that are not Nash stable and none converged to any of these networks.

[14]Formally, Jackson and Watts (2002) define the resistance between two networks as the minimum number of mutations (i.e., deviations from an improving path) necessary to evolve from one network to the other. In Treatment **M**, the resistance between the (starting) PNS network $\{A\}$ and the Pareto superior PNS network $\{K\}$ is four.

(Treatment $\mathbf{M}$). That result, however, does not hold for Treatment $\mathbf{U_A}$.

Finally, but importantly, we can compare the behavior between Treatments $\mathbf{U_S}$ and $\mathbf{U_A}$. As mentioned earlier, the fraction of PNS outcomes is larger in $\mathbf{U_S}$ (47%) than in $\mathbf{U_A}$ (31%), although this 16 p.p. difference is not statistically significant at conventional levels.[15] When we restrict the sample to convergent networks, the difference increases to 56 - 27 = 29 p.p. (Panel B of Table 2) and is statistically significant.[16] The difference between these two treatments is intriguing. We conjecture that the disparity may be rooted in the symmetry of payoffs of the PNS network $\{H\}$ in Treatment $\mathbf{U_S}$ [2-2-2] compared to the asymmetry of payoffs of the PNS network $\{L\}$ in Treatment $\mathbf{U_A}$ [3-3]. Indeed, in the latter case, the two agents at the center of each component have strong incentives to deviate, in the hope of reaching later on the same configuration but with someone else bearing the cost of two links. However, we would need additional treatments to investigate this hypothesis.

4.2 Payoffs

Table 3 presents the mean network payoff in each treatment. These values are compared with the theoretical payoff in the PNS network (Treatments $\mathbf{U_A}$, $\mathbf{U_S}$ and $\mathbf{M}$) and, in the case of Treatment $\mathbf{N}$, the average payoff of the networks in the closed cycle. We also compare them to the theoretical payoff in the efficient networks.

We find significant losses relative to the payoffs that could be collectively obtained: empirical payoffs are between 46% and 71% of the payoffs generated by the efficient networks. It means that playing non-cooperatively comes at a substantial cost. This is not all that surprising since efficiency requires sacrifices from some agents, which may be significant especially in networks other than $\{T\}$ (in all other networks, at least one subject obtains a weakly negative payoff).

Interestingly, empirical payoffs are remarkably close to the payoffs in the unique PNS network for Treatments $\mathbf{U_A}$ and $\mathbf{U_S}$, and also not too different from the Pareto superior PNS in Treatment $\mathbf{M}$. Therefore, while individuals do not always converge to the PNS network (Table 2), deviations are such that, on average, participants typically do not lose much from them. The results are similar when we consider only the empirical payoffs of the convergent networks. Finally, payoffs in Treatment $\mathbf{N}$ are 50% higher than the average

[15]A simple one-tailed *t-test* (*z-test*) of the likelihood of convergence to the PNS network between Treatments $\mathbf{U_S}$ and $\mathbf{U_A}$ yields a *p-value* of 0.104 (0.100).

[16]Assuming observational independence, a one-tailed *t-test* of the difference in the mean shares of the PNS final network among convergent networks has a *p-value* of 0.051. Since participants are reshuffled between matches within a session, this independence assumption may not hold. The effects are imprecisely estimated in part due to the the small number of match-level observations.

Table 3: Summary of Network Payoffs

Treatment	Empirical		Predicted		
	All	Convergent	PNS	Closed cycle	Efficient
N	63.1 (26.6)	—	—	43.1[†]	108
$\mathbf{U_A}$	85.4 (17.9)	84.8 (16.5)	96	—	120
$\mathbf{U_S}$	81.5 (12.3)	79.4 (12.8)	84	—	114
M	52.9 (44.7)	62.7 (41.5)	0 or 70[§]	—	114

Notes: Standard deviation in parenthesis. [§]Networks $\{A\}$ and $\{K\}$ respectively; [†]Unweighted average payoffs of all networks in the cycle.

payoff in the closed cycle. This means that subjects not only remain mostly within the closed cycle, they even stay more often in the high payoff networks within the cycle.[17] In section 6, we discuss heterogeneity in the payoffs of individuals.

4.3 Summary

Subjects in our game understand the strategic nature of network formation and systematically avoid networks with non-minimally connected components. The collective gain does not appear to drive the decisions of subjects who, instead, seem to focus on their individual payoffs. The unique PNS is–to some extent–predictive of behavior, especially in the case of symmetric network structures. In the absence of a PNS network, individuals remain in network structures within the closed cycle, while under multiple PNS networks, they deviate from myopic rational choices and often reach the Pareto superior PNS network. Finally, payoffs are close to PNS predictions and significantly below efficiency predictions in all treatments.

[17]In particular, almost half of the final outcomes within the closed cycle are in networks $\{F\}$ and $\{N\}$, the two highest paying networks in the cycle.

5 Single decisions

In this section, we estimate an empirical model to understand and predict each decision to stay or stray from improving paths. The uncertainty from the random pairing of partners makes it difficult to calculate an *ex ante* optimal strategy in this game. The safest response to this uncertainty is to always take myopically rational actions (Jackson and Watts, 2002). In our games, this strategy would lead to the closed cycle in Treatment $\mathbf{N}$ and to the unique PNS network in Treatments $\mathbf{U_A}$ and $\mathbf{U_S}$. However, it would perform very poorly in Treatment $\mathbf{M}$, with agents stuck in the inferior PNS network $\{A\}$. Moreover, agents in the PNS network in Treatment $\mathbf{U_A}$ and the Pareto-Superior PNS network in Treatment $\mathbf{M}$ would obtain unequal earnings, as their payoff crucially depends on their position within the network.

These considerations may lead to alternative strategies that do not consist solely of myopic rational actions. We consider three intuitive features of the linking process that might influence these strategies: the turn, the asymmetry between link formation and link deletion, and the cost of a deviation. With regards to the first feature, we conjecture that with 12 guaranteed turns, subjects may be more willing to experiment and play riskier strategies earlier in the game. As for the second, subjects may see the accumulation of excessive links as relatively less problematic, since link deletion can be implemented unilaterally whereas link formation requires mutual consent. Finally, the willingness to experiment by straying from the improving path may also be influenced by the magnitude of the potential immediate loss from that particular deviation.

5.1 Descriptive statistics

At each turn, each subject in a pair must choose to either "act" or "pass". If subjects in the pair are initially unlinked, acting implies proposing a link and passing implies remaining unlinked. Instead, if subjects are initially linked, acting implies removing a link and passing implies remaining linked. We are interested in the extent to which actions are myopic rational in each of these four cases and for each treatment.

Table 4 summarizes the proportion of myopic rational actions across turns. We organize the data into four groups of turns. We use the last certain turn that subjects get unless everyone agrees on the network outcome (Turn 12) as a natural point to partition and further split each of these partitions into two. This split captures behaviors at different stages. First, subjects attempt to get familiar with the current match and try different strategies which, with high probability, can be reversed later if desired (Turns [1-6]). Then, subjects adjust their behavior as the last certain turn approaches (Turns [7-12]). After that, subjects enter the random stopping phase where, presumably, they behave under the assumption that matches can be terminated at any time (Turns [13-18]). Finally, Turns 19 and above are set in a different category because the sample size is dramatically reduced as turns advance and the sample becomes non-representative of the population.[18]

Table 4: Myopic Rationality of Actions

	Turns			
	[1-6]	[7-12]	[13-18]	≥ 19
A. All	0.74	0.82	0.89	0.91
	(0.006)	(0.006)	(0.006)	(0.009)
B. By decision problem				
i. Stay unlinked (Pass)	0.37	0.39	0.57	0.65
	(0.025)	(0.022)	(0.035)	(0.083)
ii. Stay linked (Pass)	0.88	0.88	0.88	0.85
	(0.009)	(0.013)	(0.014)	(0.024)
iii. Remove link (Act)	0.66	0.84	0.92	0.94
	(0.010)	(0.007)	(0.007)	(0.010)
iv. Propose link (Act)	0.96	0.97	0.98	0.97
	(0.009)	(0.006)	(0.007)	(0.015)
C. By treatment				
Treatment **N**	0.83	0.83	0.88	0.94
	(0.011)	(0.011)	(0.012)	(0.014)
Treatment $\mathbf{U_A}$	0.81	0.80	0.89	0.97
	(0.012)	(0.012)	(0.012)	(0.018)
Treatment $\mathbf{U_S}$	0.76	0.79	0.90	0.92
	(0.013)	(0.012)	(0.012)	(0.018)
Treatment **M**	0.56	0.86	0.90	0.86
	(0.015)	(0.010)	(0.011)	(0.019)

Although formal tests are presented in the regression analysis of section 5.2, Table 4 is instructive. Panel A suggests that actions are more myopically rational as players get closer to the end of the match.

Panel B investigates myopic rationality by type of decision. We examine choices under

[18]The split is arbitrary. Similar results are obtained if the first and third partition are changed marginally. The key issue is to introduce a separation at Turn 12.

four mutually exclusive conditions, namely when the rational action is: (i) to pass and stay unlinked; (ii) to pass and stay linked; (iii) to remove an existing link; and (iv) to propose a new link. By comparing conditions (i) with (ii), and (iii) with (iv), we find evidence that individuals deviate more from improving paths in decisions that reduce the number of links than in decisions that increase the number of links. By comparing conditions (i) with (iii), and (ii) with (iv), subjects deviate more by being excessively passive (failing to act when they should) than by being excessively active (acting when they should not).[19] However, our regressions results (Table 9) suggest that this last result does not hold once we control for subject fixed effects and the marginal payoff from myopic rational choices.

Panel C displays myopic rationality across treatments and confirms the results of Panel A: in all four treatments, subjects are significantly less myopic rational before Turn 12 than after Turn 12 ($p < 0.001$). Interestingly, the difference in myopic rationality between [1-6] and [7-12] described in Panel A is entirely driven by Treatment **M**. This supports the hypothesis that early deviations are due in part to farsightedness. Indeed, in Treatment **M** – and only in that treatment – three instances of non-myopic rational choices are needed to escape the basin of attraction of PNS network $\{A\}$. Figure A.1 in Appendix A.3 illustrates the findings of Panels B and C for every turn of the game (up to Turn 18).

Finally, Table 5 presents the number of instances in which the group of six subjects chooses to "stay" v. "leave" the PNS network, once the group has arrived to it, broken down by treatment and turn (which naturally, excludes Treatment **N**). We also report the total number of observations (turns times number matches) in each case. Notice that leaving a network is easier than staying on it, as it only requires one out of three pairs to change the current state.

Table 5: Movements from the PNS Network

	Turns [1-12]			**Turns [$\geq$ 13]**		
	Stay	Leave	(Total)	Stay	Leave	(Total)
Treatment $\mathbf{U_A}$	17	4	384	19	1	128
Treatment $\mathbf{U_S}$	69	24	384	44	0	143
Treatment **M** - $\{A\}$	0	32†	384	–	–	177
Treatment **M** - $\{K\}$	51	19	384	67	9	177

Notes: † All movements away from $\{A\}$ were performed on the first turn.

[19] A set of t-tests (not reported for brevity) confirms that for each turn group, the mean differences in myopic rationality both between conditions (i) and (iii) and between conditions (ii) and (iv) are negative and statistically significant at the 0.1 percent level.

Although the most frequent action is to stay in the PNS network once it is reached, there is still a non-negligible fraction of instances in Turns [1-12] where individuals leave it (19% to 26%). This tendency practically disappears in the treatments with a unique PNS network ($\mathbf{U_A}$ and $\mathbf{U_S}$) when each turn can be final. Surprisingly, even though Treatment **M** has a rather predictable outcome (44% of matches end up in the Pareto superior PNS network, see Table 2), subjects sometimes leave that network even after Turn 12. By contrast, individuals invariably leave the stochastically stable but low-payoff PNS network $\{A\}$ in Turn 1 and *never* come back to it.

5.2 Regression Analysis

In this section, we present a regression analysis of individual decisions. We first describe the empirical specification and estimation strategy that we will use to test the subsequent hypotheses. Then, we describe our hypotheses followed by the results.

5.2.1 Specification

As a formal test, we estimate a linear probability model (LPM) with individual fixed effects and regress the probability that a subject chooses the myopic rational action on the attributes of the problem. We choose LPM with fixed-effects instead of a non-linear model (e.g., logit) because its coefficients are easier to interpret, especially in the presence of both fixed-effects and interaction terms where the derivation of marginal effects can be non-trivial (Ai and Norton, 2003; Greene, 2010).[20] For each treatment, we estimate the following specification:

$$\mathbb{P}(Y_{nt} = 1 \mid \mathbf{X_{nt}}, c_n) = \beta_0 + \mathbf{X_{nt}}\,\boldsymbol{\beta} + c_n \tag{1}$$

where Y_{nt}^{ij} indicates whether the action that moves subject n at Turn t is myopic rational ($= 1$) or not ($= 0$), and $\mathbf{X_{nt}^{ij}}$ captures the vector of attributes. Meanwhile, c_n captures the unobservable characteristics of subject n which may affect how she makes decisions. Unobservable individual characteristics are unlikely to be independent from the attributes of the decisions, and hence, we implement an individual fixed effects specification. The standard errors are clustered at the session level. At the end of the section, we briefly discuss some extensions and alternative representations.

[20]In Appendix A.1, we show that the partial effects estimates are qualitatively similar using an LPM and a Logit model with interactions (but without fixed effects), as one would expect (Wooldridge, 2010, p.563). We do not consider the fixed-effects Probit model given its known bias (Greene, 2004).

We can use the regression framework to investigate the four types of decisions described in Panel B of Table 4. Consider first the following reduced specification:

$$\mathbb{E}(Y_{nt}^{ij} \mid \mathbf{X}) = \beta_0 + \beta_1 \cdot morelink_{ij} + \beta_2 \cdot act_{ij} + \beta_3 \cdot (morelink_{ij} \times act_{ij}) + \varepsilon \qquad (2)$$

where $morelink_{ij}$ and act_{ij} are dummy variables and ε is the residual. The variable $morelink_{ij}$ takes on a value of 1 if between networks i and j the network with more links gives the individual a higher payoff. The variable act_{ij} takes on a value of 1 if the myopic rational choice is to act (Propose or Remove) instead of pass.

Under the LPM, the interpretation of these β-coefficients is straightforward. The coefficient β_0 captures the probability that a subject stays unlinked in accordance to the myopic rational strategy (myopic rat.). Similarly, $\beta_0 + \beta_1$ captures the probability that a subject stays linked in accordance to the myopic rational strategy. Table 6 provides interpretations for the different combinations of coefficients.

Table 6: Regression Coefficients and Types of Decision Problems

	Interpretation	$more\ link_{ij}$	act_{ij}	Function
i.	$\mathbb{P}$(myopic rat. | myopic rat. = stay unlinked)	0	0	β_0
ii.	$\mathbb{P}$(myopic rat. | myopic rat. = stay linked)	1	0	$\beta_0 + \beta_1$
iii.	$\mathbb{P}$(myopic rat. | myopic rat. = remove link)	0	1	$\beta_0 + \beta_2$
iv.	$\mathbb{P}$(myopic rat. | myopic rat. = propose link)	1	1	$\beta_0 + \beta_1 + \beta_2 + \beta_3$

We extend this basic specification with three sets of additional variables (and the individual fixed effects) to explore individual strategies. The specification for the extended model is:

$$\begin{aligned}\mathbb{E}(Y_{nt}^{ij} \mid \mathbf{X}) = \beta_0 + \beta_1 \cdot morelink_{ij} + \beta_2 \cdot act_{ij} + \beta_3 \cdot (morelink_{ij} \times act_{ij}) \\ + \gamma \cdot mpay_{ij} + \textstyle\sum_{t=1}^{4} \chi_t \cdot turn\_sp(t) + c_n + \varepsilon\end{aligned} \qquad (3)$$

where $mpay_{ij}$ denotes the marginal payoff from making a myopic rational choice to evolve from network i to network j. We also include a linear spline on the turn variables, $turn\_sp$, with knots at turns 6, 12, and 18 to control for possible turn effects.[21] The knot choices mimic the turn grouping we did for the descriptive analysis.

[21]Hence, the variable $turn\_sp(1)$ is the spline for Turns [1-6], $turn\_sp(2)$ is for Turns [7-12], $turn\_sp(3)$ is for Turns [13-18] and $turn\_sp(4)$ is for Turns 19 and greater.

5.2.2 Hypothesis and results

Hypothesis 2 *Subjects are more likely to follow the improving path:*

(*a*) *After Turn 12;*

(*b*) *When the myopic rational action increases the number of links;*

(*c*) *When the marginal loss from a deviation is larger;*

(*d*) *When deviations are not necessary to reach a (Pareto-Superior) PNS.*

Hypothesis 2(a) posits that behavior may become more myopic rational when the current turn can be the final one, and therefore potentially irreversible. Hypothesis 2(b) suggests that when it is easier to reverse excessive links than insufficient links (because link formation requires mutual consent whereas link deletion does not), subjects are more willing to deviate by hoarding links. Hypothesis 2(c) builds on the idea that the cost of a "mistake" may affect the decision to stray from the improving path. Finally, Hypothesis 2(d) states that farsighted individuals may choose non-myopic rational actions in order to reach collectively superior outcomes. Our test of these hypotheses yields the following results.

Result 2 *Our analysis shows that:*

(a) Actions are more myopic rational after Turn 12.

(b) In early turns, subjects deviate from improving paths by maintaining excessive links (over-proposing and not removing redundant links). In later turns, subjects deviate by not removing redundant links.

(c) The size of marginal payoffs affects the likelihood of a deviation from myopic rationality in early turns of all treatments.

(d) Choices in early turns of Treatment **M** *are less myopic rational compared to those in the other treatments, which is suggestive of forward-looking behavior.*

We find strong evidence for Hypothesis 2(a). Table 7 below presents the results of regressing the likelihood of a myopic rational action on whether an observation comes after Turn 12. Consistent with the t-test of mean differences performed in section 5.1 (Table 4), we find a statistically significant and positive increase in myopic rationality among actions taken after Turn 12.[22]

[22] In Appendix A.4, we perform more elaborate tests with interactions between the turn dummy variable and the characteristics of the decision problem and find similar results. We also performed a simple regression of the time it took individuals to take an action and found no significant differences across treatments or turns (data omitted for brevity).

Table 7: Myopic Rational Action Before and After Turn 12

	$\mathbf{N}$ (1)	$\mathbf{U_A}$ (2)	$\mathbf{U_S}$ (3)	$\mathbf{M}$ (4)
$\mathbb{1}$(turn>12)	0.064***	0.072***	0.131***	0.136***
	(0.010)	(0.018)	(0.031)	(0.017)
morelink	0.128***	0.112***	0.142***	0.147***
	(0.022)	(0.019)	(0.015)	(0.009)
act	-0.292***	-0.498***	-0.281***	-0.210*
	(0.069)	(0.032)	(0.033)	(0.092)
morelink × act	0.205**	0.443***	0.269***	0.044
	(0.065)	(0.025)	(0.042)	(0.104)
mpay	0.002**	0.004***	0.006***	0.019***
	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.801***	0.776***	0.690***	0.470***
	(0.026)	(0.021)	(0.016)	(0.021)
Individual Fixed Effects	Yes	Yes	Yes	Yes
Observations	3276	3072	3162	3366
Adj. R^2	0.165	0.252	0.246	0.224

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

With Hypothesis 2(b), we test whether subjects incorporate the asymmetric need for consent between link formation v. link removal in their strategies. Since link formation requires mutual consent while removal does not, one possible strategy would be to form and maintain some redundant links early on. As the game approaches the end, subjects begin to unilaterally remove some of them. Table 8 presents the regression results based on equation (1) with individual fixed effects. Its bottom panel presents estimates of the linear combinations of the different coefficients. These linear combinations are derived from Table 6 to allow immediate comparisons of the probabilities that individuals make myopic rational choices for the different decision problems.

Our regressions provide evidence in support of Hypothesis 2(b). Table 8 shows that in Turns [1-12] the coefficient for myopic rationality in all four treatments is highest when the myopic rational action is to stay linked (ii), followed by propose a link (iv), stay unlinked (i), and remove a link (iii). For Turns [$\geq$ 13], subjects are still most likely to deviate by not removing a link when they should (iii); however, they deviate less in Turns [$\geq$ 13] compared to in Turns [1-12].[23] Overall, the evidence suggests that subjects use redundant links as a form of insurance, as was found in Deck and Johnson (2004).

[23]Since players are assigned a fixed role ID, we add role ID to the specification in Eq.1. We found no systematic effect of role ID on myopic rationality (table omitted for brevity).

Table 8: Myopic Rationality and Types of Decision Problems

	Turns [1-12]				Turns [$\geq$ 13]			
	N	$\mathbf{U_A}$	$\mathbf{U_S}$	**M**	**N**	$\mathbf{U_A}$	$\mathbf{U_S}$	**M**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
morelink [β_1]	0.168***	0.144***	0.233***	0.256***	0.040	0.072**	0.097**	0.015
	(0.026)	(0.022)	(0.010)	(0.010)	(0.031)	(0.029)	(0.033)	(0.012)
act [β_2]	-0.265***	-0.512***	-0.277***	-0.267**	-0.374***	-0.418***	-0.168***	-0.074
	(0.062)	(0.027)	(0.047)	(0.101)	(0.105)	(0.077)	(0.046)	(0.055)
morelink × act [β_3]	0.173***	0.444***	0.263***	0.182	0.287*	0.335***	0.201***	-0.068
	(0.045)	(0.025)	(0.055)	(0.098)	(0.130)	(0.062)	(0.050)	(0.072)
Constant [β_0]	0.809***	0.816***	0.731***	0.664***	0.942***	0.921***	0.878***	0.916***
	(0.017)	(0.012)	(0.006)	(0.010)	(0.020)	(0.018)	(0.010)	(0.016)
Linear combinations								
i. β_0	0.809***	0.816***	0.731***	0.664***	0.942***	0.921***	0.878***	0.916***
[stay unlinked]	(0.017)	(0.012)	(0.006)	(0.010)	(0.020)	(0.018)	(0.010)	(0.016)
ii. $\beta_0 + \beta_1$	0.977***	0.960***	0.964***	0.920***	0.981***	0.993***	0.976***	0.931***
[stay linked]	(0.020)	(0.012)	(0.008)	(0.014)	(0.014)	(0.027)	(0.030)	(0.016)
iii. $\beta_0 + \beta_2$	0.544***	0.303***	0.454***	0.397***	0.568***	0.503***	0.711***	0.842***
[remove link]	(0.047)	(0.019)	(0.044)	(0.094)	(0.094)	(0.072)	(0.044)	(0.045)
iv. $\beta_0 + \beta_1 + \beta_2 + \beta_3$	0.885***	0.892***	0.950***	0.835***	0.894***	0.909***	1.009***	0.789***
[propose link]	(0.015)	(0.015)	(0.019)	(0.023)	(0.030)	(0.046)	(0.039)	(0.055)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2304	2304	2304	2304	972	768	858	1062

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hypothesis 2(c) examines the impact of payoff magnitudes on choices. With a myopic rational strategy, the extent of the marginal payoff should be irrelevant. This contrasts with stochastic choice theories (random utility model, quantal response equilibrium, etc.) where mistakes are less prevalent if the associated costs are higher. It also relates to the traditional exploration-exploitation dilemma, where lower opportunity costs are conducive to the inspection of alternative (hopefully better) options. The extended specification of equation (3) allows us to investigate this possibility. We interact the payoff variable with the interactions between *morelink* and *act* to capture differential effects of marginal payoffs across decision problems.

The results of the regressions are presented in Table 9. We linearly combine the coefficients for the payoff variables to explore the heterogeneity of the payoff-size effects across decision problems. We use a strategy similar to the way we linearly combined in Table 6 the coefficients of the *morelink*, *act* and *morelink* $\times$ *act* variables to examine the myopic rationality of the different decision problems. Hence, for example, γ_0 measures how the size of the marginal payoff affects the probability that subjects take the myopic rational choice to stay unlinked, and so on.

For Turns [1-12] in Treatments **N**, $\mathbf{U_A}$ and $\mathbf{U_S}$, myopic rational actions are positively and significantly correlated with the size of marginal payoffs if the myopic rational action reduces the number of links (cases (i) and (iii)). For Treatment $\mathbf{U_A}$ it is also correlated if the myopic rational action increases the number of links. Several of these coefficients lose their significance in Turns [$\geq$ 13]. Meanwhile, for Treatment **M**, all of the payoff-coefficients are significant in both [1-12] and [$\geq$ 13] except when the myopic rational choice is to remove a link. These results support Hypothesis 2(c) and provide additional insights on how subjects deviate from improving paths. The evidence suggests that subjects pay more attention (and react more) to the opportunity loss from staying unlinked, especially early in the game.

Finally, with Hypothesis 2(d), we conjecture that strategic agents would deviate from improving paths if it is necessary to reach a collectively superior outcome. By design, such deviations are only pertinent for Treatment **M**: they are necessary to escape the zero payoff, stable network {A} in the first few turns. We therefore expect a lower share of myopic rational actions in the early turns of Treatment **M** compared to the later turns of that treatment and to all turns of the other treatments.

We find empirical support for this hypothesis. We regress the myopic rationality of decisions on an indicator variable for Treatment **M** and present the results in Table 10. Panel A shows that when pooled across all decision types (column 1), individual actions are more likely to deviate from myopic rationality in Turns [1-6]. Columns 2–5 show a higher

Table 9: Myopic Rationality and Marginal Payoffs

	Turns [1-12]				Turns [≥ 13]			
	N (1)	$\mathbf{U_A}$ (2)	$\mathbf{U_S}$ (3)	**M** (4)	**N** (5)	$\mathbf{U_A}$ (6)	$\mathbf{U_S}$ (7)	**M** (8)
morelink	0.335***	0.496***	0.355***	0.500***	0.156	0.118**	0.151	0.109**
	(0.053)	(0.141)	(0.044)	(0.106)	(0.092)	(0.049)	(0.092)	(0.036)
act	-0.313**	-0.617***	-0.385***	0.283***	-0.081	0.085	-0.389**	0.167
	(0.104)	(0.154)	(0.059)	(0.072)	(0.159)	(0.311)	(0.145)	(0.097)
morelink × act	0.217*	0.583***	0.471***	-0.286***	-0.026	-0.241	0.527**	-0.486**
	(0.113)	(0.153)	(0.045)	(0.068)	(0.172)	(0.349)	(0.187)	(0.165)
mpay [γ_0]	0.012**	0.029**	0.018***	0.039***	0.011**	0.006**	0.012*	0.015***
	(0.004)	(0.010)	(0.003)	(0.007)	(0.004)	(0.002)	(0.005)	(0.002)
mpay × morelink [γ_1]	-0.013***	-0.026**	-0.017***	-0.030***	-0.010	-0.005	-0.010	-0.007**
	(0.004)	(0.010)	(0.003)	(0.008)	(0.006)	(0.004)	(0.006)	(0.002)
mpay × act [γ_2]	0.008	0.017	0.010	-0.051***	-0.032	-0.043	0.026	-0.021*
	(0.009)	(0.011)	(0.006)	(0.010)	(0.024)	(0.029)	(0.015)	(0.011)
mpay × morelink × act [γ_3]	-0.008	-0.017	-0.013*	0.048***	0.033	0.047	-0.031*	0.031**
	(0.009)	(0.012)	(0.006)	(0.011)	(0.023)	(0.031)	(0.015)	(0.013)
Constant	0.652***	0.390**	0.502***	-0.035	0.750***	0.803***	0.775***	0.719***
	(0.060)	(0.139)	(0.048)	(0.038)	(0.072)	(0.041)	(0.049)	(0.042)
Linear combinations								
i. γ_0	0.012**	0.029**	0.018***	0.039***	0.011**	0.006**	0.012*	0.015***
[stay unlinked]	(0.004)	(0.010)	(0.003)	(0.007)	(0.004)	(0.002)	(0.005)	(0.002)
ii. $\gamma_0 + \gamma_1$	-0.001	0.003**	0.002	0.009***	0.001	0.001	0.001	0.008***
[stay linked]	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
iii. $\gamma_0 + \gamma_2$	0.020**	0.046***	0.028***	-0.012	-0.021	-0.037	0.038**	-0.006
[remove link]	(0.006)	(0.007)	(0.006)	(0.010)	(0.025)	(0.028)	(0.012)	(0.011)
iv. $\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$	-0.000	0.002**	-0.002	0.006***	0.002	0.005	-0.004	0.018***
[propose link]	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.005)	(0.003)
Turn spline variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2304	2304	2304	2304	972	768	858	1062

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Myopic Rationality and Treatment **M**

	All decision types	Myopic rational action to [. . .]			
		stay unlinked	stay linked	remove link	propose link
	(1)	(2)	(3)	(4)	(5)
	Panel A. Decisions in Turns [1-6]				
Treatment **M**	-0.242***	-0.270***	-0.098**	-0.057	-0.098**
	(0.024)	(0.022)	(0.028)	(0.076)	(0.030)
Constant	0.805***	0.748***	0.977***	0.392***	0.900***
	(0.006)	(0.007)	(0.006)	(0.025)	(0.004)
Observations	4608	2254	538	364	1452
Adj. R^2	0.0924	0.176	0.141	0.212	0.0844
	Panel B. Decisions in Turns [7-12]				
Treatment **M**	0.046*	0.037	-0.070***	0.052	-0.021
	(0.020)	(0.029)	(0.017)	(0.090)	(0.049)
Constant	0.810***	0.827***	0.988***	0.384***	0.887***
	(0.005)	(0.008)	(0.005)	(0.013)	(0.012)
Observations	4608	2578	855	482	693
Adj. R^2	0.0709	0.125	0.0711	0.0682	0.253
	Panel C. Decisions in Turns [$\geq$ 13]				
Treatment **M**	-0.007	-0.005	-0.056**	0.184*	-0.101
	(0.013)	(0.017)	(0.018)	(0.092)	(0.093)
Constant	0.901***	0.924***	0.995***	0.552***	0.897***
	(0.004)	(0.005)	(0.006)	(0.015)	(0.024)
Observations	3660	1972	633	230	825
Adj. R^2	0.0699	0.0953	0.000907	0.0677	0.238
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

rate of deviations in Treatment **M** across all decision types, and they are all statistically significant except for when the rational action is to remove a link (column 4).[24] Consistent with an attempt to escape network {A}, the magnitude of the coefficient is largest for the decision to stay unlinked (column 2). Panels B and C show that the difference between Treatment **M** and all other treatments vanishes in Turns [7-12] and Turns [$\geq$ 13], except for when the rational action is to stay linked (column 3). It reinforces the idea that deviations are motivated by farsightedness, and therefore have an effect only in the first few turns.

This finding provides evidence for forward-looking behavior in a fairly complicated network formation game. It is in line with Pantz (2006) who found that some subjects manage to reach the forward-looking network structure, as well as Kirchsteiger et al. (2016) who found evidence for farsightedness, although only in cases that require one or two anticipatory steps. Payoff-motivated deviations are particularly impressive in our setting given the substantial complexity of the environment: a large network (six subjects), a significant resistance (four mutations to evolve from the starting stable network to the Pareto superior PNS network), and a considerable uncertainty (due to random pairing and random ending).

As a robustness check, in Appendix A.5, we use a parsimonious model that incorporates insights from Result 2 to conduct an out-of-sample (or out-of-treatment) exercise. We estimate a logit model (without individual fixed effects) of myopic rationality that takes into account the importance of marginal payoff, group sizes, and stages of the game (before/after Turn 12). We then estimate the coefficients of the model with a sample that excludes observations from each of the treatments and use these coefficients to predict myopic rationality in the excluded treatment. We show that a parsimonious model based on these results predicts myopic rationality of actions rather well.

5.3 Summary

The analysis at the single decision level suggests that subjects take for the most part the myopic rational action. At the same time, we highlight *important* and *systematic* deviations. Indeed, we observe less myopically-rational actions in turns with a sure future than in random-ending turns. Deviations also tend to take the form of excessive links, possibly because they can be removed unilaterally, although proving this hypothesis would require further work. Deviations are also more prevalent the smaller the marginal payoff losses, as expected in a behavioral theory where "mistakes" depend inversely on loss magnitudes. Finally, deviations also occur as a sign of farsightedness, that is, when they are needed in order to escape a low-payoff PNS network and reach a high-payoff PNS one.

[24] The lack of statistical significance is likely due to the fact that, as discussed earlier, redundant links are used as insurance in all treatments. Therefore the share of myopic rational actions are small overall.

6 Choices by subjects

So far we have studied choices at the network outcome and single decision levels. One question that remains unanswered is the degree of heterogeneity between subjects. A simple way to address this question is to take an intermediate approach and determine how often *each subject* plays the myopic rational strategy.

Figure 2 plots the cumulative distribution function (CDF) of the fraction of myopic rational choices by each subject in each treatment. A steep CDF reflects homogeneity across subjects whereas a right shift captures a more myopic rational behavior on aggregate. In Treatments **N**, $\mathbf{U_A}$ and $\mathbf{U_S}$ behavior is to a large degree myopic rational and homogeneous: 80% of subjects choose the myopic rational action 75% of the time or more. In Treatment **M**, behavior is slightly less myopic rational and more heterogeneous. A Kolmogorov-Smirnov test confirms this observation: the CDF of Treatment **M** is different from the CDF of Treatments **N**, $\mathbf{U_A}$ and $\mathbf{U_S}$ at the 1% level, whereas no statistical difference is observed between the CDFs in Treatments **N**, $\mathbf{U_A}$ and $\mathbf{U_S}$ at the 10% level.

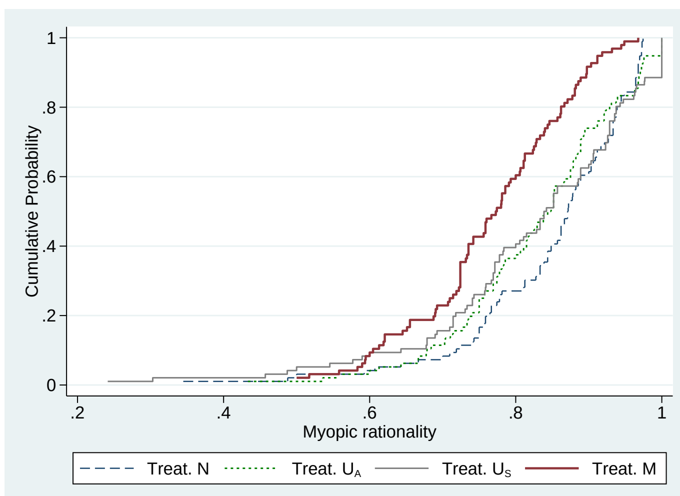


Figure 2: Empirical CDF of myopic rationality by treatment

Heterogeneity can also be studied by searching for clusters of people (as in Camerer and Hua Ho (1999) for example). This allows us to quantify the degree of similarity of subjects' choices within and between clusters. We use documented differences in behavior across treatments and turns to choose the clustering variables (see Table 4, Panel C). A test of differential myopic rationality between Turns [1-6] and [7-12] shows that the difference is only statistically significant for Treatment **M**, whereas myopic rationality before and after Turn 12 is significant in all treatments. We therefore retained four variables: myopic rationality in Treatments **N**, $\mathbf{U_A}$, and $\mathbf{U_S}$ before Turn 12; myopic rationality in Turns [1-6] and in Turns [7-12] in Treatment **M**; and myopic rationality in Turns [$\geq$ 13] in all treatments.

There are many clustering methods but they usually require the number of clusters and the clustering criterion to be set ex-ante rather than endogenously optimized. Mixture models, on the other hand, treat each cluster as a component probability distribution. Thus, the choice of the model and the number of clusters is made using Bayesian statistical methods (Fraley and Raftery, 2002). Following Brocas et al. (2014), we implement a model-based clustering analysis with the *mclust* package in R (Scrucca et al., 2016). We use *mclust*'s default values for the maximum number of clusters (nine) and models (fourteen) to consider. The algorithm allows cluster distributions to be diagonal, spherical, or ellipsoidal and clusters to have equal or varying volumes, shapes and orientations. It then finds the combination of model and number of clusters that yields the maximum Bayesian Information Criterion (BIC).

Hypothesis 3 *There are three types of subjects: (i) myopic rational, (ii) random, and (iii) strategic (who deviate from myopic rationality only in early turns, especially in Treatment* ***M****). Earnings are lowest for random subjects and highest for strategic subjects.*

We anticipate substantial heterogeneity across individuals. In a game where the option value of farsightedness is difficult to compute, focusing exclusively on the current costs and benefits of an action, as 'myopic rational' subjects would do, seems a plausible, reasonably sophisticated strategy. Since the game is inherently difficult, we also expect to observe some individuals to be "lost in the network", and exhibit close to 'random' behavior. Finally, the most intriguing behavior relates to subjects who realize the appeal of myopic rational choices but also try to exploit its shortcomings. These 'strategic' subjects will deviate more frequently early in the game (when actions are reversible) and in Treatment **M** (where the deviation is necessary to escape the low payoff stable network and reach the Pareto superior stable one). They are also expected to accumulate the highest earnings.

Result 3 *Individuals are endogenously grouped into: (i) a cluster with (mostly) myopic rational behavior (48%); (ii) a cluster with (mostly) random behavior (8% of subjects); and (iii) two clusters with different degrees of strategic behavior (44%). Earnings are lowest for subjects with erratic behavior, but are not very different between the remaining clusters.*

Figure 3 depicts the performance of the models as a function of the distribution, shape, volume, orientation and number of clusters. Models with a small number of clusters (two to four) outperform models with a large number of clusters. The model that maximizes the BIC–which we will retain for our analysis–has *four* clusters with diagonal distribution, varying volume and equal shape (VEI).[25]

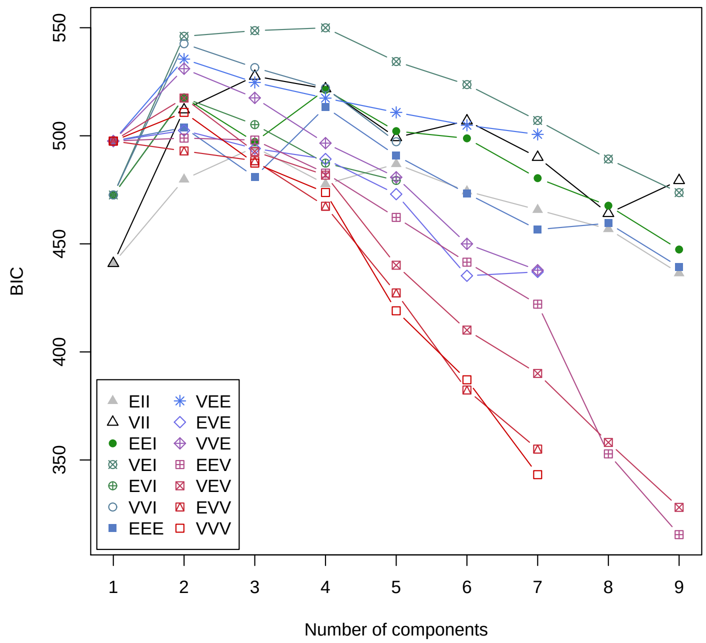


Figure 3: Bayesian Information Criterion (BIC) by model and number of clusters

Table 11 shows the average myopic rationality for each cluster and clustering variable in the four-cluster VEI model. We also report the overall frequency of myopic rational choices, average earnings, and number of subjects in the cluster. The clusters are sorted based on the overall myopic rationality (column 5), from highest to lowest.

Subjects in Cluster 1 are the most myopic rational. They exhibit some strategic behavior by deviating from the improving path in the early turns of Treatment **M**, but even then, they take more myopic rational actions compared to those in other clusters. They very rarely deviate from myopic rationality during the stochastic ending turns. On the opposite end, subjects in Cluster 4 are the least myopic rational in all stages of the game and do not adjust their actions in the stochastic ending turns. This cluster represents the

[25] In Appendix A.6 we provide a graphical representation of the clusters in two-dimensional projections to visually assess the degree of homogeneity within clusters and heterogeneity across clusters.

Table 11: Clustering Based on Myopic Rational Behavior

Cluster	Treatment and Turn				Total Myopic Rational	Earnings	N
	N-$\mathbf{U_A}$-$\mathbf{U_S}$	**M**		All			
	[1-12]	[1-6]	[7-12]	[≥ 13]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	0.86	0.66	0.94	0.94	0.87	93.7	46
	(0.010)	(0.02)	(0.009)	(0.006)	(0.007)	(4.2)	
2	0.82	0.46	0.92	0.82	0.80	96.7	14
	(0.01)	(0.02)	(0.01)	(0.009)	(0.006)	(6.5)	
3	0.76	0.46	0.73	0.92	0.78	95.2	28
	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)	(5.4)	
4	0.64	0.52	0.68	0.67	0.64	90.4	8
	(0.04)	(0.08)	(0.06)	(0.03)	(0.03)	(11.5)	

Notes: Standard errors in parenthesis.

set of subjects with severe difficulties in understanding the most basic strategic aspects of the game.

Meanwhile, Clusters 2 and 3 capture two different behaviors among the strategic subjects. Column 5 shows similar rates of myopic rationality in these two clusters. In support of Hypothesis 2(d), subjects in both clusters seem to grasp the strategic necessity of deviating in the first 6 turns of Treatment **M** (column 3). However, subjects in Cluster 2 do not adapt their endgame strategy by taking more myopic rational actions after Turn 12. In contrast, and in accordance to Hypothesis 2(a), subjects in Cluster 3 deviate significantly more often before turn 12 than after turn 12 in all treatments. They are, arguably, the most strategic subjects.

Earnings are the lowest for subjects who exhibit random-like behavior (Cluster 4), but are not very different among the remaining three clusters. This can be expected for two reasons. First, because PNS networks do not necessarily generate the highest payoffs. Second, because payoffs in this game are (very) noisy signals of the strategy followed by the individual: one's payoff depends on the behavior of the five other subjects in the network as well as the subject's final position in the component. The most strategic subjects may be negatively affected by individuals who use suboptimal strategies. Also a strategic subject may move the group towards the PNS network but, in the process, end up bearing a larger number of links.

To investigate the effect of subject composition on network outcomes, we count for each match the number of subjects from each cluster. We then regress whether the match ended in a cycle (for Treatment **N**), the PNS network (for Treatments $\mathbf{U_A}$ and $\mathbf{U_S}$), or the Pareto-superior PNS network (for Treatment **M**) on the number of subjects from each cluster. Cluster 1, whose subjects' behavior is most similar to those assumed in theory, is the omitted category in the regression. The models are estimated with session fixed effects and the results are presented in Table 12.

Table 12: Cluster and Network Outcomes

	N (1)	$\mathbf{U_A}$ (2)	$\mathbf{U_S}$ (3)	**M** (4)
Cluster 2	-0.17	-0.28	-0.16	-0.27**
	(0.13)	(0.18)	(0.17)	(0.10)
Cluster 3	-0.20	0.03	-0.15	-0.09
	(0.11)	(0.23)	(0.13)	(0.10)
Cluster 4	-0.20	0.05	-0.29***	0.20
	(0.20)	(0.14)	(0.04)	(0.12)
Constant	1.25***	0.48	1.02**	0.74**
	(0.17)	(0.46)	(0.34)	(0.27)
Session FE	Yes	Yes	Yes	Yes
Observations	32	32	32	32
R^2	0.18	0.30	0.40	0.33

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We find that the subject composition significantly affects the network outcome in Treatments $\mathbf{U_S}$ and **M**. In the former, the presence of the least sophisticated Cluster 4 subjects negatively affects the likelihood of ending in the PNS network with symmetric payoffs. In the latter, the presence of Cluster 2 subjects — who do not adapt their endgame strategy by becoming more myopic rational after Turn 12 — reduces the likelihood of ending in the Pareto-superior PNS network. The proportion of different subject types does not influence the outcome in Treatments **N** and $\mathbf{U_A}$.

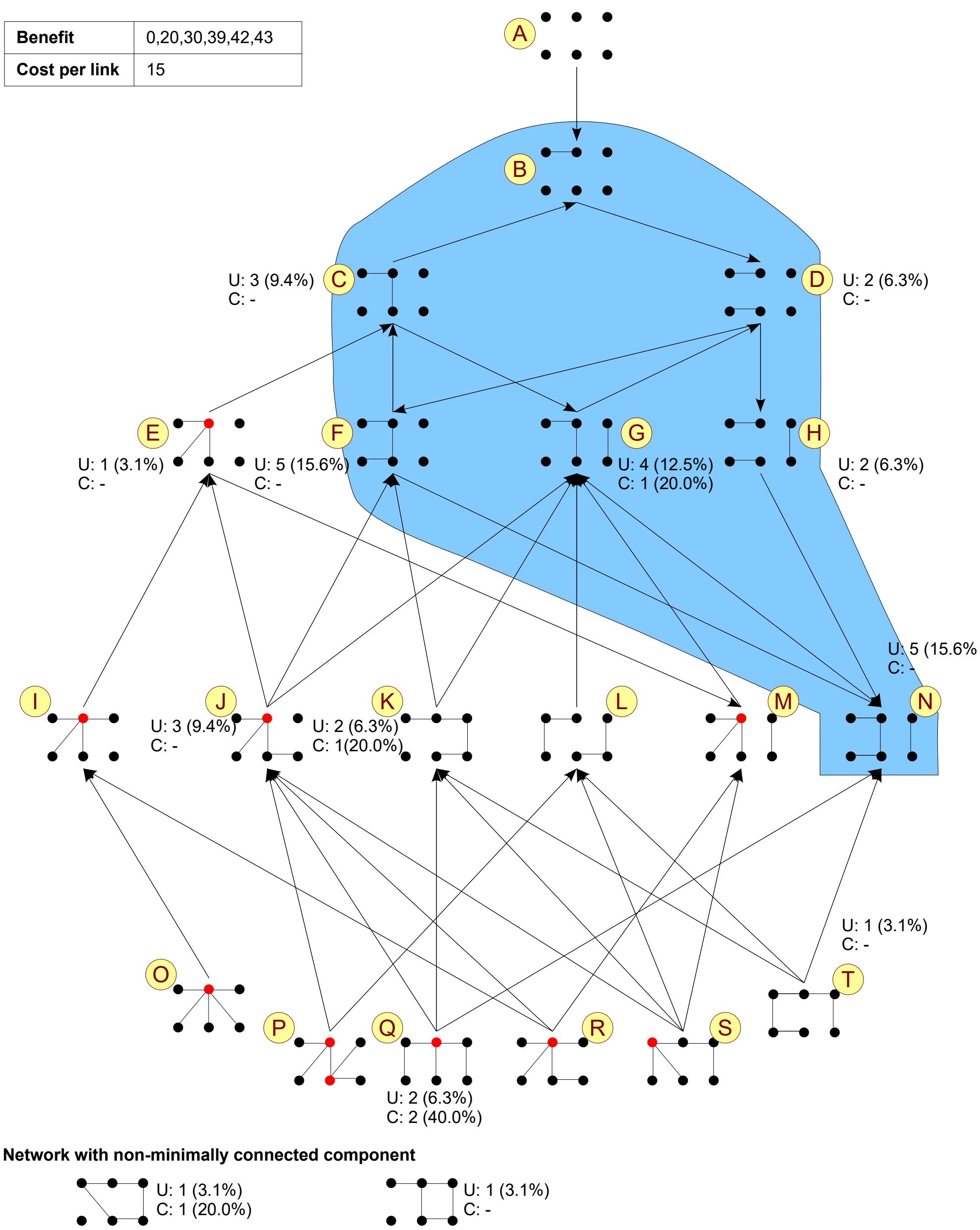
Overall, the cluster analysis highlights the significant heterogeneity in individual behavior, especially with respect to the level of myopic rational decisions across turns and treatments. It also demonstrates the importance of group composition for network outcomes and earnings, with the presence of a random player significantly decreasing the likelihood of reaching some PNS networks.

7 Conclusion

We study the dynamic formation of networks where links are formed through mutual consent, but can be removed unilaterally. Our subjects rarely converge to the efficient network (the network where all six subjects are connected), which suggests that they do not consider the total value of the network as a key criterion when making their decisions. Instead, choices are largely consistent with (mostly myopic) individual maximization of payoffs. The process often, but certainly not always, converges to the PNS network if it exists. Interestingly, not all PNS networks are equal, and a symmetric network structure seems to predict network outcomes better. We also observe significant deviations whenever they are necessary to leave a low-payoff PNS and reach a Pareto Superior one. As for single decisions, although myopic rationality is predominant, we also observe systematic deviations from it. In particular, myopic rationality is less prevalent at the margin when actions are reversible, when marginal payoff losses are smaller, and when actions involve excessive links that can be removed unilaterally later on. Finally, we also notice a significant heterogeneity in behavior across subjects, with a combination of myopic rational, strategic and random subjects.

Despite the recent advances, there is still much to learn about network formation, both theoretically and experimentally. On the theory front, it would be interesting to incorporate behavioral imperfections into existing models. The tendency observed in our data towards fewer deviations from myopic rationality as marginal losses increase and as matches enter the probabilistic ending phase suggests that individuals optimize subject to imperfect choice, imperfect foresight and/or imperfect understanding of the game. To our knowledge, however, no model has yet been developed to capture these frictions. On the experimental front, ecological validity is a concern. Indeed, we feel that our cost and benefit representation of adding and removing links captures the essence of social networks in an excessively stylized and abstract way. The use of laboratory studies in the field or laboratory studies that exploit social technologies (Facebook, Twitter, LinkedIn, etc.) would add a more realistic dimension to the network formation problem without compromising the controlled environment of the laboratory.

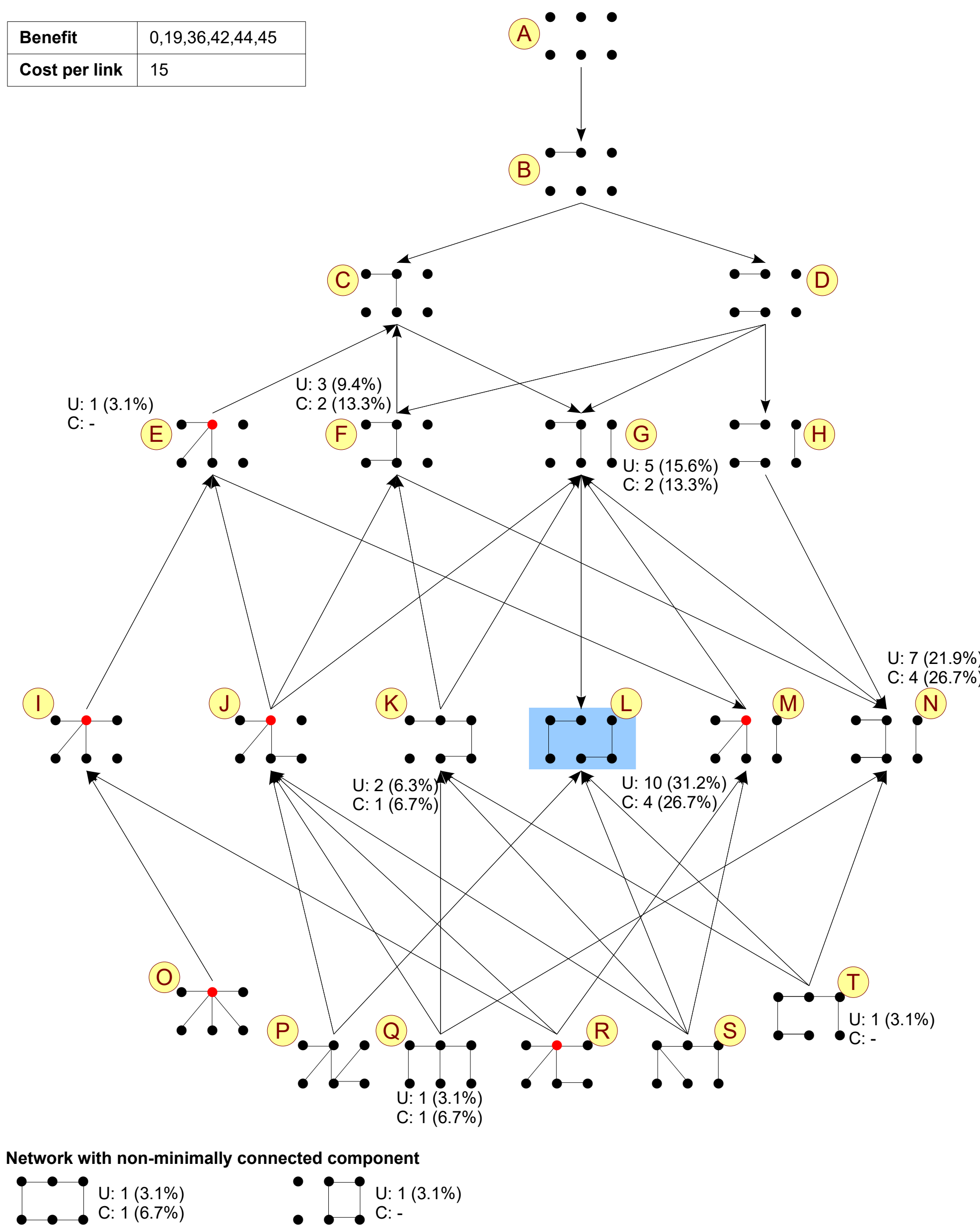
Benefit	0,20,30,39,42,43
Cost per link	15



Notes. Letters refer to all minimally connected network structures. Numbers next to each network refer to the frequency (and percentage) that the process ends in that network: U = Unconditional on convergence, C = Conditional on no change in the last 3 turns. Networks that are part of the closed cycle are inside the shaded region.

Figure 4: Treatment **N**. No PNS network and a Closed Cycle.

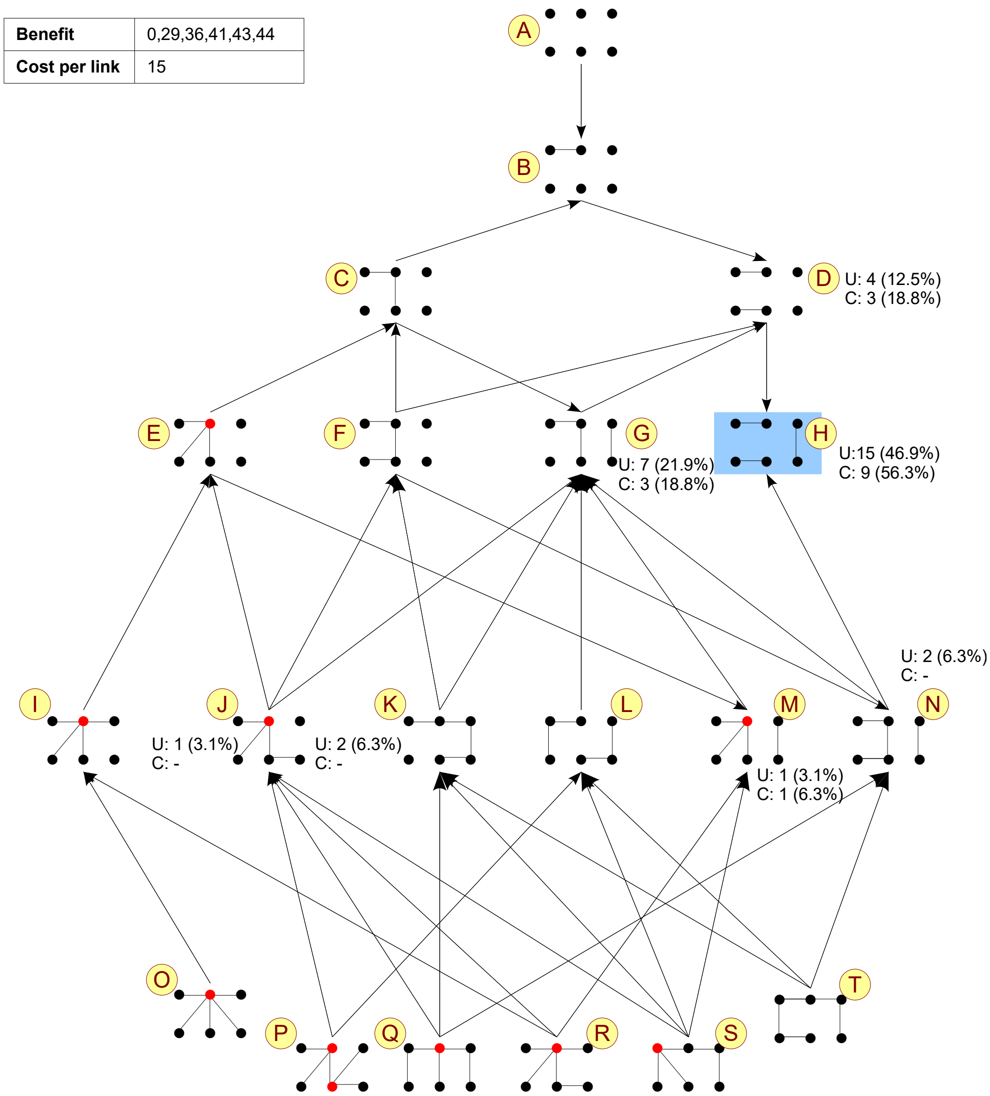
Benefit	0,19,36,42,44,45
Cost per link	15



Notes. Letters refer to all minimally connected network structures. Numbers next to each network refer to the frequency (and percentage) that the process ends in that network: U = Unconditional on convergence, C = Conditional on no change in the last 3 turns. PNS network is shaded.

Figure 5: Treatment $\mathbf{U_A}$. Unique PNS network with asymmetric payoffs.

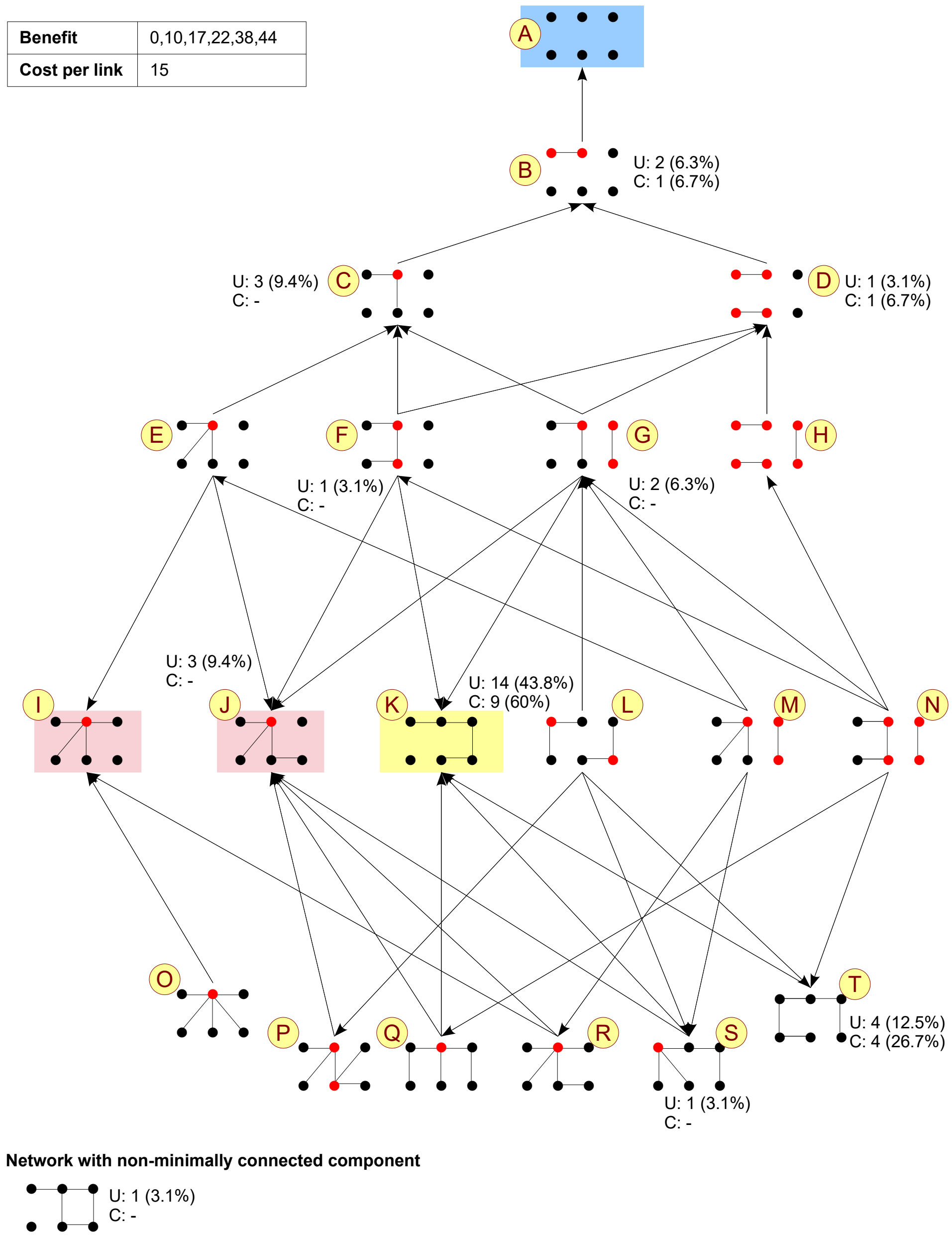
Benefit	0,29,36,41,43,44
Cost per link	15



Notes. *Letters refer to all minimally connected network structures. Numbers next to each network refer to the frequency (and percentage) that the process ends in that network: U = Unconditional on convergence, C = Conditional on no change in the last 3 turns. PNS network is shaded.*

Figure 6: Treatment $\mathbf{U_S}$. Unique PNS network with symmetric payoffs.

Benefit	0,10,17,22,38,44
Cost per link	15



Notes. *Letters refer to all minimally connected network structures. Numbers next to each network refer to the frequency (and percentage) that the process ends in that network: U = Unconditional on convergence, C = Conditional on no change in the last 3 turns. Non-Nash PS networks are shaded pink, "Myopic" PNS network is shaded blue, Pareto-Superior PNS network is shaded yellow.*

Figure 7: Treatment **M**. Multiple Pareto rankable PNS networks.

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APPENDIX

A Additional analyses

A.1 Marginal Effects in Linear Probability Model and Logit

In this section, we illustrate the robustness of the LPM partial effect estimates when the individual fixed effects are not included. Table A.1 below presents the marginal effects from LPM and logit where both are estimated *without the fixed effects*. Panel A is similar to Table 8 in the main paper, albeit without the fixed effects. Comparisons of the estimated coefficients in Panels A and B suggest that the partial effect estimates we obtain from LPM are very close to those from logit estimates.

Table A.1: LPM v. Logit: Myopic Rationality and Types of Decision Problems

	Turns [1-12]				Turns [$\geq$ 13]			
	N	$\mathbf{U_A}$	$\mathbf{U_S}$	**M**	**N**	$\mathbf{U_A}$	$\mathbf{U_S}^{\dagger}$	**M**
Panel A. Linear Probability Model								
morelink [β_1]	0.169***	0.144***	0.254***	0.240***	0.048**	0.055**	0.175**	0.018**
	(0.021)	(0.023)	(0.011)	(0.011)	(0.019)	(0.017)	(0.052)	(0.006)
act [β_2]	-0.303***	-0.543***	-0.382***	-0.292**	-0.394***	-0.448***	-0.139**	-0.136**
	(0.059)	(0.027)	(0.031)	(0.092)	(0.102)	(0.073)	(0.041)	(0.058)
morelink $\times$ act [β_3]	0.193***	0.462***	0.311***	0.231**	0.292**	0.359***		-0.048
	(0.039)	(0.024)	(0.034)	(0.083)	(0.110)	(0.061)		(0.081)
Panel B. Logit Model (Marginal Effects)								
morelink [β_1]	0.247***	0.316***	0.339***	0.297***	0.165***	0.160***	0.164***	0.006
	(0.021)	(0.018)	(0.015)	(0.027)	(0.033)	(0.031)	(0.039)	(0.015)
act [β_2]	-0.219***	-0.345***	-0.272***	-0.219***	-0.262***	-0.302***	-0.218***	-0.156**
	(0.044)	(0.021)	(0.025)	(0.066)	(0.054)	(0.055)	(0.043)	(0.053)
morelink $\times$ act [β_3]	0.193***	0.462***	0.311***	0.231**	0.292**	0.359***		-0.048
	(0.039)	(0.024)	(0.034)	(0.083)	(0.110)	(0.061)		(0.080)
Observations	2304	2304	2304	2304	972	768	858	1062

Notes: †For post-turn 12 in Treatment $\mathbf{U_S}$, we drop the interaction terms since $morelink \times !mrat2act! = 0$ predicts myopic rationality perfectly and cannot be estimated by the logit model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Geodesic distance to efficient and PNS networks

In this section, we provide a complementary study of the difference between observed and predicted outcomes to the one presented in section 4.1. More precisely, we calculate the shortest (or "geodesic") distance between the resulting networks and the closest network in the closed cycle (for Treatment **N**) or the PNS networks (for Treatments $\mathbf{U_A}$, $\mathbf{U_S}$ and **M**) as well as the distance between the resulting networks and the efficient networks. For the latter, we separately calculate the distance to the closest of all the efficient networks $\{O, P, Q, R, S, T\}$ and to the line network $\{T\}$.[1]

Panel A of Table A.2 shows that for Treatments **N** and $\mathbf{U_S}$, the distance to the closed cycle and the PNS network respectively is substantially shorter than the distance to the efficient networks. For Treatment **M**, the distance is shorter to the Pareto superior PNS network $\{K\}$ but longer to the stochastically stable initial PNS network $\{A\}$. For Treatment $\mathbf{U_A}$, however, the distance from the PNS network is equal to the distance from the efficient line network and marginally longer than the distance from the closest efficient network, suggesting a larger dispersion in behavior.

Panel B of Table A.2 presents the average distance between outcomes and predicted networks conditional on convergence (no change in the last three turns).[2] For Treatments $\mathbf{U_S}$ and **M**, the result provides further support for a reduced distance to the Pareto superior and the unique PNS network, respectively. In contrast, the distance from the convergent network to the efficient network is lower than to the PNS network in Treatment $\mathbf{U_A}$. Results in that treatment are explained by the fact that outcomes are split almost equally between the PNS network $\{L\}$ and the pairwise unstable network $\{N\}$. Since the distance between these two networks is two and both of them are at a distance of one to the efficient networks, the distance from the stable network and the efficient networks are similar. It is difficult to infer from the outcomes alone where the formation processes is leading toward, and why $\{N\}$ is appealing. Our analysis of individual decisions (Result 2) provides a plausible explanation for these findings.

[1] If agents were to aim at the efficient network, the line network is the most likely outcome since it distributes payoffs most equally. For example $\{O\}$, which is never played in our experiment, is efficient but requires one player to form 5 links and therefore bear significant payoff losses (30 to 32 tokens depending on the treatment).

[2] We do not consider Treatment **N** since convergence is not expected.

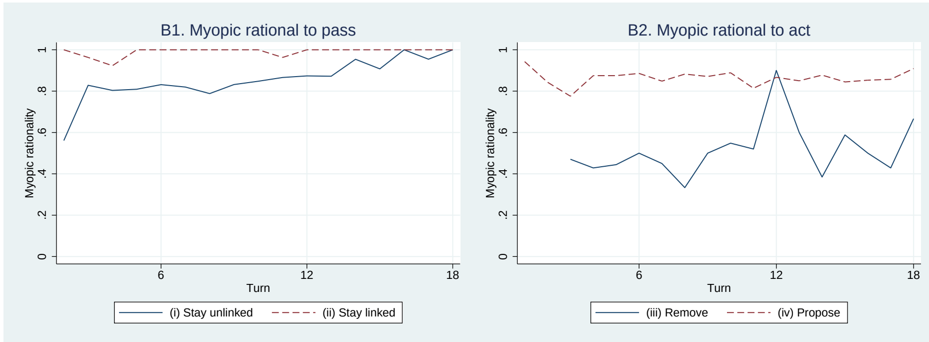
Table A.2: Average distances from outcomes

Treatment	Closed cycle†	PNS	Shortest Efficient	Efficient
	Panel A. **All**			
N	0.41	-	1.66	2.03
$\mathbf{U_A}$	-	1.41	1.28	1.41
$\mathbf{U_S}$	-	1.00	1.94	2.06
M - {A}	-	3.66	1.41	1.66
M - {K}	-	0.91	1.41	1.66
	Panel B. **Conditional on Convergence**			
N	1.00	-	1.00	1.80
$\mathbf{U_A}$	-	1.53	1.20	1.33
$\mathbf{U_S}$	-	0.75	2.13	2.25
M - {A}	-	3.93	1.07	1.07
M - {K}	-	0.60	1.07	1.07

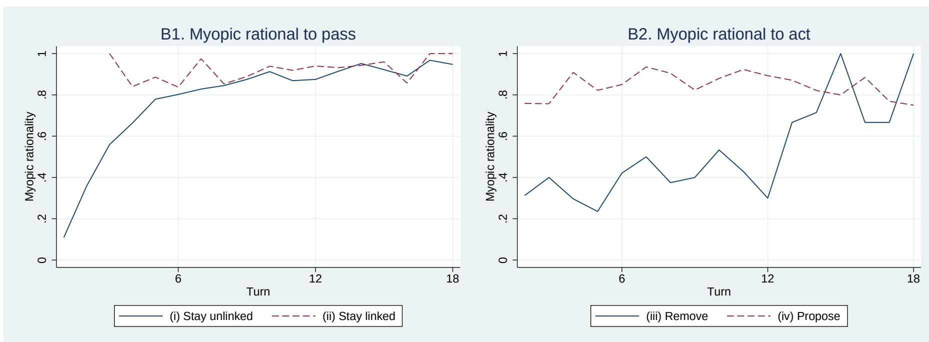
Notes: †Distance to the closest network in the cycle.

A.3 Myopic rationality by treatment and decision problem

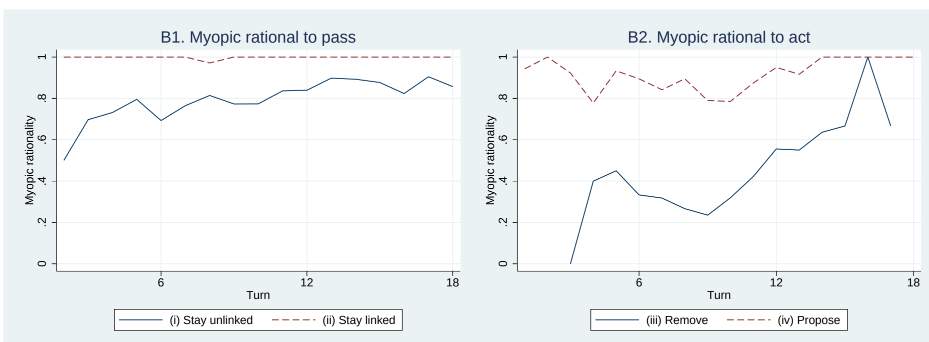
Figure A.1 further illustrates the results in Panels B and C of Table 4. We plot for each treatment the proportion of myopic rational behavior across turns when passing is rational (B1) and when acting is rational (B2). In all treatments, players maintain more links in all turns than would be observed if they played myopically rational all the time. The gap is bigger and the variation larger for decisions where acting is myopic rational (figures on the right), although the difference narrows as the match nears its end.



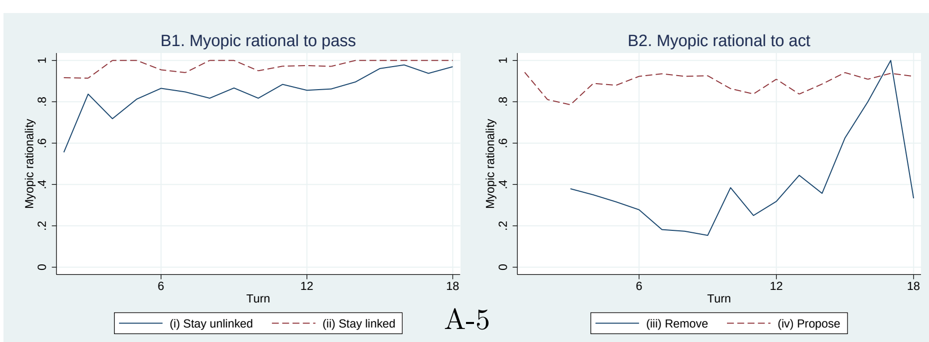
(a) Treatment **N**



(b) Treatment $\mathbf{U_A}$



(c) Treatment $\mathbf{U_S}$



(d) Treatment **M**

Figure A.1: Myopic rationality by treatment and decision problem

A.4 Myopic rationality by turn

In this section, we provide further robustness checks of a structural break at Turn 12 by interacting different types of decision with whether the decision was taken after Turn 12. We estimate models based on equations (2) and (3), but interacted each of the variables with an indicator variable of whether an observation comes after Turn 12, $\mathbb{1}(turn > 12)$. Table A.3 presents the results. We present the p-value of a joint test of all interacted variables at the bottom of the table as a test of structural break. For all treatments and specifications, the null hypothesis of no structural break at Turn 12 is rejected at the 5% significance level.

Table A.3: Myopic Rationality and Test of Structural Break at Turn 12

	N		$\mathbf{U_A}$		$\mathbf{U_S}$		**M**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(turn>12)	0.130***	0.056	0.105***	-0.008	0.169***	0.226**	0.263***	0.552***
	(0.023)	(0.044)	(0.017)	(0.055)	(0.042)	(0.076)	(0.008)	(0.049)
morelink	0.163***	0.165***	0.145***	0.137***	0.236***	0.180***	0.253***	0.141***
	(0.023)	(0.023)	(0.021)	(0.020)	(0.011)	(0.017)	(0.009)	(0.020)
... × $\mathbb{1}$(turn>12)	-0.121***	-0.127***	-0.088***	-0.087***	-0.162***	-0.138**	-0.231***	-0.114***
	(0.029)	(0.030)	(0.019)	(0.019)	(0.038)	(0.045)	(0.015)	(0.025)
act	-0.274***	-0.269***	-0.524***	-0.513***	-0.294***	-0.303***	-0.273**	-0.227*
	(0.062)	(0.060)	(0.029)	(0.029)	(0.045)	(0.043)	(0.099)	(0.103)
... × $\mathbb{1}$(turn>12)	-0.087	-0.081	0.103	0.107	0.077	0.091	0.194*	0.195*
	(0.082)	(0.088)	(0.063)	(0.064)	(0.061)	(0.058)	(0.083)	(0.085)
morelink × act	0.185***	0.197***	0.458***	0.477***	0.265***	0.315***	0.188*	0.191
	(0.048)	(0.043)	(0.026)	(0.024)	(0.054)	(0.062)	(0.096)	(0.110)
... × $\mathbb{1}$(turn>12)	0.079	0.051	-0.130**	-0.161**	-0.046	-0.098	-0.291**	-0.391***
	(0.092)	(0.106)	(0.052)	(0.047)	(0.066)	(0.069)	(0.095)	(0.108)
mpay		0.003**		0.005***		0.007***		0.015***
		(0.001)		(0.001)		(0.002)		(0.002)
... × $\mathbb{1}$(turn>12)		-0.000		-0.003		-0.003		-0.002
		(0.003)		(0.002)		(0.002)		(0.003)
turn		0.004		0.003		0.010**		0.038***
		(0.004)		(0.002)		(0.003)		(0.003)
... × $\mathbb{1}$(turn>12)		0.003		0.009**		-0.007		-0.041***
		(0.004)		(0.003)		(0.005)		(0.004)
Constant	0.811***	0.748***	0.818***	0.727***	0.732***	0.602***	0.663***	0.263***
	(0.016)	(0.036)	(0.014)	(0.030)	(0.012)	(0.034)	(0.009)	(0.023)
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbb{P}$(pooling)	0.004	0.014	0.003	0.005	0.023	0.011	0.000	0.000
Observations	3276	3276	3072	3072	3162	3162	3366	3366
Adj. R^2	0.169	0.174	0.253	0.260	0.245	0.260	0.154	0.307

Notes: The model is estimated using a linear probability model. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Out-of-sample model predictions

As a robustness check, we study the capacity of our empirical model to *predict* actions. Our prediction model uses a relatively parsimonious specification that incorporates insights from Result 2. We estimate the following Logit model:

$$
\begin{aligned}
logit(\mathbb{P}(Y_{nt} = 1 \mid \mathbf{X_n t}, c_n)) = \; & \beta_0 + \beta_1 \cdot morelink_{ij} + \beta_2 \cdot act_{ij} + \beta_3 \cdot (morelink_{ij} \times act_{ij}) + \\
& + \beta_4 \cdot \mathbb{1}(turn > 12) + \beta_5 \cdot [morelink_{ij} \times \mathbb{1}(turn > 12)] + \\
& + \beta_6 \cdot [act_{ij} \times \mathbb{1}(turn > 12)] + \beta_7 \cdot [morelink_{ij} \times act_{ij} \mathbb{1}(turn > 12)] + \\
& + \gamma_0 \cdot mpay + \gamma_1 \cdot (mpay \times morelink) + \\
& + \gamma_2 \cdot [mpay \times \mathbb{1}(turn > 12)] + \gamma_3 \cdot [mpay \times morelink \times \mathbb{1}(turn > 12)] + \\
& + \theta \cdot turnSpline_{1-6} + \varepsilon
\end{aligned}
\tag{A.1}
$$

In this equation, we supplant the basic model of equation 1 with (i) *mpay* and (ii) $mpay \times morelink$ variables to incorporate Results 2(b) and 2(c). To incorporate the insight from Result 2(a) and account for the structural break at Turn 12, all of these variables are interacted with the indicator variable $\mathbb{1}(turn > 12)$. Furthermore, to incorporate Result 2(d), we add a spline for Turns [1-6] to capture deviations from myopic rationality in early turns of Treatment **M**. To maintain model parsimony, we do not include the individual fixed effects.

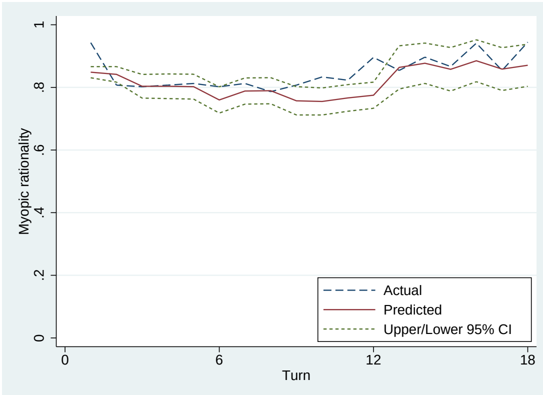
We use the model to conduct an out-of sample (or out-of-treatment) prediction exercise. For each treatment, we estimate the coefficients of the model with a sample that excludes observations from that treatment. Once the coefficients are recovered, we use the model to predict the actions in the excluded treatment. Table A.4 shows the coefficients from the estimation exercise. We then use these coefficients to predict the out-of-sample actions of the first 18 turns. Figure A.2 graphically depicts for each treatment the plot of the myopic rationality of actual choices (dashed line), out-of-sample predicted choices (solid line), and 95% confidence interval of predicted choices.

The model generally predicts actions well, even though it performs less well in predicting initial behavior and switches at the beginning of the probabilistic turns. Indeed, actions in all treatments are more likely to be outside the prediction intervals in the first few turns and in the choices immediately after Turn 12 (where the model predicts a steeper change than empirically observed). However, the absolute differences are always relatively small. The largest discrepancy occurs in the first three turns of Treatment **M**, where the proportion of myopic rational choices is very significantly below the model prediction.

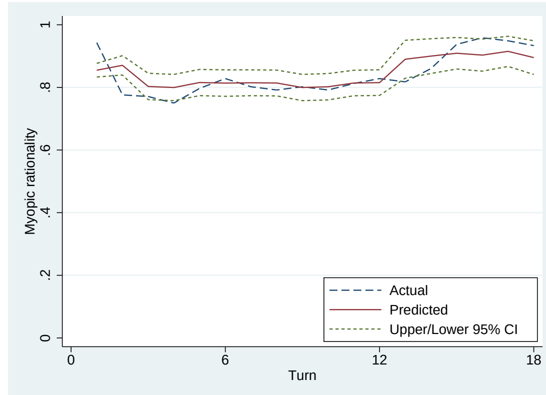
Table A.4: Predictive Logistic Model of Myopic Rationality

	N (1)	$\mathbf{U_A}$ (2)	$\mathbf{U_S}$ (3)	**M** (4)
$\mathbb{1}$(turn>12)	2.448***	2.104***	2.854***	1.669***
	(0.444)	(0.431)	(0.584)	(0.393)
morelink	2.989***	3.171***	3.480***	3.761***
	(0.318)	(0.326)	(0.337)	(0.391)
… × $\mathbb{1}$(turn>12)	-2.290***	-2.039***	-2.467***	-1.323**
	(0.736)	(0.498)	(0.694)	(0.670)
act	-1.722***	-1.294***	-1.335***	-1.763***
	(0.163)	(0.198)	(0.191)	(0.081)
… × $\mathbb{1}$(turn>12)	-0.241	-0.565*	-0.821***	-0.515*
	(0.251)	(0.300)	(0.265)	(0.287)
morelink × act	0.673***	0.058	0.327**	-0.060
	(0.181)	(0.184)	(0.160)	(0.337)
… × $\mathbb{1}$(turn>12)	-0.809*	-0.150	-0.104	-0.363
	(0.445)	(0.295)	(0.373)	(0.321)
mpay	0.141***	0.127***	0.176***	0.082***
	(0.015)	(0.016)	(0.024)	(0.015)
… × $\mathbb{1}$(turn>12)	-0.104***	-0.064*	-0.114**	-0.051
	(0.033)	(0.036)	(0.051)	(0.033)
mpay × morelink	-0.096***	-0.098***	-0.139***	-0.088***
	(0.023)	(0.029)	(0.032)	(0.024)
… × $\mathbb{1}$(turn>12)	0.134**	0.090**	0.127**	0.082***
	(0.053)	(0.043)	(0.050)	(0.031)
turn spline: before 6†				0.090**
				(0.043)
Constant	-0.440**	-0.279*	-0.958***	-0.053
	(0.177)	(0.153)	(0.244)	(0.235)
Observations	9600	9804	9714	9510
Pseudo R^2	0.192	0.165	0.180	0.173

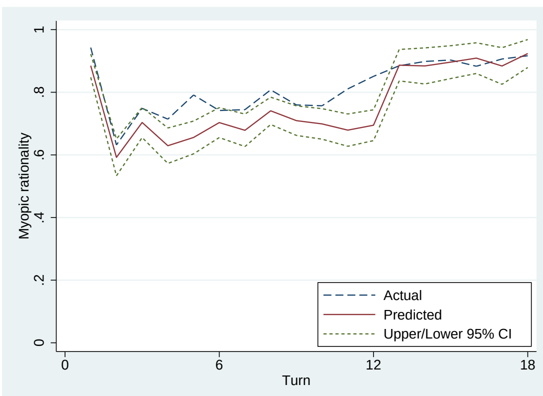
Notes: The table reports the coefficients for logistic regressions at the action level. Each column reports coefficient estimates from a model that is estimated on the set of observations that excludes those from the treatment described on its heading. Standard errors are clustered at the session level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



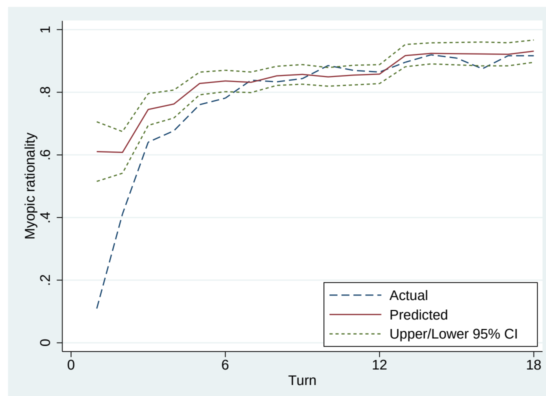
(a) Treatment **N**



(b) Treatment $\mathbf{U_A}$



(c) Treatment $\mathbf{U_S}$

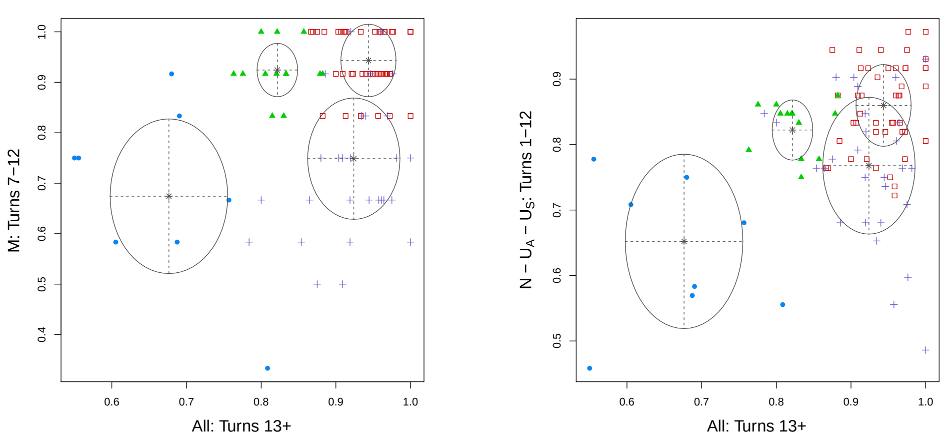


(d) Treatment **M**

Figure A.2: Out-of-sample logit prediction by treatment

A.6 Cluster representation

With four clustering variables, individuals are captured by a point in a 4-dimensional space. This makes it challenging to provide a visual representation of all the information. We therefore retain the pairs of variables that discriminate best among clusters. Figure A.3 presents the two-dimensional projection of each individual for the following variable pairs: (a) Turns 13+ in all treatments and Turns 7-12 in Treatments **M**; and (b) Turns 13+ in all treatments and Turns 1-12 in Treatments $\mathbf{N}$-$\mathbf{U_A}$-$\mathbf{U_S}$. It includes information about the clusters in the best fitting model, that is, VEI with four clusters. Individuals in different clusters are represented with different shapes and colors: red squares (Cluster 1), green triangles (Cluster 2), purple crosses (Cluster 3) and blue circles (Cluster 4). The $*$ symbol represents the mean value of the cluster. The dashed lines capture the two eigenvalues of the variance-covariance matrix of the cluster and give the variances along the principal directions. Finally, the ellipses are the contours of the bivariate Normal distribution.



(a) (b)

Figure A.3: Cluster Analysis

The least myopic rational Cluster 4 (blue circles) has the smallest number of individuals and most distinct behavior, but is also the most heterogeneous. On the other extreme, cluster 1 (red squares) has the highest levels of myopic rationality. Cluster 2 (green triangles) is very homogeneous and departs from cluster 1 mostly in late turns. By contrast, cluster 3 (purple crosses) is relatively heterogeneous and departs from cluster 1 mostly in early turns. Overall, Figure A.3 provides evidence that our grouping method achieves a reasonable degree of homogeneity within clusters and heterogeneity between clusters.

B Instructions

Welcome. This is an experiment on individual decision making in groups, and you will be paid for your participation in cash at the end of the experiment. The entire experiment will take place through computer terminals, and all interactions between participants will take place through the computers. You will remain anonymous to me and to all the other participants during the entire experiment; the only person who will know your identity is the Lab Manager who is responsible for paying you in the end. Moreover, it is important that you do not talk or in any way try to communicate with other participants during the experiment.

We will start with a brief instruction period. During the instruction period, you will be given a complete description of the experiment and will be shown how to use the computers. You must take a quiz after the instruction period, so it is important that you listen carefully. If you have any questions during the instruction period, raise your hand and your question will be answered so everyone can hear. If any difficulties arise after the experiment has begun, raise your hand, and an experimenter will come and assist you. Please note that you are not being deceived and you will not be deceived: everything I tell you is true.

Your earnings during the experiment are denominated in tokens. Depending on your decisions, you can earn more tokens or lose some tokens. At the end of the experiment, we will count the number of tokens you have earned in all of the matches and you will receive \$1.00 for every 4 tokens. You will be paid this amount plus the show-up fee of \$5. Different participants may earn different amounts. Everyone will be paid in private and you are under no obligation to tell others how much you earned.

The experiment will consist of 8 matches. In each match, you will be put in a group with 5 other participants in the experiment. Since there are 12 participants in today's session, there will be 2 groups in each match. You are not told the identity of the participants in your group. Your payoff in each match depends only on your decisions, the decisions of the other 5 participants in your group and on chance. What happens in the other group has no effect on your payoff and vice versa. Your decisions are not revealed to participants in the other group.

We will now explain how each match proceeds. At the beginning of the match, the computer randomly assigns each of you to a group consisting of 6 participants. Next, the computer randomly assigns with equal probability a role to each of the participants as "Subject 1", "Subject 2" and so on up to "Subject 6". Then, the match begins.

Each match consists of several turns. At the beginning of each turn, the computer randomly pairs all subjects within each group with one another. We shall call the subject that you are paired with at each turn as your "Current Partner". Once everyone receives a Current Partner, a turn begins.

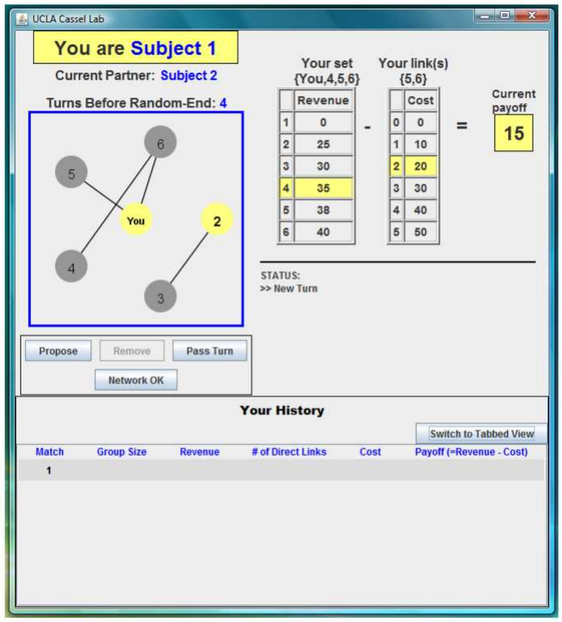


FIGURE 1:
BEGIN A TURN

At the beginning of each turn, you will see a screen similar to that shown here. The top panel provides the information and interface that you will use to interact with other subjects within your group. Meanwhile, the bottom panel lists your payoff history throughout the experiment. Payoff information in each match, including the practice matches, is recorded here.

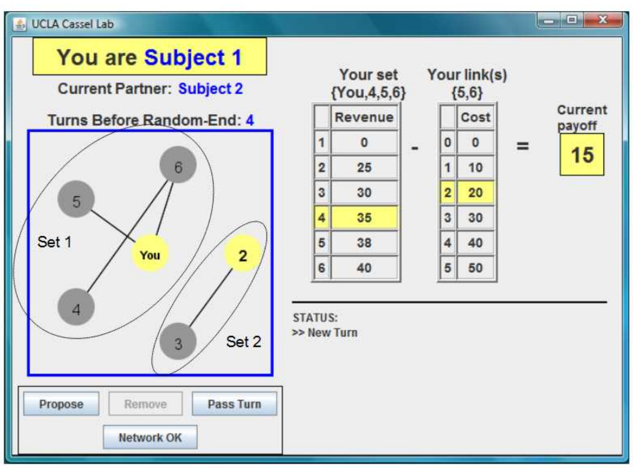


FIGURE 2:
SETS, LINKS
AND ACTIONS
[example 1]

This is the top panel. On the top-left is your role in this match. In this example, you are Subject 1. The computer also informs you of your Current Partner at each turn. In this turn, your Current Partner is Subject 2.

In the middle of the left panel, you will see a network representation of the connections between all subjects in your group. Other subjects in your group are represented by nodes with their role ID numbers. Meanwhile, you are always represented by the center node labeled "YOU". In each turn, the node for your Current Partner is colored YELLOW unlike the rest of the subjects. From the color, you can see here that your Current Partner is Subject 2.

The lines connecting the nodes represent the links between subjects in your group. Everyone in your group sees the same sets of links. In this example, you have direct links to Subjects 5 and 6. Through Subject 6, your are also indirectly connected with Subject 4. Subjects who are either directly or indirectly connected belong in the same "Set". In this example, there are two sets. The first consists of You, Subjects 4, 5, and 6. The second set consists of Subjects 2 and 3.

At each turn, the joint actions of you and your current partner affect how the two of you are linked. You take actions by clicking one of the action buttons below the network representation. Through your actions, you can either propose a link, remove a link, or maintain how you are connected with your partner.

In this first example, since you are not linked to Subject 2, only three actions are available: "Propose", "Pass Turn", and "Network OK". The "Remove" button is not active. Clicking "Propose" lets the computer know that you would like to propose a link with your Current Partner. If your partner does the same, the computer will create a link between you and your partner. Otherwise, no link will be created. In other words, a link is created if and only if BOTH partners propose a link to each other.

If you don't want to link with your Current Partner, you can either click "Pass Turn" or "Network OK". In either case, a link will not be created. However, notice the difference between the two actions. When you pass a turn, you tell the computer that you want to keep the way you are linked with your current partner in this turn. However, you may still want to change how you are linked with some of the other subjects. So, your buttons will remain active in the next turn

Meanwhile, if you choose "Network OK", you tell the computer that as long as the network doesn't change, you are happy with the way you are linked with everyone in your group. Therefore, if you click "Network OK", you won't need to take further actions until the network changes. Your buttons will therefore be inactive. However, these buttons will immediately become active once the decisions of other pairs either break or make a link. If all active subjects choose "Network OK" in the same turn, then the match ends.

The turn ends once everyone in your group has taken an action. The computer then begins a new turn, and you will be randomly assigned a new Current Partner. Please note that since pairs are selected randomly, you may be paired with the same partner in consecutive turns.

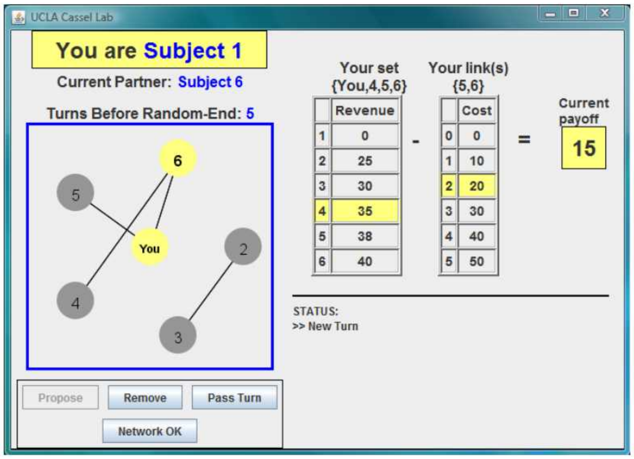


FIGURE 3: SETS, LINKS AND ACTIONS [example 2]

This figure illustrates a new turn in which you are paired with Subject 6. Now, since you are already directly linked with this subject, the three actions available to you are: “Remove”, “Pass Turn” and “Network OK”. The “Propose” button is deactivated in this turn.

Your link with Subject 6 will remain intact only if BOTH you and Subject 6 don't want to remove it. If at least one subject in the pair wants to remove it, your direct link with your Current Partner will be broken at the end of the the turn. Obviously, the link will also be broken if both subjects in a pair choose to remove it.

In each match, the computer will continue to generate new turns for at least 12 turns unless all subjects choose “Network OK”. However, if a match does not end after 12 turns, the match enters the random-end stage. In the random-end stage, at each turn, the computer randomly decides whether it will end the match or generate a new turn. Each time, there is a 20% probability that it will decide to end the match. On average, this implies about 5 additional turns in each match. The number of remaining turns before this random-end stage is displayed above the network representation.

The network representation updates links that are made and broken in real time. You can see changes to the network immediately after each pair makes their decisions within each turn. Similarly, you can also keep track of changes within each turn through the “Status” indicator on the lower right panel. This status indicator resets at each new turn.

We will next discuss about the payoff. Your payoff depends on the size of your set and the number of direct links at the end of the match. Your set size, which is the number of subjects who are either directly or indirectly connected to you, determines your revenue. Meanwhile, your cost is determined by the number of direct links you have.

The right panel provides you with all of the information necessary to calculate your payoff.

The table on the left gives you the revenue schedule for different set sizes. Above it, you can see the list of subjects in your set. In this example, your set consists of You and Subjects 4, 5, and 6. Therefore, as part of a set of size 4, your revenue is 35.

Next to the revenue table is the cost schedule for different numbers of direct links. Each direct link incurs a constant cost. In this particular example, the cost for each link is 10 and, therefore, the total cost is 10 times the number of subjects with whom you are directly linked. Above that table, you can see that you are directly linked to Subjects 5 and 6. Since you have two direct links, the current total cost is 20 tokens.

Your current revenue and cost at any stage of the game are highlighted in YELLOW. They are updated in real time as the actions of subjects make and break links within each turn. The rightmost box entitled "Current Payoff" calculates your payoff at each stage of the game. The current payoff is simply the revenue minus cost, which in this case is 15. This payoff information is also updated in real time. Note that the revenue and cost tables may change from match to match.

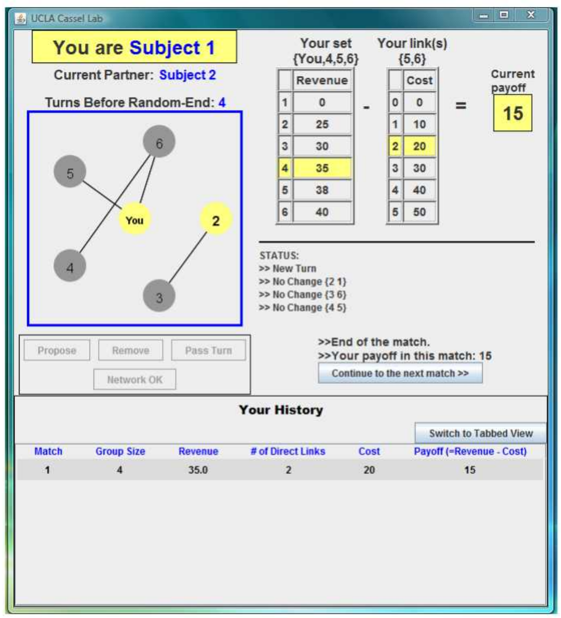


FIGURE 4: END OF A MATCH

This figure illustrates what you will see at the end of a match. Below the status indicator, you will see your payoff for this match. At the end of the match, please click "Continue to the Next Match". In each new match, you will be randomly assigned to a new group. A new match will begin only after all groups have completed their matches. This continues for 8 matches, after which the experiment ends.

At the end of the final match in the experiment, you will see the following screen.

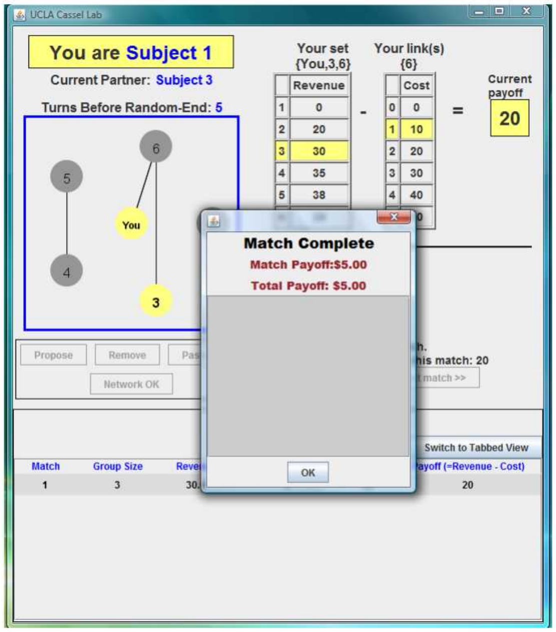


FIGURE 5: END OF A SESSION

This final screen tells you the total payoff that you will receive for this experiment. When you see this screen, don't click OK until you have written down your total payoff on the payoff sheet provided. After you have written down your total payoff, click OK to conclude the session. (*)

The following slides summarize the rules of the experiment:

Summary of the rules (1/2)

- This session consists of 8 matches. In each match, you will be put with 5 other participants in a group. Groups are reshuffled in each new match.
- Each match consists of several **turns**.
  - In each turn, you are randomly paired with a current partner in your group
  - A turn ends once everyone in your group has taken an action.
- Use one of four **action buttons** to affect your link with your partner:
  - **Propose** tells the computer you want to propose a link with a partner. A link is created if and only if **both** you and your partner propose.
  - **Remove** tells the computer you want to remove an existing link with a partner. A link is removed if **either** you or your partner wants to remove it.
  - **Pass turn** tells the computer you want to keep the state of your connection with your partner.
  - **Network OK** tells the computer you are happy with the current network configuration. After choosing “Network OK”, you don't need to take subsequent actions until the network changes.

Summary of the rules (2/2)

- A match ends in one of the following two ways:
  - After all active participants have chosen “Network OK” in the same turn;

    OR
  - If the match has not ended after 12 turns, the computer randomly decides the end of the match. Any extra turn afterward may be the last with a 20% chance.
- Your payoff is revenue minus cost. The revenue depends on the size of your set, while the cost depends on the number of your direct links.
- A new match begins only after all groups have finished their matches. In a new match, you will be randomly matched with another 5 participants. Moreover, the revenue and cost tables may also change between matches.

We will now begin the Practice session and go through two practice matches to familiarize you with the computer interface and the procedures. During these practice matches, please do not hit any keys until you are asked to. Remember, you are not paid for these matches. At the end of the practice matches you will have to answer some review questions.

Throughout the session, pay attention to the network representation display and status indicators. Also, notice the movements of the yellow highlights on your Revenue and Cost tables, as well as updates to your Current Payoff.

[START GAME]

You have just received a new turn. First, pay attention to your role. If you are Subject 1, 2, or 3, please click “Propose”. For Subject 1, 2, or 3, notice a link has just been created between you and your partner if your partner is also Subject 1, 2 or 3.

Now, if you are Subject 4, 5, or 6, please click the “Pass Turn” button. Notice here that a link is created if and only if BOTH partners propose a link. If only one partner proposes a link, no link is created.

You have moved to a new turn. We will now see how the “Network OK” action works. If you are either Subject 5 or 6, please click “Network OK”. For the rest of the group, please click “Pass Turn”.

You have moved to a new turn. For Subjects 5 or 6, since the network has not changed after you clicked “Network OK”, all of your buttons are now inactive. Notice that they will become active following a change in the network.

For others, please check your Current Partner. If your partner is not Subject 5 or 6, click the “Remove” button if it's active or “Propose” otherwise. For Subjects 5 and 6, notice how a change in the network activates your buttons.

If you are not Subject 5 or 6 and your buttons are still active, please click “Pass Turn”. If you are Subject 5 or 6 and your buttons are active, please click “Pass Turn”. Notice here that if your buttons are inactive due to a “Network OK” action in a previous turn, a change in the network will immediately activate your buttons. In the following, we will do the same exercise for Subjects 1 to 4.

You have moved to a new turn. If you are Subject 3 or 4, please click “Network OK”. For the rest of the group, please click “Pass Turn”.

You have moved to a new turn. Subjects 3 and 4, notice that your buttons are inactive. If the network changes in this turn, your buttons will become activated.

For all others, check your Current Partner. If your partner is not Subject 3 or 4, click “Remove” if it's active or click “Propose” otherwise. If you are not Subject 3 or 4 and your buttons are still active, click “Pass Turn”. Now, if you are Subject 3 or 4, please click “Pass Turn”.

You have moved to a new turn. If you are either Subject number 1 or 2, please click “Network OK”. For the rest, please click “Pass Turn”.

You have moved to a new turn. For Subject 1 or 2, your buttons are now inactive. For all others, if your Current Partner is not Subject 1 or 2, click the “Remove” button if it's active, or click “Propose” otherwise. For everyone else who has not taken an action, please click “Pass Turn”.

You have moved to a new turn. Notice from the message above the network display that this is the last turn before the random-end stage. During the paid match, you will have 12 turns before entering this stage. If the match has not ended after 12 turns, the computer will randomly decide the end of the match.

We will now deliberately end the match. If your buttons are active, please click the “Network OK” button. This ends the first practice match. The bottom part of your screen contains a table summarizing the results for all matches you have participated in. This is called the history screen. It will be filled out as the experiment proceeds. Now click “Continue to the Next Match”. We will now begin with the second practice match.

[NEXT MATCH]

You are in a new match. Note here that the revenue and cost tables have changed as they may during the real matches. We'll now examine the behavior of the “Remove” action.

If you are either Subject 2, 4, or 6, please click “Remove”. For Subjects 1, 3, and 5, please click “Pass Turn”. Hence, notice that a link is broken if at least one of the partners chooses to remove it.

You have moved to a new turn. Next, we'll see what will happen if the network changes within the turn in which you click “Network OK”. If you are Subject number 1, 3, or 5, please click the “Network OK” button. For all others, please click your “Remove” button.

You have moved to a new turn. For Subjects 1, 3, or 5 notice that if in the previous turn the network changed after you clicked “Network OK”, your action buttons are active in this turn. If the network did not change after you clicked “Network OK”, your buttons remain inactive. Now, if you are either Subject 2, 4, or 6, click “Network OK”. For all others, if you haven't taken an action in this turn, please click the “Remove” button if it's active, or “Propose” otherwise.

You have moved to a new turn. Similarly for Subjects 2, 4, and 6, notice that if in the previous turn the network changed after you clicked “Network OK”, your buttons are now active. If the network did not change after you clicked “Network OK”, your buttons are still inactive. If the network changes in the same turn and after you choose “Network OK”, your buttons stay active in the following turn.

We will now end the match. If your buttons are active, please click “Network OK”. This ends the second practice match.

*** END OF PRACTICE SESSION ***

The practice matches are over. Please click “Continue to the next match” and complete the quiz. It has 8 questions in two pages. You will move to the next page once everyone in your group has completed the questions in that page correctly. On your table, you will find the screenshots that you will need to answer these questions. Raise your hand if you have any questions.

[WAIT for everyone to finish the quiz]

Are there any questions before we begin with the paid session? We will now begin with the 8 paid matches. Please pull out your dividers. If there are any problems or questions from this point on, raise your hand and an experimenter will come and assist you.

[START MATCH 1]

[After MATCH 8, read:]

This was the last match of the experiment. Now, please write down your ID on the payment sheet. Your ID is located on top of your physical monitor and it began with CASSEL. At this point, if you haven't clicked "Continue to the next match", please do so. Your total payoff is displayed on your screen. Please record this payoff in the earned column of your sheet and sign it. Once you have written it down, please click OK.

Your Total Payoff will be this amount rounded up to the nearest dollar plus the show-up fee of $5. We will pay each of you in private in the next room. Remember you are under no obligation to reveal your earnings to the other subjects.

If you are done, please line up behind the yellow line until the lab manager calls you to be paid. Do not converse with the other subjects or use your cell phone. Thank you for your cooperation.