DISCUSSION PAPER SERIES

No. 8757

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INDUSTRIAL ORGANIZATION and PUBLIC POLICY

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ISSN 0265-8003

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Discussion Paper No. 8757
January 2012

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CEPR Discussion Paper No. 8757

January 2012

ABSTRACT

The Strategic Formation of Networks: Experimental Evidence*

We use a laboratory experiment to explore dynamic network formation in a six-player game where link creation requires mutual consent. The analysis of network outcomes suggests that the process tends to converge to the pairwise-stable (PWS) equilibrium when it exists and not to converge at all when it does not. When multiple PWS equilibria exist, subjects tend to coordinate on the high-payoff one. The analysis at the single choice level indicates that the percentage of myopically rational behavior is generally high. Deviations are more prevalent when actions are reversible, when marginal payoff losses are smaller and when deviations involve excessive links that can be removed unilaterally later on. There is, however, some heterogeneity across subjects.

JEL Classification: C73, C92 and D85
Keywords: laboratory experiments, myopic rationality, pairwise stable equilibria and social networks

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* We would like to thank Manuel Castro, Matthew Jackson, and Saurabh Singhal for helpful comments and the financial support of the Microsoft Corporation (Carrillo) and the American-Indonesian Cultural and Educational Foundation (Gaduh).

Submitted 24 December 2011

1 Introduction

Social networks facilitate information exchange when formal channels are unavailable (Munshi, 2007). They also work as a means to smooth consumption in the absence of formal insurance markets (Udry, 1994; Fafchamps and Lund, 2003). Even markets can be seen not as anonymous institutions of exchange but as networks that facilitate exchange between buyers and sellers (Kranton and Minehart, 2001). Sociologists have, for a while now, recognized the importance of networks and social structure, and more recently, economists too have joined the fray (Granovetter, 2005; Jackson, 2005).

Within the economic literature, one question of interest is how networks are formed. Two seminal theoretical papers advanced explorations of this question for different link formation rules. Bala and Goyal (2000) study efficient and Nash-stable networks in non-cooperative games where links are made and broken unilaterally. Meanwhile, Jackson and Wolinsky (1996) address a similar problem with an underlying game that requires links between two agents to be mutually agreed, although they can be broken unilaterally.

In addition, there is a small but growing experimental literature that builds on the theory. However, the bulk of this literature focuses on the former type of rule, namely when links can be made and broken unilaterally (Callander and Plott, 2005; Berninghaus, Ehrhart and Ott, 2006; Berninghaus, Ehrhart, Ott and Vogt, 2007; Falk and Kosfeld, 2003; Goeree, Riedl and Ule, 2009). In contrast, our experiment joins a small number of recent studies that have investigated network formation with the latter type of rule, that is, when link creation requires mutual consent (Pantz, 2006; Kirchsteiger, Mantovani, Mauleon and Vannetelbosch, 2011).

Our experiment differs methodologically from those studies in two important respects. *First*, we consider networks of six rather than four subjects. Since the number of network combinations grows exponentially with the number of players, this is the maximal complexity compatible with an analytical treatment of the problem.[1] *Second*, in previous experiments the pairwise-stable (PWS) equilibria always existed and was the empty network, or the full network, or both. Instead, we consider four treatments with unique, multiple, or no PWS equilibrium. In the two treatments with a unique PWS equilibrium, the network size is 'intermediate' (two groups of three subjects and three groups of two). This rich structure in both the set of possible networks and the set of equilibria allows for a multi-way com-

[1] For instance and as developed below, with 4 players there are 64 possible networks and 6 minimally-connected architectures whereas with 6 players there are 32,768 possible networks and 20 minimally-connected architectures.

parison between observed and predicted choices.[2] Finally, our setting also allows us to conduct an in-depth study of the determinants of myopically rational choices, both at the single decision level and at the subject level.

The results of the experiment can be summarized as follows. The analysis of *outcomes* suggests that the network formation process tends to converge to the PWS equilibrium when it exists and not to converge at all when it does not. However, convergence is by no means guaranteed, especially when the stable and efficient networks are close to each other. When multiple PWS equilibria exist, subjects often manage to reach the high-payoff one (a result in line with Kirchsteiger et al. (2011)).

To understand better the choices of our subjects, we then study each *single decision*. The percentage of myopically rational behavior is generally high. However, descriptive and regression analyses indicate four instances where this percentage is decreased. First, at the beginning of the match because subjects realize that decisions can be reversed later on. Second, when deviations are necessary to escape the low-payoff PWS equilibrium. Third, when the marginal payoff losses are small, as predicted by theories of imperfect choice. And fourth, when the myopic rational decision is to remove links because such an action does not require the consent of others and therefore can be taken later on.

Finally, a cluster analysis performed at the *subject level* reveals different patterns of behavior across individuals. More than half of our subjects exhibit a behavior close to the theoretical predictions, with a sustained increase in myopic rationality as the end of the match approaches, and low myopic rationality when required to reach the farsighted high-payoff equilibrium. About a quarter of the subjects play poorly without differentiating between treatments or between early and late turns. The rest exhibit an interesting pattern, with initially low myopic rationality (consistent with costless experimentation) and a dramatic increase in myopic rationality (around 20%) when choices are potentially irreversible.

The paper is organized as follows. In Section 2, we present the conceptual framework and network models that are pertinent to our experiment. Section 3 elaborates the experimental design and introduces our treatments. Then, in the following three sections, we present our analyses of the properties of the final network configuration (Section 4), individual choices (Section 5) and subject heterogeneity (Section 6). Section 7 concludes.

[2] Other minor differences include a benefit function from network membership that depends exclusively on the size of the network, a long sequence of choices with an average of 102 individual decisions per match, and a reshuffling of partners after each match.

2 Network environment and basic definitions

A network is a collection of links connecting "nodes" which, in our case, represent independent agents. A link between two agents can only form if *both* of them 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.[3] We assume that the benefit is allocated equally amongst the members of a component. Payoffs are computed as the difference between benefits and costs.

Given that link formation needs mutual consent while link destruction does not, what network is likely to emerge? A candidate is the pairwise-stable network. A network is *pairwise-stable* (PWS) if: (i) all existing links are weakly preferred by both agents in the link and are strictly preferred by at least one of them; and (ii) all non-existing links are such that at least one of the agents on the non-existing link strictly prefers its absence (Jackson and Wolinsky, 1996). One other plausible equilibrium is when agents maximize the total payoffs received by all agents. This is referred to the *strongly efficient network*.[4]

In our game, where benefits are strictly a function of the group size and are distributed equally across component members, stable and efficient networks must always be *minimally connected*. A network is minimally connected if the removal of any existing link increases the number of components. To see why, notice that when benefits are strictly a function of the component size, for any network that is not minimally connected, removing a link that does not split a component will increase the net payoff of two individuals without affecting the net payoffs of any other agent.

The stability notions elaborated above do not provide a prediction of where the dynamic process of link formation will end. Jackson and Watts (2002) model the dynamic process by assuming that pairs of agents meet at random and decide whether to propose a link to each other when none exists, or sever an existing one. If agents exhibit myopic behaviors and make their decisions based solely on the marginal payoff they receive from the potential link that they are considering (and not on the option value

[3]We distinguish between "network" and "component". A network describes the link configurations that include the full graph (i.e., all of the agents) while a component is a sub-graph in which there exists a path between any two agents.

[4]Following Jackson and Wolinsky (1996), we define the "efficient network" as a network that maximizes the total value of the network, which is equal to the total payoffs received by all agents, and not in the Paretian sense.

of forming or severing links in the future), then the network will evolve following an *improving path*. An improving path is a sequence of networks where each network differs by one link from the previous one in the sequence; a link in a subsequent network is added when both agents (myopically) agree to add it and an existing one is severed when at least one of the two agents (myopically) prefers its deletion.

Starting from any network, Jackson and Watts (2002, Lemma 1) show that improving paths lead to either a PWS network or a cycle. A set of networks forms a *cycle* if there is an improving path from any network to any other network in this set. A set of networks is in a *closed cycle* if no network in the set is on the improving path of a network that is not in the set. Since improving paths assume myopic behavior, they predict for example that players will be stuck in an empty network when the initial costs of developing networks exceed the link costs, but thereafter are beneficial. Also, there might be multiple PWS networks, some more attractive than others. In that case, depending on the starting network configuration, the improving path will lead to one PWS network or another, independently of their properties.

Two theoretical approaches have been proposed to deal with predictions under multiplicity. One approach maintains myopic behavior but introduces stochastic mutations in the formation of networks. This way, every network is attained with positive probability and, from there, agents move to a PWS network through a myopic improving path (Jackson and Watts, 2002). Another alternative is to explicitly consider the possibility of farsighted behavior. Here, agents realize the long run benefits of myopically suboptimal choices and move away from one PWS network into another one, also called *farsighted-dominant* network, by comparing for each subject involved the initial and final networks rather than the two consecutive networks (Herings, Mauleon and Vannetelbosch, 2009). Finally but quite importantly for our experiment, notice that different agents in a component may receive different payoffs (they all have the same benefits but some may have more direct links than others). This poses another multiplicity problem: even within a PWS network, agents have incentives to make or break links in order to change their final position in the network (typically trying to keep the same component size but have other agents bear most of the link costs).

3 Experimental setting and procedures

3.1 The basic configuration

Our experiment examines how well efficient networks, PWS networks and farsighted dominant networks predict the outcome of a dynamic linking game. We are interested in environments with a *large number of network configurations* where mutual, pairwise consent is needed to form a link but not to break it, and links are costly to individuals. To this end, we implement a stochastic dynamic linking game that slightly modifies the procedure proposed by Jackson and Watts (2002). We consider networks with $n = 6$ players. This means $n(n-1)/2 = 15$ possible bilateral undirected links between different players, and therefore $2^{n(n-1)/2} = 32,768$ possible networks in our game. Naturally, the number of *network architectures* is substantially smaller, since several networks are identical up to a permutation of the identity of subjects. With 6 players there are 20 minimally-connected network architectures.[5]

We specifically look at a setting where the benefits from network memberships are distributed equally across all members. An example of such a setting is the formation of risk-sharing networks analyzed by Bramoullé and Kranton (2007). As such, we deviate from much of the network experimental literature that implements the connections model where the benefits of indirect links decay with distance. The advantage of our approach is that payoffs from decisions are straightforward to calculate. This is made even simpler by the fact that we maintain the unit cost of a link to be constant both within and across treatments. By doing so, we dramatically reduce the likelihood that some decisions are made out of payoff miscalculations.

Each match consists of multiple turns and starts with an empty network. At each turn, the computer randomly assigns the six players into three pairs. Once paired, players choose their actions with respect to their partner in the pair. A new turn begins after all players have taken their actions. If all players are satisfied with the network outcome, they can collectively end the game. Ideally, we would like to have matches end only when all players have agreed on the outcome. However, this would make sessions unmanageably long. Furthermore, some agents could choose actions randomly knowing that they always have the option to change it in the future. It would also

[5] Although six players may not seem like a large network, it is the biggest manageable size given the exponential growth of possible combinations. For comparison, Pantz (2006) and Kirchsteiger et al. (2011) have $n = 4$ players, which means 6 bilateral undirected links, 64 possible networks and 6 minimally-connected network architectures.

favor those who stubbornly refuse to give up until a specific configuration is reached. We therefore decided to implement a match-ending rule that provides enough opportunity for players to converge but, at the same time, allows decisions to be meaningful and the experiment to be time manageable: Subjects play for 12 turns unless all players 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. At the same time, it allows for an interesting comparison of behavior before and after the 12$^{\text{th}}$ turn. Finally, notice that each turn is composed of six decisions, one for each player, providing an average of $17 \times 6 = 102$ individual decisions per match (unless subjects decided to stop before).

Figure 1 shows the user interface. At each turn, players make decisions by clicking on one of the action buttons. If a player 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". Once a pair of partners have taken their actions, the result is displayed on the screen. Hence, when each player 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. On the other hand, it may encourage a war of attrition where players want to see what others are doing in a turn before choosing their action.

Now, if a player is not only satisfied with the relationship with his partner but also with the overall network, instead of choosing "Pass Turn", he can choose "Network OK".[6] As mentioned above, the match immediately ends if all players within a turn choose "Network OK".

The user interface 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. It also 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 configuration. This succinct but comprehensive visual display allows the subject to compute rather easily 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, notice

[6]Once a player 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.

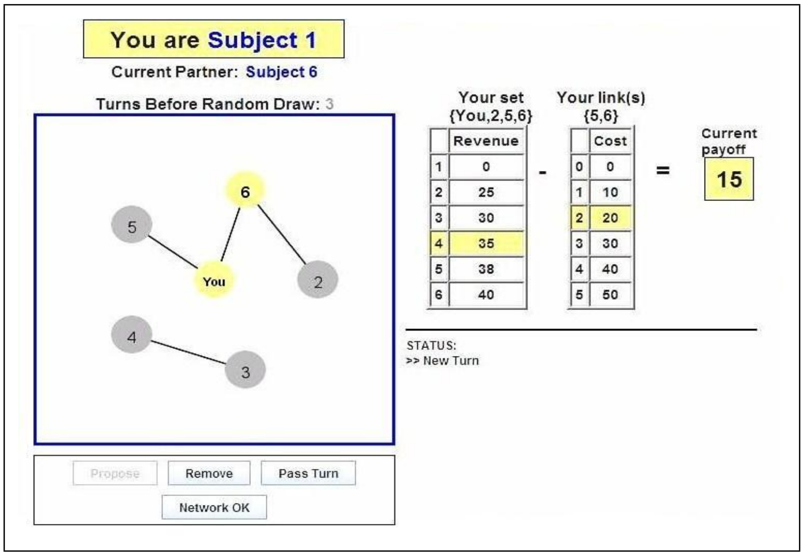

Figure 1: User interface for the linking game.

that the node representing the subject is always located at the center and labeled "You" while the nodes representing the other players in a match are labeled by their roles and surround the subject's node at an equal distance from it. By always putting the subject's node at the center, even though the underlying connections between subjects in a match are identical, each subject sees different graphical representations. We therefore avoid leading participants towards focal networks such as the star or wheel network.

3.2 Treatments

Since we are primarily interested in comparing observed and predicted outcomes under different scenarios, the benefits are not based on any particular functional form. With this freedom, we can set the payoffs such that we have unique PWS equilibria with intermediate sizes, no equilibrium or multiple equilibria. Meanwhile, each direct link incurs a constant cost. We avoid potential confusion by maintaining the same cost per link across treatments and only vary the benefits.

Our experiment includes four treatments. They are graphically depicted in Treatments 1, 2, 3 and 4 that are inserted at the end of the paper for future reference. These network graphics illustrate how we construct the different equilibria. First, we draw a "supernetwork", comprising the 20 possible minimally-connected six-node networks (labeled $\{A\}$ to $\{T\}$) and all the arcs connecting pairs of networks that differ from one another by a single link. We put all networks with identical number of links in the same row and order them from top row (network with no links) to bottom row (networks with 5 links).[7] The direction of the arc in the supernetwork represents the improving path (forming a new link or removing an existing link).

The four treatments we consider differ on existence and number of PWS equilibria. Treatment 1 has no PWS equilibrium. There is a unique closed cycle comprised of networks $\{B, C, D, F, G, H, N\}$ within which the dynamic process is expected to stay. Treatment 2 has four PWS equilibria, networks $\{A, I, J, K\}$, and network $\{K\}$ farsightedly dominates the other three. If players exhibit myopic behavior and follow the improving path, they will all stay on the empty network $\{A\}$. If for some reason (a perturbation, a mistake, etc.) they reach any of the other PWS networks, $\{I, J, K\}$, they will also stay there. However, with some form of forward-looking behavior, players might be able to reach the higher-return PWS network $\{K\}$. Treatments 3 and 4 each has a unique PWS equilibrium, networks $\{H\}$ and $\{L\}$, with three components of two subjects and two components of three subjects respectively.

Meanwhile, the efficient networks are identical across treatments, namely all the minimally-connected networks that comprise the six players, that is, networks $\{O, P, Q, R, S, T\}$. We choose to have the same efficient networks in all treatments to facilitate comparisons. Also, we choose several efficient networks and one of them focal ($\{T\}$, the line that comprises all agents) in order to give a fair chance to the efficient outcome. The information is summarized in Table 1.

3.3 Implementation details

The experiment was conducted in the California Social Science Experimental Laboratory at the University of California at Los Angeles (UCLA) in August 2010. All experimental subjects were UCLA students. We conducted 8 experimental sessions with 12 subjects in each session. Subjects played two sets of four treatments for a total of 8 matches in each session. We shuffled the order of the treatments such that: (i) the orders of the treatments in the first half and the second half of each session are different; (ii) no two sessions have identical treatment sequences; and (iii) each treatment is implemented in exactly two sessions for each order in the sequence. This shuffling was

[7] Networks that are not minimally connected are necessarily off the improving paths. They are omitted unless a match ends in one of them.

Table 1: Efficient and PWS networks

Treatment	Benefit for component size						Cost per link	Efficient	Pairwise stable
	1	2	3	4	5	6			
1	0	20	30	39	42	43	15	$[6]_{\{O,P,Q,R,S,T\}}$	None
2	0	10	17	22	38	44	15	$[6]_{\{O,P,Q,R,S,T\}}$	$[1\text{-}1\text{-}1\text{-}1\text{-}1\text{-}1]_{\{A\}}$ $[5\text{-}1]_{\{I,J,K^*\}}$
3	0	29	36	41	43	44	15	$[6]_{\{O,P,Q,R,S,T\}}$	$[2\text{-}2\text{-}2]_{\{H\}}$
4	0	19	36	42	44	45	15	$[6]_{\{O,P,Q,R,S,T\}}$	$[3\text{-}3]_{\{L\}}$

The number in brackets refers to the size of each component.
* *is the farsighted dominant (FD) network.*

done to neutralize the possible effects from the ordering of the treatments within a session. In total, we obtained 128 match observations – 32 matches for each treatment – from 96 distinct subjects.

With 12 subjects, there are always 2 groups in each session. To introduce anonymity in game play, after each match we reshuffled subjects into new groups and assigned a new role (1 to 6) to each subject. Each session lasted for between 90 and 120 minutes. No subject took part in more than one session. Participants interacted exclusively through computer terminals without knowing the identities of the subjects they played against. Before the paid matches, instructions were read aloud and two practice matches were played to familiarize participants with the computer interface and procedure. After that, participants 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 other subjects they were directly linked to (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 for 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 $11 and $43 with an average of $29. A copy of the instructions is included in Appendix B.

4 Network outcomes

We first analyze the general properties of the network formation game. We are particularly interested in studying convergence and stability of the final network configuration as well as the empirical payoffs obtained by players.

4.1 Network convergence: efficiency vs. stability

Result 1 *Agents recognize the underlying incentives of network formation and avoid networks that are not minimally connected.*

We begin by noting that players show understanding of the basic tenets of the experimental game. Table 2 summarizes the network outcomes of the four treatments in this experiment. We first focus on whether players end up in networks that are not minimally connected. Remember that removing links that do not reduce component size is always Pareto improving in our game. The second column in Table 2 suggests that players understand this idea. Out of 128 matches, only 5 matches (or 4%) end up in a network that is not minimally connected. This is remarkable since Pareto-inferior, non-minimally-connected networks can sometimes be necessary intermediate steps towards farsighted goals.

Table 2: Summary of network outcomes

Treatment	Not Min. Conn.	Efficient	PWS	FD	Closed cycle
1	2 (6.3%)	3 (9.4%)	-	-	21 (65.6%)
2	1 (3.1%)	5 (15.6%)	3* (9.4%)	14† (43.8%)	-
3	0 (0.0%)	0 (0.0%)	15 (46.9%)	-	-
4	2 (6.3%)	2 (6.3%)	10 (31.3%)	-	-

$N = 32$ for each treatment.
* *Includes networks* $\{A, I, J\}$; † *Includes network* $\{K\}$.

Result 2 *The process tends to converge to the stable network when it exists and not to converge when no stable network exists. It rarely leads to the efficient networks.*

Before discussing the results, we need an operational definition of convergence. Callander and Plott (2005) suggest that a network has converged if it maintains the same state in the last T turns before the end of the game. Alternatively, in our experiment we can use the "Network OK" action. In this case, a network is said to have converged if: (i) all agents are satisfied with the current network, or (ii) when not all have done so by the end of the match, those who have not did not unilaterally change the network when given the opportunity, or were unable to unilaterally do so.

The first definition may "over-detect" convergence since it includes cases where the lack of change is merely the result of how pairs were randomly assigned in the last T turns before the random end of a match (naturally, a longer T makes this possibility less likely). The second definition, on the other hand, may "under-detect" convergence. Indeed, a player may delay choosing "Network OK" not because she thinks she can improve her own payoff, but hoping to benefit from a possible mistake by another player.

Table 3 presents the rate of convergence under the first definition with $T = 3$ and under the second definition.[8] Under the first definition, convergence tends to occur only in treatments where a stable network (or networks) exists. The convergence rate is lowest in Treatment 1 (around 20%), where the improving paths lead to a closed cycle. For the other treatments, including the one with multiple PWS equilibria, convergence is above 50%. Convergence under the second definition is always low (15% or less) indicating that this notion is probably too strict.

We now go back to Table 2 and look at how well the theory predicts the final network. The graphical illustrations of Treatments 1 to 4 elaborates on this information: it displays the number of final outcomes for each network architecture $\{A\}$ to $\{T\}$ both conditional on no change in the last 3 turns (labeled C) and unconditional on convergence (labeled U). In the absence of a PWS network (Treatment 1), 65.6% of the matches end with a network within the closed cycle.[9] More interestingly and ignoring conver-

[8]Assuming 3 turns is arbitrary. It corresponds to 18 individual decisions to keep the same configuration, which we believe is reasonably large. As a robustness check, we performed the analysis with $T = 5$. With 5 turns, the frequency of convergence decreases but the qualitative conclusions remain the same (data omitted for brevity but available from the authors).

[9]Even more so, matches stay within the closed cycle most of the time: in 55.5% of all the moves after Turn 6 subjects remain in a network that is within the closed cycle. Also,

Table 3: Network convergence

Treatment	No change last 3 turns‡	Network OK†
1	7 (21.9%)	1 (3.1%)
2	20 (62.5%)	3 (9.4%)
3	17 (53.1%)	5 (15.6%)
4	18 (56.3%)	3 (9.4%)

$N = 32$ for each treatment

† *Either 6 players chose* <Network OK> *or 5 players did so with the remaining player unable or unwilling to alter the network.*

‡ *Includes* <Network OK> *networks.*

gence for now, we find that 53.2%, 46.9% and 31.3% of the final networks in Treatments 2, 3 and 4 are PWS networks, including the farsighted-dominant one (FD). Finally, the dynamic formation process rarely leads to any of the efficient networks.[10]

Table 4: Average distances from outcomes

Treatment	PWS	FD	Closed cycle	Shortest efficient	Efficient line
1	-	-	0.41 †	1.66	2.03
2	3.66 ‡	0.91	-	1.41	1.66
3	1	-	-	1.94	2.06
4	1.41	-	-	1.28	1.41

† *We calculate the distance to the closest network in the cycle.*

‡ *We only consider the empty network $\{A\}$.*

the process ends at least once in all the networks of the cycle except in $\{B\}$.

[10]The treatment that ends with the efficient network the most is Treatment 2 (15.6%). However, in this treatment, all efficient networks that became the final outcome are just one link away from the farsighted-dominant stable architecture.

To study in more detail the difference between observed and predicted (stable or efficient) outcomes, we calculate the shortest (or "geodesic") distance between the resulting networks and the closest network in the closed cycle (for Treatment 1) or the PWS networks (for Treatments 2, 3 and 4) 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 $\{T\}$.[11] Table 4 shows that for Treatments 1 and 3, the distance to the closed cycle and the PWS network respectively is substantially shorter than the distance to the efficient networks. For Treatment 2, the distance is shorter to the farsighted dominant network (FD) but longer to the PWS empty network $\{A\}$ (PWS). For Treatment 4, however, the distance from the PWS network is equal to the distance from the efficient line network and longer than the distance from the closest efficient network, suggesting a larger dispersion in behavior.

We next examine the following question: When stable networks exist, how well do they predict the outcome conditional on convergence? Hereafter, we employ the operational definition of convergence as the lack of change in the last 3 turns. Table 5 suggests a mixed picture. For Treatments 2 and 3, more than half of the convergent networks are stable. For Treatment 4, only 4 out of 18 convergent networks are PWS (Treatment 1 is not included in this analysis as it predicts no convergence). The difference between Treatments 3 and 4 is intriguing. A possible reason is the asymmetry of players' payoffs *within* components. Indeed, with [2-2-2] all subjects earn equal amounts and have little room for improvement. By contrast, with [3-3] the players in the center of the component may deviate so as to keep the same network structure but push someone else to bear the cost of having two links.

Table 6 presents the average distance of the network outcomes from the different networks conditional on convergence. For Treatments 2 and 3, the results provide further support for convergence to the FD PWS and the unique PWS networks respectively. For Treatment 4, the distance from the convergent network to the efficient networks is lower than to the PWS network. This result (as well as that from Table 4) comes from the fact that most of the network outcomes in this treatment, both conditional and unconditional on convergence, are split almost equally between the stable network $\{L\}$ and network $\{N\}$. Since the distance between these two networks is

[11] 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).

Table 5: Summary of network outcomes conditional on convergence

Treatment	Efficient	PWS	FD	N
2	4 (20.0%)	1* (5.0%)	11 (55.0%)	20
3	0 (0.0%)	9 (52.9%)	-	17
4	1 (5.6%)	4 (22.2%)	-	18

* *Includes networks* $\{A, I, J\}$.

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 therefore difficult to infer from the network outcomes alone where the formation processes is leading toward. In our analysis of individual decisions (Result 6), we provide a plausible explanation for our findings here.

Table 6: Average distance from outcomes conditional on convergence

Treatment	PWS	FD	Any efficient	Efficient line
2	3.75*	0.75	1.25	1.35
3	0.88	-	2.06	2.18
4	1.61	-	1.28	1.39

* *We only consider the empty network* $\{A\}$.

4.2 Network stability: myopic vs. farsighted

Result 3 *Agents are able to "coordinate" away from the myopic improving path to reach a higher return, farsightedly-dominant stable network.*

As elaborated in the previous section, the strict use of myopic improving paths may lead to suboptimal choices, especially in the presence of scale economies. Treatment 2 implements such scale economies: agents with one link obtain positive payoffs for components of size 2 and above and agents with two links obtain positive payoffs for components of size 5 or 6 only. Thus, starting from the empty network $\{A\}$, the improving path will stay there. Meanwhile, $\{K\}$, the PWS networks that farsightedly dominate the three other PWS networks have a [5-1] architecture.

Tables 2 and 5 show that the dynamic link formation process did lead by and large to the farsighted-dominant stable network. Indeed, the percentage of Treatment 2 matches that end in the farsighted-dominant stable network is 43.8% (unconditional on convergence) and 55.0% (conditional). By contrast, only 9.4% (unconditional) and 5.0% (conditional) end in one of the other three PWS networks. The results are further supported in Tables 4 and 6: the FD PWS network has a four to five times lower distance to the average outcome than the empty PWS network, even though all games start at the empty network $\{A\}$.

Our results are in line with Pantz (2006) who found that many of her games did reach the forward-looking equilibrium architecture. Our setup, however, is substantially more challenging for players. Indeed, there are 20 possible minimally-connected architectures. Starting from the empty network $\{A\}$, players must go through *three* non-improving paths before they reach networks $\{F, G\}$, and only from there they may converge to $\{K\}$ (if they reach $\{E\}$, the improving path will lead them to the stable networks $\{I, J\}$, see the graphical illustration of Treatment 2). Despite the attraction of the empty network, none of the 32 games ended in $\{A\}$.

4.3 Payoffs

Result 4 *Aggregate payoffs are substantially lower than in the efficient networks and similar to the payoffs in the PWS networks.*

Table 7 presents the average sum of payoffs generated by the network in each treatment, also called “network value”. These values are compared with the average value of the networks in the closed cycle (for Treatment 1), with the values of the PWS networks (for Treatments 2, 3 and 4), and with the values of the efficient networks (for all treatments). We find substantial welfare losses due to individual maximization: the empirical payoffs are between 46% and 71% of the payoffs generated by efficient networks. In fact, the observed payoffs are smaller but close to the payoffs in the FD PWS equilibrium for Treatment 2 and to the payoffs in the unique PWS equilibrium for Treatments 3 and 4. For Treatment 1, the payoff is 50% higher than the average payoff in the closed cycle. Similar results are obtained when we focus on convergent networks.

4.4 Summary

Our results at the network level can be summarized as follows. Players understand the strategic nature of network formation and avoid almost en-

Table 7: Summary of network values

Treatment	Obtained (all)	Obtained (convergent)	PWS	FD	Closed cycle	Efficient
1	63.13 (26.58)	-	-	-	43.1 †	108
2	52.91 (44.68)	62.70 (41.53)	0 ‡	70	-	114
3	81.47 (12.33)	79.35 (12.80)	84	-	-	114
4	85.38 (17.88)	84.78 (16.51)	96	-	-	120

† *We calculate the unweighted average payoffs of all networks in the cycle.*

‡ *We only consider the empty network* $\{A\}$.

tirely non-minimally-connected networks in all treatments. Network efficiency does not appear to be an important motivation for players in any treatment. The existence of one or several stable networks is necessary for convergence: when no equilibrium exists (Treatment 1) the process hardly converges. At the same time, it is not sufficient: convergence is much weaker in Treatment 4 than in Treatments 2 or 3. Finally, subjects are reasonably forward-looking when this is needed to reach higher-paying equilibria.

5 Individual decisions

Having analyzed aggregate outcomes, we now study each individual decision. 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. If, on the contrary, subjects are initially linked, acting implies removing a link and passing implies remaining linked. We are interested in the extent to which decisions are *myopic rational* in each of these four cases and for each treatment. An individual decision is myopic rational if it makes her weakly better off given the linking problem she faced when making her decision.

5.1 Descriptive statistics

Remember that in every turn, all three pairs of players choose an action. However, players observe the outcomes of the other pairs within that turn who have acted before them. This way, we always know whether the decision of a subject conforms to myopic rationality or not. Table 8 summarizes the share of individual actions that are myopic rational across turns. We organize the data into four groups of turns. We use Turn 12, which is the last certain turn that players get unless everyone agrees on the network outcome, as a natural point to partition matches into "early" turns (or turns with a certain future) and "late" turns (or turns with an uncertain future). We further split the early turns into two equal groups of six turns. The late turns are also split into two groups: up to Turn 18 and Turn 19 or later.

This split captures behaviors at different stages of the game. First, players may be attempting to get familiar with the particulars of the match and try different strategies with almost no irreversible effect on final outcomes (Turns [1-6]). Then, players adjust their behavior as the potential ending turn approaches (Turns [7-12]). After that, players enter the random stopping phase where, presumably, they behave under the assumption that matches can be terminated at any time (Turns [13-18]). Finally, we consider Turns 19 and above in a separate category because the sample size is dramatically reduced as turns advance and the sample becomes non-representative of the population.[12] Overall, this gives us four groups, three of which have identical number of turns.

We observe in Panel A of Table 8 that decisions are more myopic rational as players get closer to the end of the match. There appears to be jumps between [1-6] and [7-12] and also between [7-12] and [13-18], which indicates that players adjust their strategies over the course of a match.

Panel B investigates myopic rationality further by grouping the data by the types of decision problem that players faced. Here, we examine decisions under four mutually exclusive conditions, namely when the rational action is: (i) to pass and remain unlinked; (ii) to pass and remain linked; (iii) to remove an existing link; and (iv) to propose a new link. Comparing the myopic rationality under conditions (i) with (ii), and (iii) with (iv), we find evidence that players tend to be less myopic rational in decisions that reduce the number of links. Furthermore, by comparing conditions (i) with (iii), and (ii) with (iv), individuals appear to deviate more from the improving paths by failing to act when they should than by acting when they should not. However, our regressions below suggest that this last result does not hold once we control for individual fixed effects and the marginal payoff from myopic rational choices.

Meanwhile, Panel C displays myopic rationality across treatments. In

[12]For instance, there were 2712 choices in Turns [13-18] and only 672 in Turns [19-24].

Table 8: Myopic rationality of individual decisions

	Turns			
	[1-6]	[7-12]	[13-18]	≥ 19
A. All	0.741	0.819	0.894	0.910
	(0.438)	(0.385)	(0.308)	(0.286)
B. By decision problem				
B1. Passing is myopic rational				
i. Stay unlinked	0.663	0.837	0.916	0.940
	(0.473)	(0.369)	(0.277)	(0.238)
ii. Stay linked	0.956	0.967	0.979	0.967
	(0.206)	(0.179)	(0.144)	(0.180)
B2. Acting is myopic rational				
iii. Remove link	0.374	0.392	0.571	0.647
	(0.484)	(0.489)	(0.496)	(0.485)
iv. Propose link	0.882	0.878	0.877	0.846
	(0.323)	(0.328)	(0.328)	(0.362)
C. By treatment				
Treatment 1	0.829	0.826	0.885	0.944
	(0.377)	(0.379)	(0.320)	(0.229)
Treatment 2	0.563	0.856	0.905	0.862
	(0.496)	(0.351)	(0.294)	(0.345)
Treatment 3	0.764	0.788	0.895	0.919
	(0.425)	(0.409)	(0.306)	(0.274)
Treatment 4	0.811	0.805	0.890	0.969
	(0.392)	(0.397)	(0.313)	(0.175)
D. By relative component size				
Small	0.893	0.927	0.926	0.909
	(0.310)	(0.261)	(0.263)	(0.288)
Large or equal	0.711	0.786	0.883	0.911
	(0.453)	(0.410)	(0.322)	(0.285)

Standard deviations in parenthesis

all four treatments, players are significantly less myopic rational before Turn 12 than after it. Interestingly, the difference in myopic rationality between [1-6] and [7-12] is entirely driven by Treatment 2. This is quite natural since subjects need to play against myopic rationality at least three times in order to escape the empty network, zero payoff PWS equilibrium $\{A\}$.

Figure 2 illustrates the results in Panels B and C together. 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 than what is myopically rational throughout the match. 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.

Panel D takes each pair of players and determines which one belongs to the smallest component (pre-choice if they are initially not linked and assuming a link removal if they are initially linked). Subjects in the small component play the myopic rational strategy rather consistently (around 90% of the time for all groups of turns). By contrast, in the large component they tend to stay there more often than predicted by myopic rationality, especially in [1-6] and [7-12]. The result is consistent with Panel B, where we showed that players have a tendency not to cut links as often as they would if they followed the myopic rule.

Finally, to further illustrate how individual strategies change throughout the match, we examine the turns in which individual decisions led them to a PWS network in the middle of a match. Table 9 presents the number of instances in which individuals choose to "enter", "stay" and "leave" a PWS network, broken down by treatment (2, 3 or 4) and turn (before vs. after Turn 12). The last column reports the total number of turns in that set. We observe that individuals are quite prone to leave the PWS network in Turns [1-12], but this tendency is dramatically reduced when the ending turn becomes uncertain, especially for Treatments 3 and 4. Surprisingly, even though Treatment 2 has one of the most predictable outcomes (43.8% of matches end up in the FD PWS network, see Table 2), individuals move away from the stable network after Turn 12 more frequently than they do in the other treatments.[13]

[13] In 7 out of the 9 cases, individuals move from $\{K\}$ to $\{F\}$. This suggests an attempt to place oneself at the edge of the network in the hope of increasing the individual's payoff.

Figure 2: Myopic rationality by treatment and decision problem

Table 9: Movements to and from PWS networks

Turns	Enter	Stay	Leave	Total turns
Turns [1-12]				
Treatment 2†	28	51	19	384
Treatment 3	30	69	24	384
Treatment 4	7	17	4	384
Turns [$\geq$ 13]				
Treatment 2†	14	67	9	177
Treatment 3	9	44	0	143
Treatment 4	8	19	1	128

† Refers to FD PWS network $\{K\}$

5.2 Regression analysis

To study more thoroughly individual decisions, we perform a binary choice regression analysis. We regress the probability that an individual chooses the myopic rational action on the attributes of the problem. That is, for each treatment we estimate a linear probability model (LPM) for the following specification:

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

where Y_{nt}^{ij} indicates whether the action is myopic rational, $\mathbf{X_{nt}^{ij}}$ captures the attributes that move individual n from network i to j in the supernetwork at turn t. Meanwhile, c_n captures the unobservable characteristics of the individual n which may affect how she makes decisions. We do not assume that the unobservable individual characteristics are independent from the attributes of the decisions, and hence, implement an individual fixed effects specification. We also cluster standard errors by session.

We choose the fixed-effects linear probability model (LPM) instead of a logit model because it is easier to interpret the marginal effects for the former, especially with regards to the interaction terms (see e.g., Ai and Norton, 2003).[14] At the end of the section, we briefly discuss some extensions and alternative representations.

We can use the regression framework to investigate the four types of de-

[14]We do not consider the fixed-effects probit model given its known bias (see Greene, 2004, for a discussion of its bias).

cisions described in Panel B of Table 8. Consider the following specification:

$$Y_{nt}^{ij} = \beta_0 + \beta_1 \cdot morelink_{ij} + \beta_2 \cdot act_{ij} + \beta_3 \cdot (morelink_{ij} \times act_{ij}) + \varepsilon \quad (2)$$

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.

Table 10: The regression coefficients and the types of decision problems

	Interpretation	$more\ link_{ij}$	act_{ij}	Function
i.	$\mathbf{P}$(M. rat. = 1 | M. rat. = Stay unlinked)	0	0	β_0
ii.	$\mathbf{P}$(M. rat. = 1 | M. rat. = Stay linked)	1	0	$\beta_0 + \beta_1$
iii.	$\mathbf{P}$(M. rat. = 1 | M. rat. = Remove)	0	1	$\beta_0 + \beta_2$
iv.	$\mathbf{P}$(M. rat. = 1 | M. rat. = Propose)	1	1	$\beta_0 + \beta_1 + \beta_2 + \beta_3$

Under the LPM, the interpretation of these β-coefficients is straightforward. The coefficient β_0 captures the probability that an individual does not propose a link in accordance to the myopic rational strategy. Similarly, $\beta_0 + \beta_1$ captures the probability that an individual does not remove a link in accordance to the myopic rational strategy. Table 10 provides interpretations for the different combinations of coefficients.

This specification allows us to explore how the nature of the decision problem affects game play. However, we also include three sets of additional variables (and the individual fixed effects) to explore possible individual strategies. The extended models are, therefore, variations based on the following specification:

$$\begin{aligned} Y_{nt}^{ij} = {} & \beta_0 + \beta_1 \cdot morelink_{ij} + \beta_2 \cdot act_{ij} + \beta_3 \cdot (morelink_{ij} \times act_{ij}) \\ & + \gamma \cdot mpay_{ij} + \delta \cdot chdist_{ij}^{q} \\ & + \textstyle\sum_{t=1}^{4} \chi_t \cdot turn\_sp(t) + c_n + \varepsilon \end{aligned} \quad (3)$$

First, we want to investigate whether the size of the marginal payoff affects the deviations from the improving path. The variable $mpay_{ij}$ contains the marginal payoff from making a myopic rational choice between networks i and j. With a myopic strategy, the sign (a marginal loss vs. a marginal gain) of the decision should matter but not the magnitude of the loss or the gain. However, if we assume imperfect choices (like in the Quantal Response

Equilibrium model of McKelvey and Palfrey (1995)) it is reasonable to think that deviations are less likely to occur the larger the marginal loss.

Second, we explore the possibility that individuals follow the shortest distance towards the efficient line network (Eff.Line) or the farsighted-dominant FD) PWS network. The variable $chdist(q)_{ij}$ denotes the change in the geodesic distance to network $q \in \{\text{Eff.Line, FD}\}$ if an individual takes the myopic rational choice in choosing between networks i and j. Each of these variables can take a value of 1, 0, or -1 and they are included one at a time in the regression. A negative coefficient on $chdist(q)$ indicates that all else the same, players are more likely to choose a myopic rational action if it moves them closer to network q.

Finally, we control for possible turn effects using a linear spline on the turn variables, *turn_sp*, with knots at turns 6, 12, and 18.[15] The knot choices mimic the turn grouping we did for the descriptive analysis.

Result 5 *The improving paths predict better individual decisions at later turns than at earlier turns.*

We first perform a test for pooling for all of our specifications to investigate whether there is a structural change after Turn 12. Table 11 presents our results. In all but one specification, we can reject the null hypothesis that the coefficients before and after Turn 12 are equal at 1% significance; in all cases, we can reject the hypothesis at 5% significance.

We therefore analyze the two sets of turns separately. We begin by examining the extent to which improving paths drive individual behaviors. If improving paths were the sole driver of network evolution, the constant terms in all of these specifications would be one and the coefficients on all other variables would be zero. Table 12 presents the regression results of our basic model with individual fixed effects. The constant terms are much lower than one, and the coefficients of the other variables are significantly different from zero, suggesting deviations from the improving paths.

To see more clearly the extent to which individuals deviate, we included estimates of the linear combinations of the coefficients for the constant term, *morelink*, *act*, and $morelink \times act$. These linear combinations are derived from Table 10 to allow immediate comparisons of the probabilities that individuals make myopic rational choices for the different decision problems.

Pairwise comparisons of estimates confirm that, all else the same, individuals are more myopic rational in Turns [≥ 13] compared to [1-12]. Of the

[15]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 greater than 18.

Table 11: Pooled FE LPM on the likelihood of myopic rational action

	Treatment 1		Treatment 2			Treatment 3		Treatment 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(turn>12)	0.130***	0.063	0.263***	0.486***	0.472***	0.169**	0.204*	0.105***	0.018
	(5.54)	(1.31)	(31.72)	(9.16)	(9.58)	(4.07)	(2.67)	(6.32)	(0.32)
morelink	0.163***	0.153***	0.253***	0.142***	0.109**	0.236***	0.138***	0.145***	0.123***
	(7.13)	(6.62)	(27.72)	(7.94)	(5.36)	(22.35)	(5.92)	(6.81)	(5.72)
... × **1**(turn>12)	-0.121**	-0.125***	-0.231***	-0.108**	-0.089**	-0.162**	-0.119*	-0.088**	-0.069**
	(-4.16)	(-5.49)	(-15.03)	(-4.45)	(-3.75)	(-4.23)	(-2.60)	(-4.73)	(-3.66)
act	-0.274**	-0.255**	-0.273*	-0.234	-0.182	-0.294***	-0.277***	-0.524***	-0.483***
	(-4.38)	(-4.45)	(-2.77)	(-2.12)	(-1.91)	(-6.56)	(-7.61)	(-18.38)	(-15.46)
... × **1**(turn>12)	-0.087	-0.084	0.194	0.233*	0.198	0.077	0.079	0.103	0.076
	(-1.06)	(-0.85)	(2.32)	(2.56)	(2.34)	(1.26)	(1.54)	(1.63)	(1.18)
morelink × act	0.185**	0.186**	0.188	0.202	0.152	0.265**	0.291**	0.458***	0.454***
	(3.83)	(4.65)	(1.96)	(1.77)	(1.45)	(4.90)	(5.37)	(17.77)	(16.66)
... × **1**(turn>12)	0.079	0.056	-0.291*	-0.416**	-0.384**	-0.046	-0.078	-0.130*	-0.142*
	(0.86)	(0.50)	(-3.07)	(-4.03)	(-3.57)	(-0.70)	(-1.26)	(-2.52)	(-3.12)
mpay		0.003*		0.015***	0.013***		0.005*		0.005**
		(2.67)		(9.26)	(10.84)		(2.88)		(4.94)
... × **1**(turn>12)		-0.000		-0.002	-0.001		-0.002		-0.003
		(-0.06)		(-0.52)	(-0.23)		(-0.91)		(-1.40)
turn		0.005		0.030***	0.031***		0.010*		0.004
		(1.23)		(9.00)	(10.97)		(3.20)		(1.93)
... × **1**(turn>12)		0.002		-0.034***	-0.035***		-0.007		0.007
		(0.51)		(-7.53)	(-8.83)		(-1.47)		(2.05)
chdist(Eff. Line)		-0.024**			-0.096***		-0.055**		-0.034*
		(-3.68)			(-5.96)		(-5.21)		(-2.39)
... × **1**(turn>12)		0.010			0.046*		0.030*		0.040*
		(0.61)			(2.92)		(2.65)		(3.02)
chdist(FD)				-0.087***					
				(-6.94)					
... × **1**(turn>12)				0.039*					
				(2.89)					
Constant	0.811***	0.736***	0.663***	0.286***	0.327***	0.732***	0.635***	0.818***	0.704***
	(49.21)	(21.15)	(70.98)	(11.99)	(12.77)	(59.12)	(20.63)	(57.31)	(21.23)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P(pooling)	0.004	0.002	0.000	0.000	0.000	0.023	0.004	0.003	0.001
N	3276	3276	3366	3366	3366	3162	3162	3072	3072
Adj. R^2	0.169	0.176	0.154	0.331	0.336	0.245	0.270	0.253	0.264

t statistics in parentheses. Standard errors are clustered at the session level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: FE LPM on myopic rationality: effect of type of decision

	Turns [1-12]				Turns [$\geq$ 13]			
	Tr. 1 (1)	Tr. 2 (2)	Tr. 3 (3)	Tr. 4 (4)	Tr. 1 (5)	Tr. 2 (6)	Tr. 3 (7)	Tr. 4 (8)
morelink [β_1]	0.168***	0.256***	0.233***	0.144***	0.040	0.015	0.097*	0.072*
	(6.51)	(25.39)	(22.96)	(6.51)	(1.28)	(1.25)	(2.96)	(2.43)
act [β_2]	-0.265**	-0.267*	-0.277***	-0.512***	-0.374**	-0.074	-0.168**	-0.418***
	(-4.28)	(-2.64)	(-5.96)	(-18.75)	(-3.56)	(-1.35)	(-3.65)	(-5.45)
morelink $\times$ act [β_3]	0.173**	0.182	0.263**	0.444***	0.287	-0.068	0.201**	0.335**
	(3.81)	(1.86)	(4.79)	(17.47)	(2.21)	(-0.95)	(4.02)	(5.38)
Constant [β_0]	0.809***	0.664***	0.731***	0.816***	0.942***	0.916***	0.878***	0.921***
	(46.84)	(69.11)	(127.02)	(65.97)	(46.10)	(57.06)	(89.13)	(51.57)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear combinations:								
i. β_0	0.809***	0.664***	0.731***	0.816***	0.942***	0.916***	0.878***	0.921***
	(46.84)	(69.11)	(127.0)	(65.97)	(46.10)	(57.06)	(89.13)	(51.57)
ii. β_0+β_1	0.977***	0.920***	0.964***	0.960***	0.981***	0.931***	0.976***	0.993***
	(48.56)	(64.59)	(114.4)	(77.36)	(70.81)	(56.75)	(32.78)	(36.17)
iii. β_0+β_2	0.544***	0.397***	0.454***	0.303***	0.568***	0.842***	0.711***	0.503***
	(11.57)	(4.240)	(10.26)	(16.29)	(6.020)	(18.73)	(16.16)	(6.990)
iv. β_0+β_1+β_2+β_3	0.885***	0.835***	0.950***	0.892***	0.894***	0.789***	1.009***	0.909***
	(57.83)	(35.82)	(49.59)	(60.15)	(30.18)	(14.40)	(25.63)	(19.83)
N	2304	2304	2304	2304	972	1062	858	768
Adj. R^2	0.142	0.125	0.256	0.267	0.264	0.171	0.242	0.228

t statistics in parentheses. Standard errors are clustered at the session level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

16 combinations of treatments and decision problems, the point estimates are always larger in later turns with only one exception: Treatment 2 when the myopic rational choice is to propose.

Result 6 *In early turns, individuals deviate from improving paths by maintaining excessive links (over-proposing and not removing redundant links). In later turns, individuals deviate mainly by not removing redundant links.*

Panel B of Table 8 suggests that subjects keep, if anything, too many links. We hypothesize that the asymmetry of the linking game may explain this behavior. Since link formation requires mutual agreement while removal does not, one possible strategy would be to form and maintain some redundant links early on. As the game approaches the end, individuals begin to unilaterally remove them. The exact turn when the individual removes the last redundant link will depend on his risk preference and beliefs regarding the likelihood that he will be able to remove it before the game ends.

We find some evidence in support of this hypothesis. As described in Figure 2, deviations from myopic rationality are more pronounced in all treatments when they imply excessive links (proposing unprofitable links and keeping redundant links) than when they imply insufficient links. We find evidence of this same behavior in our regressions. As shown in Table 12, 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 [≥ 13], the least myopic rational decision is still by far to remove a link (iii), except for Treatment 2. The order of the other coefficients are somewhat perturbed although it is difficult to make strong conclusions since most coefficients are very high (90% and above).

Result 7 *The size of marginal payoffs affects the likelihood of a deviation from myopic rationality in early turns for Treatments 1, 2 and 4 and in all turns for Treatment 2.*

With a myopic rational strategy, the size of the marginal payoffs should be irrelevant: individuals would choose actions that give them non-zero gain, irrespective of their size. To investigate whether this is the case, we implement the extended specification of (3). We then interact the payoff variable with the interactions between *morelink* and *act* to capture differential effects of marginal payoffs across different decision problems.

The results of the regressions are presented in Table 13. We linearly combine the coefficients for the payoff variables to explore the heterogeneity

Table 13: FE LPM on myopic rationality: effect of marginal payoff

	Turns [1-12]				Turns [$\geq$ 13]			
	Tr. 1 (1)	Tr. 2 (2)	Tr. 3 (3)	Tr. 4 (4)	Tr. 1 (5)	Tr. 2 (6)	Tr. 3 (7)	Tr. 4 (8)
morelink	0.311***	0.428**	0.303**	0.455*	0.120	0.053	0.124	0.127*
	(5.66)	(4.32)	(5.15)	(3.20)	(1.38)	(1.14)	(1.39)	(2.40)
act	-0.309*	0.249*	-0.381***	-0.613**	-0.063	0.227	-0.390*	0.084
	(-2.98)	(3.39)	(-6.18)	(-4.02)	(-0.37)	(2.19)	(-2.71)	(0.27)
morelink × act	0.213	-0.251**	0.454***	0.579**	-0.043	-0.531*	0.524*	-0.241
	(1.90)	(-3.83)	(9.54)	(3.83)	(-0.24)	(-3.01)	(2.78)	(-0.69)
mpay [γ_0]	0.011*	0.034**	0.015*	0.026*	0.009	0.011**	0.010	0.006
	(2.89)	(5.24)	(3.35)	(2.74)	(2.24)	(4.65)	(2.09)	(2.19)
mpay × morelink [γ_1]	-0.012*	-0.024*	-0.014*	-0.024*	-0.008	-0.002	-0.009	-0.005
	(-3.20)	(-3.37)	(-3.30)	(-2.45)	(-1.59)	(-0.64)	(-1.73)	(-1.31)
mpay × act [γ_2]	0.008	-0.048**	0.011	0.017	-0.033	-0.027	0.027	-0.043
	(0.95)	(-4.86)	(1.75)	(1.57)	(-1.33)	(-2.28)	(1.90)	(-1.50)
mpay × morelink × act [γ_3]	-0.008	0.045**	-0.013	-0.018	0.035	0.038*	-0.032	0.048
	(-0.82)	(4.07)	(-2.23)	(-1.47)	(1.46)	(2.64)	(-2.11)	(1.55)
Constant	0.659***	0.012	0.534***	0.408*	0.767***	0.736***	0.793***	0.798***
	(10.74)	(0.29)	(9.33)	(2.94)	(11.60)	(18.08)	(16.89)	(16.57)
turn_sp(1) & turn_sp(2)	Yes	Yes	Yes	Yes	No	No	No	No
turn_sp(3) & turn_sp(4)	No	No	No	No	Yes	Yes	Yes	Yes
chdist(EffLine)	Yes	No	Yes	Yes	Yes	No	Yes	Yes
chdist(FD)	No	Yes	No	No	No	Yes	No	No
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear combinations:								
i. γ_0	0.011*	0.034**	0.015*	0.026*	0.009	0.011**	0.010	0.006
	(2.89)	(5.24)	(3.35)	(2.74)	(2.24)	(4.65)	(2.09)	(2.19)
ii. $\gamma_0+\gamma_1$	-0.001	0.010**	0.001	0.003*	0.001	0.009**	0.001	0.001
	(-0.94)	(5.34)	(1.18)	(2.87)	(0.52)	(4.32)	(0.43)	(0.36)
iii. $\gamma_0+\gamma_2$	0.019*	-0.014	0.026**	0.044***	-0.024	-0.016	0.037*	-0.037
	(3.16)	(-1.39)	(4.17)	(5.86)	(-0.91)	(-1.23)	(3.03)	(-1.31)
iv. $\gamma_0+\gamma_1+\gamma_2+\gamma_3$	-0.000	0.007**	-0.002	0.003*	0.003	0.020**	-0.004	0.005
	(-0.03)	(5.29)	(-0.82)	(2.79)	(1.21)	(5.36)	(-0.64)	(1.14)
N	2304	2304	2304	2304	972	1062	858	768
Adj. R^2	0.154	0.375	0.300	0.294	0.291	0.282	0.270	0.246

t statistics in parentheses. Standard errors are clustered at the session level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of the payoff-size effects across decision problems. We use a strategy similar to the way we linearly combined the coefficients of the *morelink* $\times$ *act* interactions 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 individuals myopic-rationally stay unlinked; γ_0 + γ_1 measures how the payoff size influences the probability that individuals myopic-rationally stay linked, and so on.

For Turns [1-12] in Treatments 1, 3, and 4, we find that myopic rational choices are positively correlated with the size of the marginal payoffs if the myopic rational choice is to reduce the number of links (cases (i) and (iii)). Almost all of these coefficients lose their significance in Turns [$\geq$ 13]. Meanwhile, for Treatment 2, all of the payoff coefficients are significant in both Turns [1-12] and [$\geq$ 13] except when the myopic rational choice is to remove a link.

These results provide an additional insight on how individuals deviate from the improving paths, perhaps in an effort to explore shortcuts to higher-paying networks. For Treatments 1, 3, and 4, the evidence suggests that individuals take the opportunity loss from removing a link more seriously than that from staying unlinked. For Treatment 2, subjects take all losses equally into consideration. As explored in the next result, they presumably see those losses as an intermediary step towards the higher paying equilibrium.

Result 8 *Individual strategies are strongly suggestive of forward-looking behavior.*

Finally, we examine the crucial question of forward-looking behavior. We begin with Treatment 2, where there are multiple PWS architectures and one of them is farsighted-dominant. Our network outcomes analysis suggests that individuals tend to reach the FD PWS architecture (Result 3). We examine whether this conclusion is also supported by the individual-level analysis. Table 14 presents the extended regression based on (3). Two pieces of evidence corroborate the notion that individuals are forward looking.

First, remember that individuals in Treatment 2 would need to violate myopic rationality in the first few turns to escape the zero-payoff PWS network. However, once these initial "barriers" have been overcome, individuals can reach the FD PWS network by following the improving paths. We therefore expect an increase in myopic rationality within the first six turns. As shown in Table 14, the spline for the first six turns, $turn\_sp1$, is positive and significant for Treatment 2 and only for that treatment. Moreover, all other turn spline variables for Treatment 2 are not significant.

Table 14: FE LPM on the likelihood of myopic rational action

	Turns [1-12]					Turns [≥ 13]				
	Tr. 1	Tr. 2		Tr. 3	Tr. 4	Tr. 1	Tr. 2		Tr. 3	Tr. 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
morelink [β_1]	0.156***	0.121***	0.092***	0.129***	0.120**	0.018	0.027	0.016	0.016	0.061
	(6.22)	(7.94)	(5.41)	(6.56)	(4.82)	(0.80)	(1.90)	(1.16)	(0.25)	(2.12)
act [β_2]	-0.242**	-0.254	-0.206	-0.258***	-0.469***	-0.349*	0.007	0.018	-0.149**	-0.410**
	(-4.32)	(-2.18)	(-2.00)	(-6.77)	(-15.60)	(-2.99)	(0.12)	(0.37)	(-3.54)	(-5.12)
morelink × act [β_3]	0.161**	0.232	0.186	0.293**	0.438***	0.265	-0.160	-0.174	0.188*	0.319**
	(4.39)	(1.93)	(1.68)	(4.96)	(15.49)	(1.92)	(-1.96)	(-2.19)	(3.01)	(5.32)
turn_sp(1) †	-0.006	0.079***	0.079***	0.012	0.003					
	(-1.01)	(10.96)	(10.86)	(2.03)	(0.30)					
turn_sp(2) †	0.012*	-0.000	0.000	0.009	0.005					
	(2.73)	(-0.10)	(0.08)	(2.00)	(1.85)					
turn_sp(3) †						0.017*	0.002	0.003	0.006	0.016
						(2.81)	(0.64)	(0.73)	(0.91)	(1.82)
turn_sp(4) †						0.003	-0.007	-0.008	-0.007	0.001
						(1.23)	(-2.29)	(-2.35)	(-1.80)	(0.09)
chdist(Eff. Line)	-0.025*		-0.086**	-0.056**	-0.037*	-0.018		-0.036*	-0.034	0.006
	(-3.42)		(-5.37)	(-5.23)	(-2.71)	(-1.18)		(-2.60)	(-1.93)	(0.60)
chdist(FD)		-0.071***					-0.038*			
		(-5.81)					(-2.98)			
Constant [β_0]	0.773***	0.157***	0.197***	0.621***	0.707***	0.843***	0.693***	0.713***	0.857***	0.837***
	(19.37)	(7.01)	(7.17)	(15.74)	(14.06)	(28.07)	(24.16)	(32.38)	(17.34)	(18.81)
mpay	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear combinations:										
β_0	0.773***	0.157***	0.197***	0.621***	0.707***	0.843***	0.693***	0.713***	0.857***	0.837***
	(19.37)	(7.009)	(7.167)	(15.74)	(14.06)	(28.07)	(24.16)	(32.38)	(17.34)	(18.81)
$\beta_0+\beta_1$	0.929***	0.278***	0.289***	0.750***	0.827***	0.861***	0.720***	0.730***	0.872***	0.898***
	(23.24)	(9.824)	(9.472)	(21.81)	(22.47)	(53.26)	(29.77)	(32.58)	(8.398)	(15.55)
$\beta_0+\beta_2$	0.531***	-0.097***	-0.009***	0.363***	0.238***	0.495***	0.700***	0.732***	0.707***	0.426***
	(16.28)	(-0.831)	(-0.0975)	(5.535)	(5.785)	(5.184)	(14.97)	(17.31)	(11.76)	(5.469)
$\beta_0+\beta_1+\beta_2+\beta_3$	0.848***	0.257***	0.268***	0.785***	0.796***	0.778***	0.566***	0.574***	0.911***	0.807***
	(45.19)	(6.557)	(6.374)	(30.34)	(37.74)	(24.07)	(7.394)	(7.862)	(7.650)	(11.60)
N	2304	2304	2304	2304	2304	972	1062	1062	858	768
Adj. R^2	0.186	0.381	0.388	0.319	0.311	0.353	0.341	0.342	0.344	0.336

t statistics in parentheses
† Spline coefficients are for the slope of the intervals. Standard errors are clustered at the session level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Second, we find that the coefficient for the distance change to the FD PWS network, *chdist(FD)*, is negative and significant in both early and late turns (columns (2) and (7) in the table). It suggests that individuals may be implementing strategies that move them closer to the FD PWS network. Notice, however, that the impact of this variable is similar to that of the distance to the efficient-line network variable, *chdist(Eff.Line)* (columns (3) and (8) in the table). Because the two networks differ by a mere one link, we cannot identify which network is the individuals' ultimate goal. However the evidence regarding the (convergent) network outcomes for Treatment 2 (in Table 5) suggests that the FD PWS architecture is the ultimate goal.

Finally, Result 6 also supports the notion that individuals think more than one-step ahead. The strategy of maintaining redundant links in earlier turns only to shed them in later turns indicates that the PWS networks are not reached exclusively through myopic improving paths.

5.3 Model predictions

We next examine the capacity of our empirical model to predict actions. For this exercise, we include the regressors from our basic model, as well as the marginal payoff variable interacted with the *morelink* variable, in line with our previous findings. All of these variables are interacted with the *turn* $>$ *12* variable to account for coefficient differences before and after the potentially terminal turn. We also include only the spline for the first six turns, and interact it with a Treatment 2 indicator variable to account for players' forward-looking behavior in that treatment. For the prediction model, we do not include the individual fixed effects.

We use this model to do out-of-sample predictions of all treatments: we regress the above model while excluding one of the treatments, and then predict the myopic rationality of the excluded treatment. Instead of using LPM, we implemented a logit model to avoid irregularities such as having probabilities outside the $[0, 1]$ support. The results are presented in Table 15.

Figure 3 presents the plot of the actual and (out-of-sample) predicted myopic rationality for the different treatments in the first 18 turns. The model predicts aggregate behavior well. As expected, for Treatment 2 it overestimates the myopic rationality at the early stages, when it is most important to deviate in order to reach the FD PWS equilibrium. However, the predictions fit actual behaviors surprisingly well after Turn 6. In Treatments 1 and 3, the model slightly under-predicts the myopic rationality of actual play in early turns. In contrast, the model tends to over-predict myopic rationality in Treatment 4.

Table 15: Logit model used for out-of-sample predictions

	Treat. 1 (1)	Treat. 2 (2)	Treat. 3 (3)	Treat. 4 (4)
1(turn>12)	1.831***	1.669***	2.193***	1.487***
	(4.35)	(4.24)	(3.67)	(3.46)
morelink	2.817***	3.761***	3.246***	3.090***
	(7.95)	(9.62)	(9.13)	(8.47)
... × **1**(turn>12)	-1.961**	-1.323*	-2.179**	-1.737***
	(-2.67)	(-1.97)	(-3.16)	(-3.39)
act	-1.861***	-1.763***	-1.499***	-1.465***
	(-12.04)	(-21.76)	(-8.52)	(-7.87)
... × **1**(turn>12)	-0.139	-0.515	-0.705*	-0.433
	(-0.57)	(-1.80)	(-2.49)	(-1.34)
morelink × act	1.244***	-0.0600	0.803***	0.595*
	(4.97)	(-0.18)	(3.80)	(2.45)
... × **1**(turn>12)	-1.353**	-0.363	-0.578	-0.725*
	(-2.99)	(-1.13)	(-1.43)	(-2.19)
turn_sp(1) †	0.233***	0.0902*	0.206***	0.243***
	(8.62)	(2.11)	(6.90)	(7.43)
... × **1**(Treatment 2)	-0.0520**		-0.0479*	-0.0749***
	(-2.95)		(-2.36)	(-7.72)
mpay	0.117***	0.0825***	0.143***	0.109***
	(6.93)	(5.33)	(5.52)	(6.36)
... × **1**(turn>12)	-0.0686*	-0.0511	-0.0756	-0.0291
	(-2.14)	(-1.56)	(-1.46)	(-0.76)
mpay × morelink	-0.0863**	-0.0876***	-0.125***	-0.0944**
	(-3.29)	(-3.70)	(-3.93)	(-3.01)
... × **1**(turn>12)	0.112*	0.0823**	0.110*	0.0701
	(2.10)	(2.64)	(2.27)	(1.54)
Constant	-1.206***	-0.0529	-1.459***	-1.114***
	(-6.44)	(-0.22)	(-7.40)	(-6.06)
Observations	9600	9510	9714	9804
Pseudo R^2	0.206	0.173	0.190	0.183

t statistics in parentheses. Standard errors clustered at the session level.
† Spline coefficients are for the slope of the intervals.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

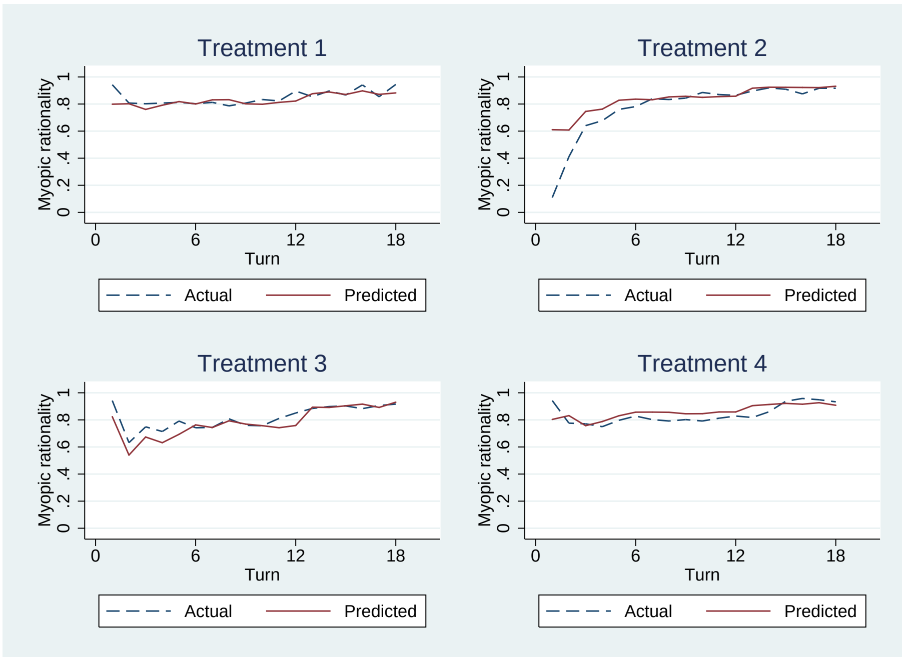

Figure 3: Out-of-sample logit prediction by treatment

5.4 Extensions and alternative representations

We have focused on the linear probability model (LPM) in the regression analysis. As a robustness check, we also estimated fixed-effects logit models for the specifications whose results we reported in Tables 12 and 14. The results for these alternative estimations are presented in Appendix A.1. For the most part, these logit estimates are qualitatively similar to those above, except for the coefficients of the interactions between *morelink* and *act*.

We also entertain the possibility that experience matters. As elaborated above, each of the four treatments were played twice in a session (in different orders). We examine whether individuals play differently the first vs. the second time they encountered them by running a test of pooling, similar to the one used to examine whether individuals play differently before vs. after Turn 12. The results are presented in Appendix A.2. In general, we find little evidence of difference in behavior between the first and second half of the experiment. The most notable difference is Treatment 2 where, in their second encounter, players tend to be less myopic rational in decisions where the myopic rational action is to either remove or propose.

5.5 Summary

The results of the analysis at the individual decision level can be summarized as follows. There is strong evidence that subjects play less myopically rational if more turns are available for sure in the future (Turns 1-12) than if their current choice may be final (Turns ≥ 13). Choices are also less myopically rational when deviations are necessary to escape the low-payoff PWS network. Deviations more often take the form of excessive links than insufficient links (possibly because links can be removed unilaterally). They are also more prevalent the smaller the marginal payoff loss, as expected under a theory of imperfect choice. Overall and with some important exceptions, the individual analysis provides support for theories of pairwise stability and forward-looking behavior.

6 Heterogeneity across 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. One simple way to address this question is to determine how often *each subject* plays the myopic rational strategy.

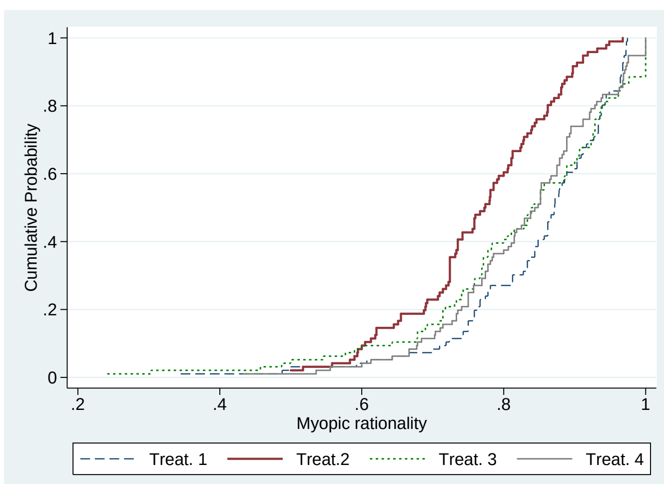

Figure 4: Empirical CDF of myopic rationality by treatment

Figure 4 plots the cumulative distribution function (CDF) of myopic rational behavior of subjects by treatment. A steeper CDF reflects a more homogeneous behavior across subjects whereas a right shift captures a more myopic rational behavior of the population. In Treatments 1, 3 and 4, behavior is homogeneous and myopically rational: 80% of the subjects or more play the myopic rational strategy 75% of the time or more. The picture changes in Treatment 2 where behavior is slightly more heterogeneous and less myopically rational. A Kolmogorov-Smirnov test confirms this observation: the CDF of Treatment 2 is different from the CDF of Treatments 1, 3 and 4 at the 1% level, whereas no statistical difference is observed between the CDFs in Treatments 1, 3 and 4 at the 10% level.

Another possibility is to search for clusters of people (as in Camerer and Ho (1999)). This is one of many ways to organize the data and allows us to quantify the degree of homogeneity of subjects within and between clusters. Given the documented difference in behavior between early turns [1-12] and late turns [≥ 13] and also between Treatment 2 and Treatments 1, 3 and 4, we use these four variables to cluster the subjects. 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). We implement model-based clustering analysis with the Mclust package in R (Fraley and Raftery, 2009). A maximum of nine clusters are considered for up to ten different models and the combination that yields the maximum Bayesian Information Criterion (BIC) is chosen.

For our multidimensional data, the model that maximizes the BIC yields *five* clusters. Table 16 shows the frequencies of subjects in each cluster, listed from low to high according to the general frequency of their myopic rational behavior. It also displays the average earnings by subjects in each cluster.

Clusters are clearly differentiated in terms of: (i) the total level of myopic rationality, (ii) the difference in behavior between Treatment 2 and the other treatments, and (iii) the difference in behavior between early and late turns. Subjects in cluster 1 are lowest on all three dimensions, followed by subjects in cluster 2. Their erratic and undifferentiated behavior indicates that one-quarter of our subjects have some difficulties in understanding the strategic aspects of the game. Subjects in cluster 3 start with low myopic rationality (between clusters 1 and 2 levels) but have the highest increase after turn 12 (around 20%). The near perfectly myopic rational behavior in later stages of Treatments 1, 3 and 4 (96%) suggests that, contrary to subjects in previous clusters, these individuals understand the incentives in our game and use early turns to try and reach an advantageous position. Clusters 4 and 5, which comprise more than half of the population, play

Table 16: Clustering based on myopic rational behavior

Cluster	Treat. 1, 3, 4		Treat. 2		Earnings	N
	[1-12]	[$\geq$ 13]	[1-12]	[$\geq$ 13]		
1	0.678	0.735	0.617	0.645	86.5	10
	(0.132)	(0.178)	(0.134)	(0.226)		
2	0.786	0.850	0.708	0.814	95.8	13
	(0.060)	(0.060)	(0.099)	(0.082)		
3	0.779	0.955	0.645	0.844	83.7	19
	(0.125)	(0.026)	(0.147)	(0.099)		
4	0.843	0.909	0.746	1.000	96.6	46
	(0.076)	(0.076)	(0.113)	(0.000)		
5	0.870	0.975	0.771	0.881	113.8	8
	(0.038)	(0.034)	(0.059)	(0.054)		
Total	0.808	0.897	0.710	0.897		96
	(0.104)	(0.104)	(0.127)	(0.145)		

Standard deviations in parenthesis

close to the theoretical predictions: high myopic rationality in later turns of all treatments, a somewhat lower myopic rationality in early turns of Treatments 1, 3 and 4 (due perhaps to costless experimentation), and a significantly lower myopic rationality in earlier turns of Treatment 2 (due both to experimentation and to escape the low-payoff PWS network). The main difference between the two clusters lies in the late turn treatments where myopic rationality is highest: Treatment 2 for cluster 4 and Treatments 1, 3, and 4 for cluster 5.

Earnings are correlated with behavior, with clusters 1 and 5 near the bottom and top of the distribution. However, the mapping between payoffs and myopic rationality is not monotonic. This can be expected for two reasons. First, because the PWS equilibrium does not necessarily generate the highest payoffs. Second, because each subject's payoff depends on the behavior of the five other players in the network.

7 Conclusion

The paper has studied the dynamic formation of social networks. We found that subjects rarely consider the total value of the network as a key criterion when making their decisions. Instead, choices are roughly consistent with individual maximization of payoffs. Many subjects exhibit forward-looking behavior if (and only if) this strategy leads to a dominant network configuration. Interestingly, a myopic rational behavior is less prevalent when actions are reversible, when marginal payoff losses are smaller and when they involve excessive links that can be removed unilaterally later on. There is, however, a significant heterogeneity in behavior: some subjects play very close to the theoretical predictions while others make relatively poor choices.

Despite the recent advances, there is still much to learn about network formation, both theoretically and experimentally. On the theory front, it would be desirable 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 get closer to the end strongly suggests that players optimize subject to imperfect choice, imperfect foresight and/or an imperfect processing capacity. To our knowledge, however, no model has yet been developed to capture these frictions. On the experimental front, ecological validity is a concern. Indeed, although the experiment is instructive, we feel that our cost and benefit representation of adding and removing links captures the essence of social networks in an excessively abstract way. The use of laboratory studies in the field or laboratory studies that exploit social technologies (e.g., facebook, twitter, or second life) would add a more realistic dimension to the network formation problem without compromising the controlled environment of the laboratory.

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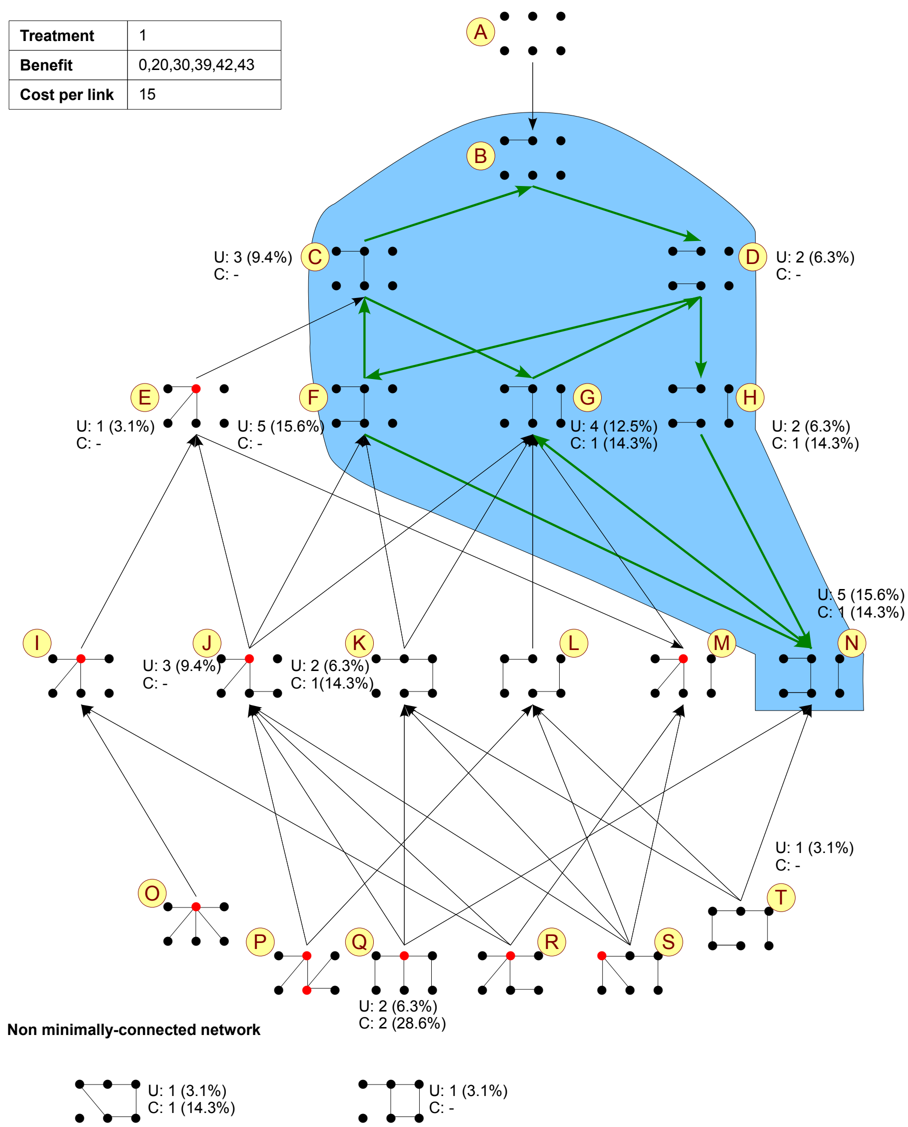
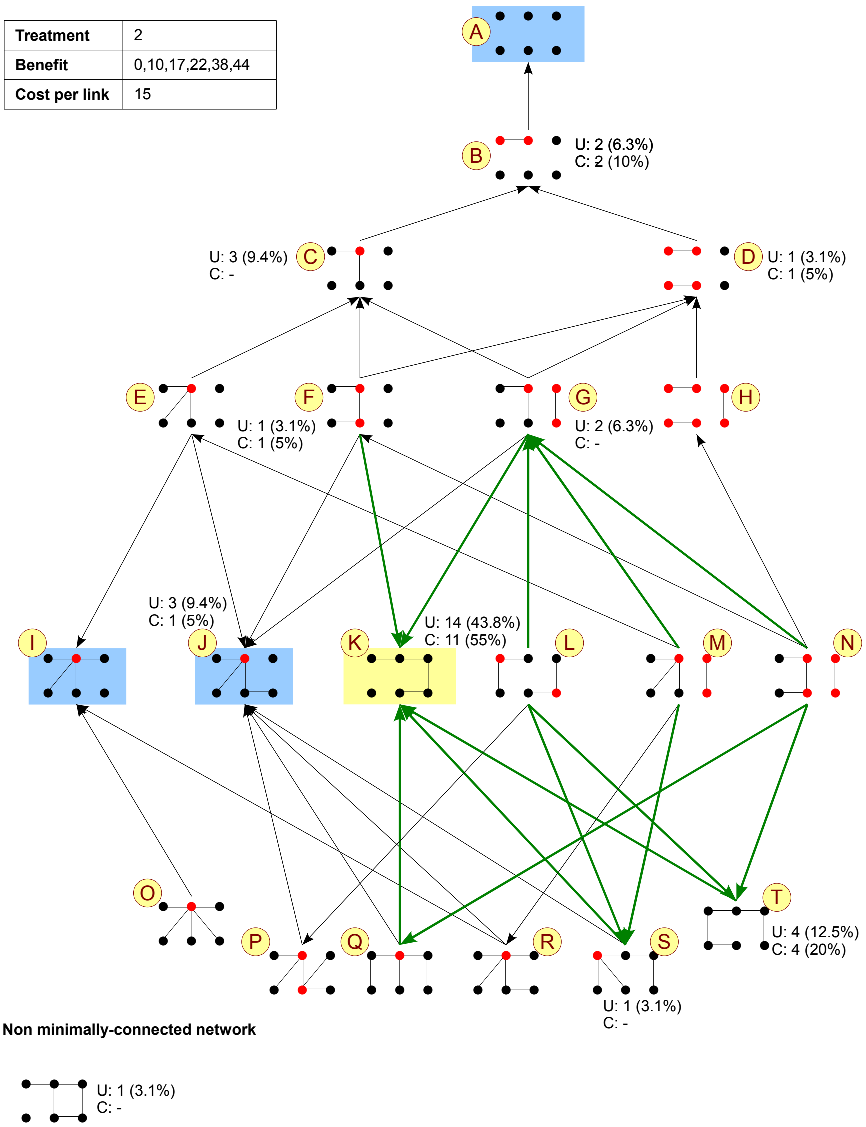


Notes. Letters refer to all minimally-connected network architectures. Numbers next to each network refer to the frequency (and percentage) that the process ends in that network. U = Unconditional on convergence, C = Conditional on no change in the last 3 turns. Networks that are part of the closed cycle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

Treatment 1. Improving paths, closed cycle, and outcomes.

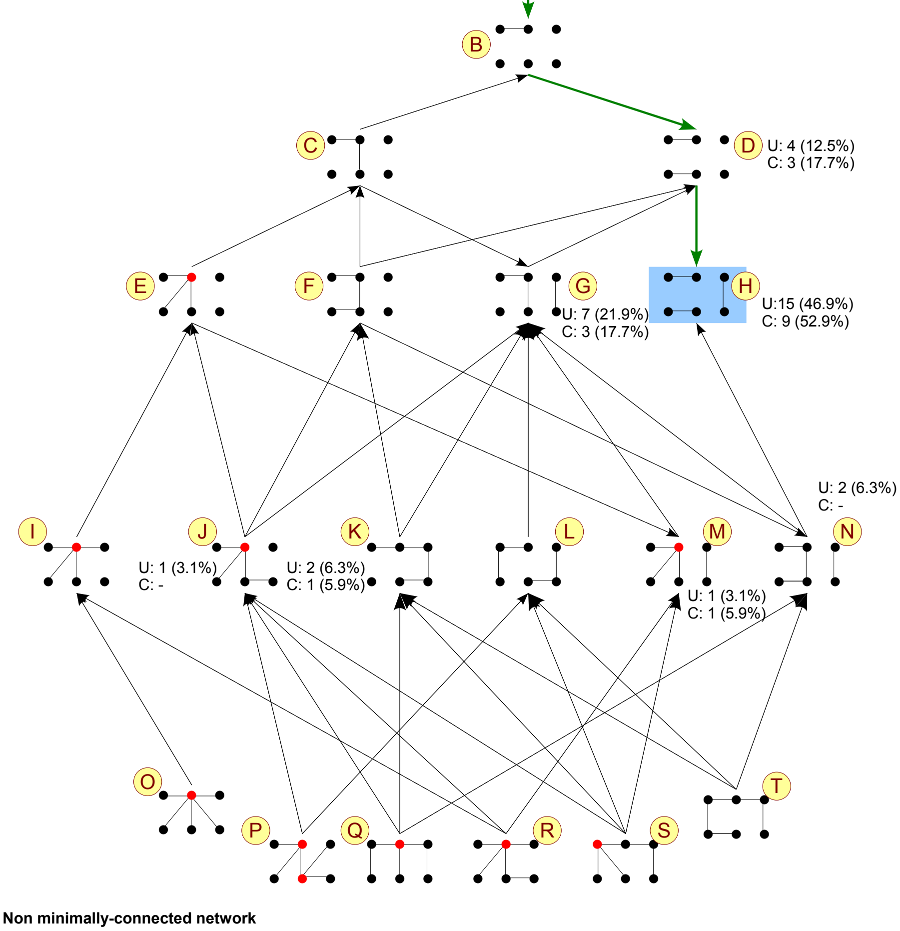
Treatment	2
Benefit	0,10,17,22,38,44
Cost per link	15



Notes. Letters refer to all minimally-connected network architectures. 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. Pairwise stable equilibria are shaded (light shade for the farsighted dominant).

Treatment 2. Improving paths, stable networks, and outcomes.

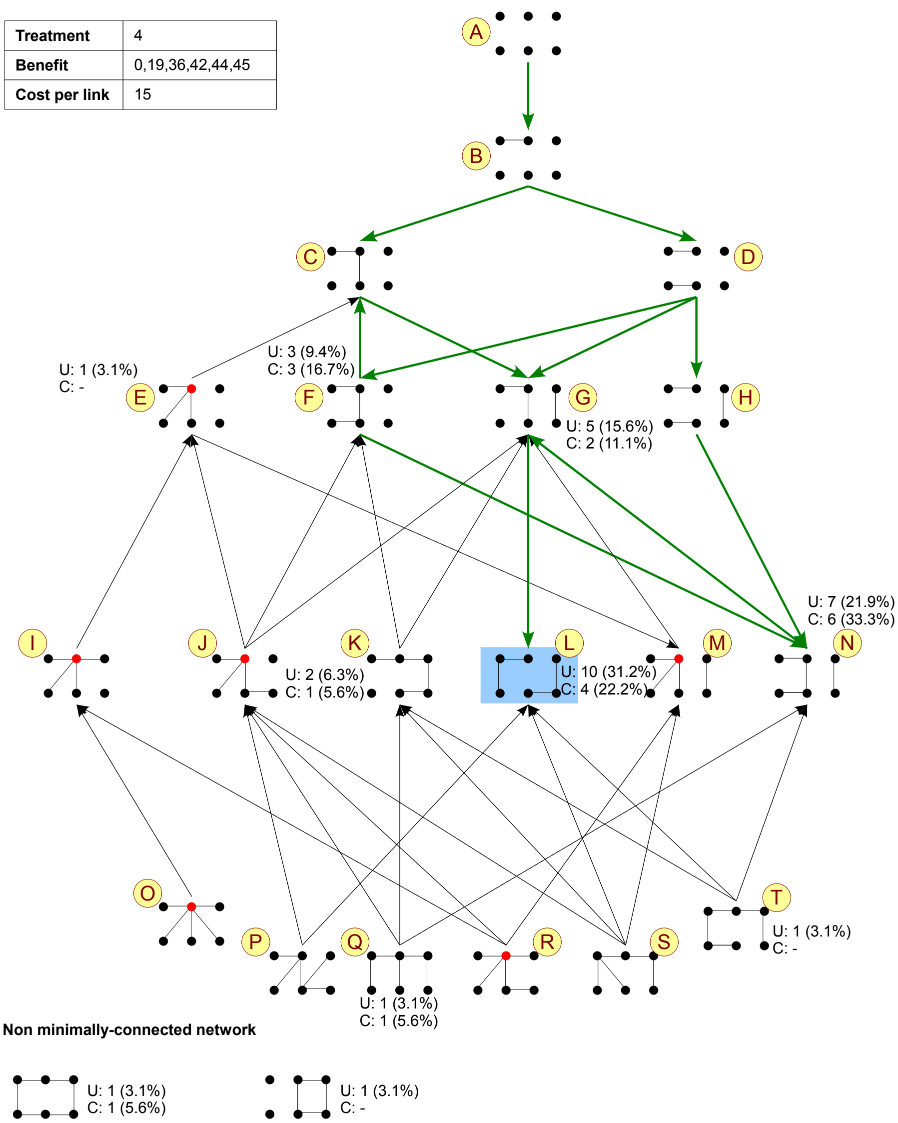
Treatment	3
Benefit	0,29,36,41,43,44
Cost per link	15



Notes. Letters refer to all minimally-connected network architectures. 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. Pairwise stable equilibrium is shaded.

Treatment 3. Improving paths, stable network, and outcomes.

Treatment	4
Benefit	0,19,36,42,44,45
Cost per link	15



Notes. Letters refer to all minimally-connected network architectures. 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. Pairwise stable equilibrium is shaded.

Treatment 4. Improving paths, stable network, and outcomes.

Appendices

A Additional analyses (not for publication)

A.1 Logit estimation

In Tables 17 and 18 we present the analogue of Tables 12 and 14 using a fixed-effects logic estimation. Note that the sign and significance of the $morelink \times act$ interaction-term coefficients often differ between the LPM and logit models. This, however, does not necessarily indicate that the two models contradict each other because, unlike in linear models (such as LPM), the coefficients on the interaction terms in non-linear models (such as logit) do not easily translate into their marginal effects (for a detailed discussion, see Ai and Norton (2003)).

A.2 Effect of experience

Table 19 presents the results regarding the effect of experience on behavior. For the basic specifications, we only find evidence of a difference in behavior for Treatment 2. With additional variables, the hypothesis of no difference in behavior is rejected for Treatment 4. Looking at the individual coefficients, we find that in Treatment 2, coefficients that are significantly different in the second half of the sessions are those for *act* and $morelink \times act$. For Treatment 4, none of the individual coefficients are significantly different in the second half of the sessions at 5% significance, and only one coefficient, namely *turn*, is significantly different at 10% significance.

Table 17: FE Logit on myopic rationality: effect of type of decision

	Turns [1-12]				Turns [$\geq$ 13]			
	Tr. 1	Tr. 2	Tr. 3	Tr. 4	Tr. 1	Tr. 2	Tr. 3	Tr. 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
morelink	2.878***	1.674***	5.044***	1.921***	2.126*	0.329	-‡	1.808*
	(5.61)	(8.54)	(5.00)	(6.15)	(2.04)	(0.93)		(2.39)
act	-1.385***	-1.199***	-1.365***	-2.608***	-2.896***	-0.964*	-1.619***	-2.854***
	(-8.46)	(-7.27)	(-7.50)	(-14.13)	(-8.05)	(-2.02)	(-3.96)	(-7.68)
morelink $\times$ act	-0.910	0.547	-1.677	1.321***	0.062	-0.651	3.481***	0.651
	(-1.67)	(1.89)	(-1.61)	(3.52)	(0.06)	(-1.06)	(4.93)	(0.76)
Constant	1.573***	0.719***	1.204***	1.682***	3.322***	2.958***	3.080***	2.804***
	(14.88)	(9.66)	(9.08)	(13.85)	(11.17)	(12.10)	(9.59)	(11.08)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ln σ_u^2								
Constant	-0.966***	-1.636***	0.114	-0.456	0.426	0.279	0.972**	-0.303
	(-3.36)	(-4.96)	(0.50)	(-1.74)	(1.16)	(0.79)	(2.64)	(-0.53)
N	2304	2304	2304	2304	972	1062	858	768

t statistics in parentheses.

† Spline coefficients are for the slope of the intervals. ‡ Dummy variable dropped due to perfect collinearity.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: FE Logit on the likelihood of myopic rational action

	Turns [1-12]					Turns [≥ 13]				
	Tr. 1	Tr. 2		Tr. 3	Tr. 4	Tr. 1	Tr. 2		Tr. 3	Tr. 4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
morelink	2.869***	1.177***	0.998***	4.420***	1.939***	1.883	0.840*	0.605	-‡	1.899*
	(5.56)	(5.28)	(4.42)	(4.35)	(5.92)	(1.78)	(2.02)	(1.42)		(2.47)
act	-1.220***	-1.326***	-1.114***	-1.305***	-2.249***	-2.587***	-0.022	0.195	-1.214**	-2.699***
	(-7.00)	(-7.00)	(-5.77)	(-6.70)	(-11.41)	(-6.88)	(-0.04)	(0.36)	(-2.70)	(-6.81)
morelink × act	-1.020	1.035**	0.802*	-1.421	1.174**	-0.257	-1.974**	-2.137**	2.372**	0.271
	(-1.84)	(3.16)	(2.42)	(-1.35)	(2.91)	(-0.23)	(-2.74)	(-2.94)	(3.13)	(0.31)
mpay	0.029*	0.105***	0.094***	0.046**	0.074***	0.051*	0.171***	0.161***	0.064	0.049*
	(2.31)	(8.50)	(7.65)	(3.17)	(4.83)	(2.35)	(7.36)	(7.01)	(1.96)	(1.98)
turn spline: before 6†	-0.051	0.361***	0.354***	0.097	-0.012					
	(-0.95)	(7.74)	(7.59)	(1.83)	(-0.20)					
turn spline: b/w 6 & 12†	0.107**	0.045	0.050	0.103**	0.063					
	(2.94)	(1.20)	(1.34)	(2.71)	(1.63)					
chdist(Eff. Line)	-0.162*		-0.471***	-0.398***	-0.265***	-0.280		-0.540***	-0.449*	0.154
	(-2.38)		(-6.80)	(-4.75)	(-3.47)	(-1.89)		(-3.82)	(-2.27)	(0.95)
chdist(FD)		-0.308***					-0.468**			
		(-4.59)					(-3.09)			
turn spline: b/w 12 & 18†						0.227*	0.038	0.043	0.059	0.308**
						(2.49)	(0.45)	(0.52)	(0.62)	(3.07)
turn spline: after 18†						0.040	-0.068	-0.072	-0.079	0.220
						(0.72)	(-1.61)	(-1.70)	(-0.83)	(0.63)
Constant	1.238***	-2.038***	-1.783***	0.323	0.540	2.049***	0.798	1.013*	2.856***	1.355**
	(4.55)	(-10.59)	(-8.89)	(1.14)	(1.74)	(4.74)	(1.81)	(2.35)	(5.34)	(2.84)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ln σ_u^2										
Constant	-0.802**	-0.791**	-0.658**	0.447*	-0.269	0.473	0.923**	0.887**	1.483***	-0.399
	(-2.94)	(-3.00)	(-2.59)	(2.02)	(-1.06)	(1.31)	(2.93)	(2.78)	(3.99)	(-0.65)
N	2304	2304	2304	2304	2304	972	1062	1062	858	768

t statistics in parentheses
† Spline coefficients are for the slope of the intervals. ‡ Dummy variable dropped due to perfect collinearity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Pooled FE LPM on the likelihood of myopic rational action

	Treatment 1		Treatment 2			Treatment 3		Treatment 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(second half)	-0.051	-0.073	-0.025	-0.024	-0.022	-0.020	0.009	-0.031	-0.094
	(-1.19)	(-1.54)	(-0.95)	(-0.37)	(-0.37)	(-0.88)	(0.21)	(-0.76)	(-1.24)
morelink	0.098**	0.090*	0.175***	0.121***	0.087*	0.184***	0.098*	0.098*	0.075*
	(4.65)	(3.19)	(10.07)	(6.39)	(3.29)	(7.83)	(2.88)	(3.25)	(3.09)
... × **1**(second half)	0.063	0.050	0.023	0.010	0.012	0.013	0.013	0.046	0.044
	(1.53)	(1.18)	(0.77)	(0.33)	(0.38)	(0.50)	(0.35)	(1.19)	(1.35)
act	-0.300*	-0.289*	-0.136	-0.021	0.024	-0.255***	-0.250***	-0.491***	-0.457***
	(-3.43)	(-3.25)	(-1.98)	(-0.31)	(0.45)	(-6.17)	(-6.03)	(-6.52)	(-5.89)
... × **1**(second half)	0.003	0.028	-0.222**	-0.279***	-0.261**	-0.069	-0.021	-0.032	-0.034
	(0.03)	(0.24)	(-3.71)	(-5.73)	(-4.13)	(-0.96)	(-0.24)	(-0.28)	(-0.29)
morelink × act	0.197*	0.200*	0.031	-0.111	-0.159*	0.224***	0.261***	0.404**	0.389**
	(2.80)	(2.89)	(0.46)	(-1.48)	(-2.80)	(6.05)	(8.67)	(4.91)	(5.06)
... × **1**(second half)	0.020	0.005	0.196*	0.313***	0.299**	0.085	0.044	0.065	0.104
	(0.21)	(0.04)	(3.17)	(5.45)	(4.66)	(1.25)	(0.60)	(0.51)	(0.84)
mpay		0.000		0.020***	0.018***		0.005*		0.004*
		(0.28)		(9.95)	(9.21)		(2.49)		(2.43)
... × **1**(second half)		0.003*		-0.006	-0.006		-0.004		-0.001
		(2.41)		(-1.59)	(-2.22)		(-1.08)		(-0.41)
turn		0.007***		0.010**	0.010**		0.012**		0.003
		(8.07)		(3.56)	(3.53)		(4.02)		(1.39)
... × **1**(second half)		-0.002		0.005	0.005		0.000		0.007
		(-1.25)		(0.87)	(0.97)		(0.12)		(2.32)
chdist(Eff. Line)		-0.015			-0.104**		-0.033		-0.027
		(-1.00)			(-4.57)		(-1.65)		(-1.77)
... × **1**(second half)		-0.020			-0.001		-0.032		-0.002
		(-0.69)			(-0.08)		(-0.82)		(-0.12)
chdist(FD)				-0.100***					
				(-6.83)					
... × **1**(second half)				-0.005					
				(-0.34)					
Constant	0.875***	0.799***	0.754***	0.391***	0.440***	0.791***	0.649***	0.864***	0.779***
	(39.30)	(28.32)	(57.19)	(17.64)	(20.91)	(56.57)	(16.69)	(33.78)	(15.19)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P(pooling)	0.300	0.127	0.042	0.000	0.001	0.148	0.260	0.120	0.021
N	3276	3276	3366	3366	3366	3162	3162	3072	3072
Adj. R^2	0.160	0.173	0.103	0.301	0.304	0.219	0.259	0.243	0.259

t statistics in parentheses. Standard errors are clustered at the session level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Instructions (not for publication)

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.

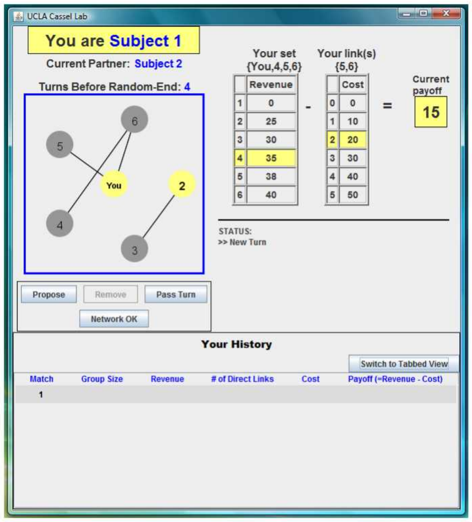


FIGURE 1:
BEGIN A TURN

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.

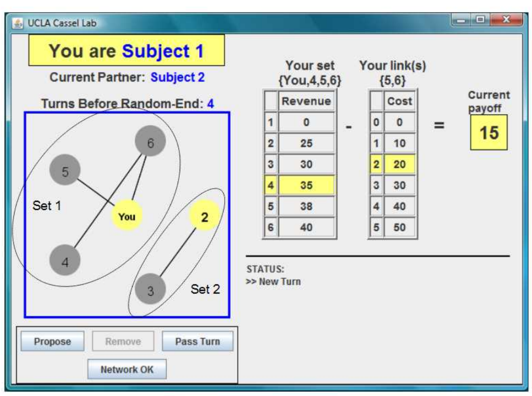


FIGURE 2:
SETS, LINKS
AND ACTIONS
[example 1]

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.

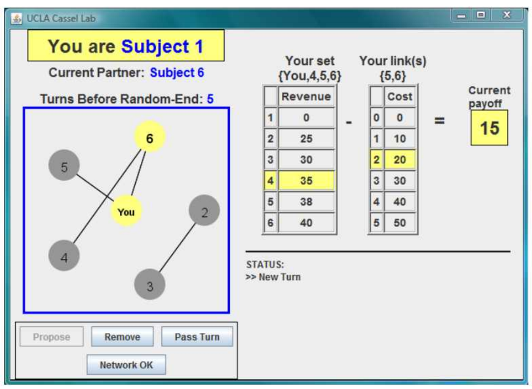


FIGURE 3: SETS, LINKS AND ACTIONS [example 2]

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.

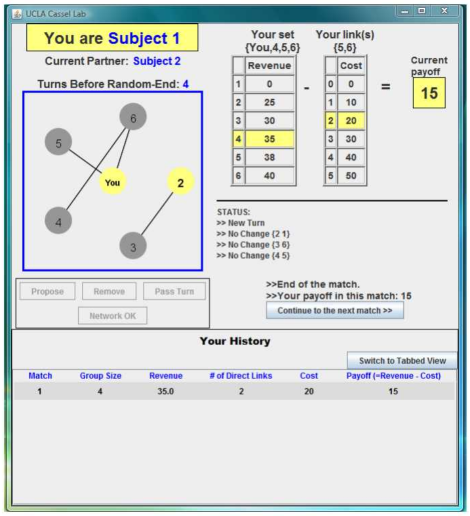


FIGURE 4:
END OF A
MATCH

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.

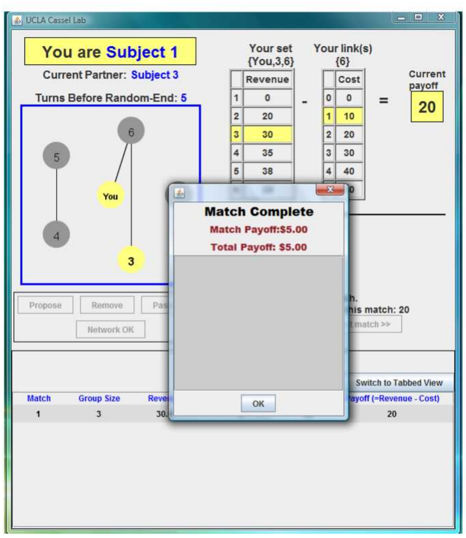
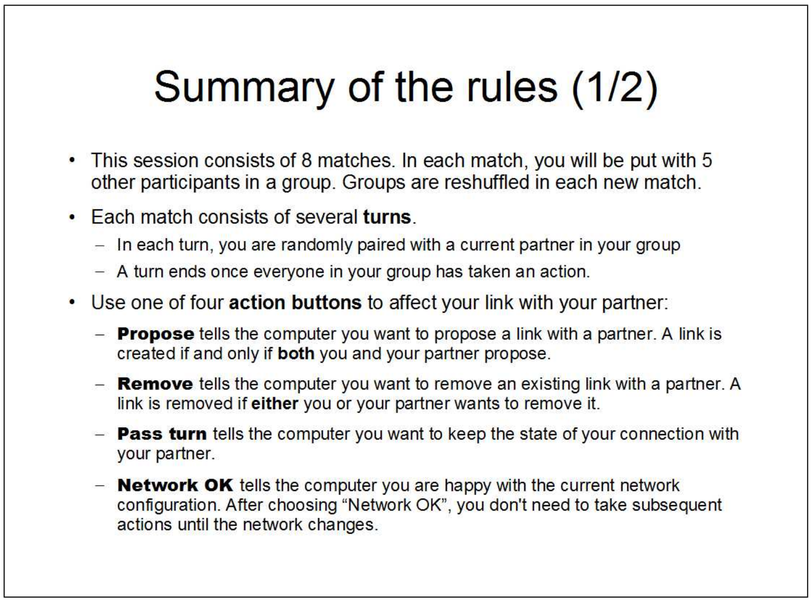
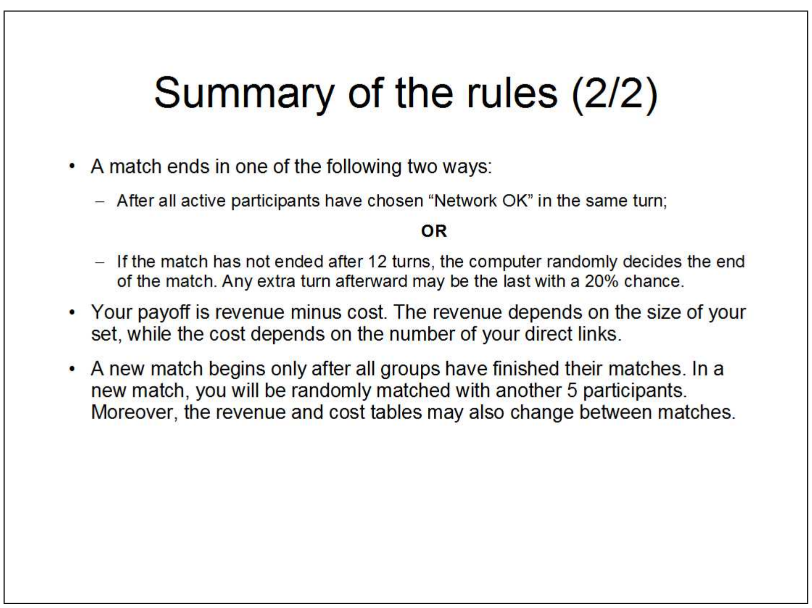


FIGURE 5:
END OF A
SESSION

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:





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.