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NETWORK STRUCTURE IN A LINK FORMATION GAME: AN EXPERIMENTAL STUDY

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In this article, we use an experiment to evaluate the performance of alternative refinements in a Myersonian link formation game with a supermodular payoff function. Our results show that a non-cooperative refinement, the global games (GG) approach, outperforms alternative cooperative refinements (strong Nash equilibrium, coalition-proof Nash equilibrium, and pairwise stable Nash equilibrium) in explaining the observed experimental behavior in the static game of complete information with three players. The results are robust to some comparative statics and the GG approach shows a high predictive power under incomplete information. However, under repeated interaction or with a greater number of players, the GG approach loses predictive power, but so do the cooperative refinements. The results illustrate the importance of coordination failure in practice and the need to design mechanisms to reduce this effect in practical decision-making problems. (*JEL* C70, C92, D20, D44, D82)

I. INTRODUCTION

Over the past 20 years, social and economic interactions have been modeled using network structures or graphs in which agents are symbolized by nodes, with their relationships represented by arcs connecting the nodes. For instance, Montgomery (1991) used these structures to show how patterns of social ties between individuals play a critical role in labor market outcomes. Jackson (2004) provided an outstanding summary of the most commonly used applications.

The use of link formation games to model network formation originated in the work of Myerson (1991). In his setting, agents simultaneously choose the agents with whom they wish to be connected, and a link is formed if and only if mutual consent is reached. The use of traditional game theory to support the study of network formation has generated valuable new insights in this area. See, for example, the work of Gilles and Sarangi (2010).

However, it is also commonly known that such link formation games can lead to multiple network configurations supported by multiple Nash equilibria (Jackson 2003). Indeed, as noted by Slikker and van den Nouweland (2000), in several circumstances, any network can be supported by Nash equilibrium. As a consequence, equilibrium selection becomes an important issue.

Jackson (2003) has argued that to accommodate the need for two players to form a link, conditions beyond the traditional non-cooperative refinements should be required. Some of these coalitional approaches are

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ABBREVIATIONS

CPNE: Coalition-Proof Nash Equilibrium
GG: Global Games
PSNE: Pairwise Strong Nash Equilibrium
SNE: Strong Nash Equilibrium

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represented by the notions of strong Nash equilibrium (SNE), coalition-proof Nash equilibrium (CPNE), and pairwise strong Nash equilibrium (PSNE) (Dutta and Mutuswami 1997; Gilles and Sarangi 2010; Jackson 2004).

By contrast, Bala and Goyal (2000) and Harrison and Muñoz (2008) have argued that in the context of network formation, non-cooperative equilibrium selection approaches are still feasible and meaningful. Using the theory of global games (GG), Harrison and Muñoz (2008) showed that the multiplicity of Nash equilibria arising in a class of Myersonian link formation games disappears when the game is perturbed by introducing small amounts of incomplete information into supermodular payoff functions. In contrast to a cooperative refinement, a non-cooperative refinement is more sensible as a prelude to a non-cooperative game with networked neighbors, as in the study by Corbae and Duffy (2008).

Although it has been argued that the supermodularity assumption in the payoff functions is constrained to a range of specific applications, expanding the set of payoff functions to which the GG approach can be applied is currently an open area of research. Despite this degree of indeterminacy, such payoff functions are a good approximation in several important problems (Morris and Shin 2003).

For instance, the information-sharing process in an entrepreneurial startup shows the importance of combining innovative people into incubators to enable them to share their experiences. Academic collaborative networks can be another example. Researchers typically benefit from contact with colleagues and relationships with third parties, provided that their experiences can be used in collaborative works. The coordination in both examples, however, is subject to failures that are similar to those analyzed in this article. Thus, if the willingness of an entrepreneur to discuss his ideas with others is strong, then the payoff of such interactions may be higher, but the individual payoff depends on whether others are also willing to share their experiences. Analogously, researchers typically benefit from coauthors' knowledge, part of which is indirectly obtained from their own interaction with third parties.

In the experiment reported herein, we review a link formation game for different comparative static predictions of various parameters of the payoff function under differing assumptions about players' information sets. Thus, we can test the predictive power of the GG approach relative to that of alternative cooperative refinements of the network configuration arising in this experimental implementation.

This article is closely related to previous experimental studies focused on testing equilibrium selection in network formation processes.[1] For example, Johnson and Gilles (2000), Callander and Plott (2005), and Falk and Kosfeld (2012) examined how pairwise stable networks form in the context of different institutional rules that may affect the behavior of agents within such networks. Another example is the experimental study of Charness and Jackson (2007), who examined the issue of equilibrium selection and the role of consent in network formation, focusing on the importance of voting rules in determining the final outcome of the game.[2] Pantz and Ziegelmeyer (2003) compared a forward-looking notion of pairwise stability to a myopic approach. In the this article, we compare the networks and strategies predicted by cooperative refinements (SNE, CPNE, and PSNE) to those generated by a non-cooperative refinement, the GG approach.

This article is also related to other experimental studies that directly test the performance of GG refinements in other economic contexts (Cabrales et al. 2007; Duffy and Ochs 2012; Heinemann et al. 2004; Heinemann et al. 2009; Shurchkov 2013). To the best of our knowledge, this study is the first application of GG to the experimental analysis of network formation.

The remainder of this article is organized as follows: In Section II, the connection model is developed, and testable predictions are derived. In Section III, the experimental design is discussed. In Section IV, the main laboratory results for the game under complete and incomplete information are presented. In Section V, the conclusion summarizes the main points of the article.

II. THE CONNECTION MODEL

A. Basics

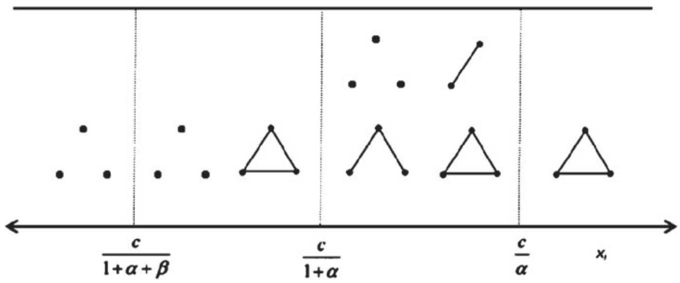
Consider a static link formation game of complete information G_x with a set of players $\mathcal{N} = \{1, 2, 3, ..., N+1\}$, where the action set for each player i is given by $A_i = \{(a_{ij})_{j \neq i} \mid a_{ij} \in \{0, 1\}\}$

1. For a survey of network experiments, see Kosfeld (2014). For the use of experiments as a tool for network analysis, see Jackson (2008).

2. Although Charness and Jackson (2007) initially considered pairwise stability to be the main solution concept to be evaluated, they eventually developed a new solution concept, robust-belief equilibrium, which rationalizes the results that they observed.

FIGURE 1

Network Structures Supported by Nash Equilibria in the Connection Model for $N = 2$



and $x \in \mathbb{R}$ is a variable scaling the level of potential income to player i by forming a link. A strategy for player i is an N-component vector of zeros and ones that identifies the set of players with whom she wishes to form links.

All players simultaneously choose to either link-request or not link-request other players. A full link is formed between two players if and only if both players link-request one another. Thus, the payoff function for player i is defined by the following:

$$(1) \quad \pi_i\left(a_i, a_{-i}, x\right) = \sum_{j \neq i} \left\{ a_{ij} a_{ji} \left(x + \sum_{k \neq i, k \neq j} a_{jk} a_{kj} \beta x \right) + a_{ij} (\alpha x - c) \right\}$$

where $c > 0$ denotes a constant cost of requesting a link; $\alpha \in (0, 1)$ is the proportion of direct benefits derived from requesting a link; and $\beta \in (0, 1)$, the proportion of indirect benefits that arise from indirect link formations.[3]

Note that if agent i wishes to connect to agent j, then even if agent j does not reciprocate by requesting a link with agent i and consequently, the link ij is not formed, agent i will incur a cost of c and receive a net return of $(\alpha x - c)$. In this sense, the benefit αx is independent of other players' actions. However, if agent j also decides to form a link with agent i, then the return to agent i will be $(x + \alpha x - c)$. In other words, there is an additional *direct* benefit x for player i for fully connecting with agent j. Finally, agent i can also *indirectly* benefit from the relationship between agents j and k when they are fully connected, provided that i is fully connected with at least one of them.[4]

Connection models with the above payoff structure are characterized by multiple Nash equilibria. Figure 1 provides a summary of the different network structures supported by a strategy profile in the set of Nash equilibria, $NE(G_x)$, for different values of x, when $N = 2$. For details of this case, we refer the reader to Harrison and Muñoz (2008).

Because multiplicity occurs in this link formation game, it is necessary to consider certain refinements to predict which network structure will emerge in equilibrium as a function of x. In this article, we consider non-cooperative and cooperative refinements and test their experimental performance. However, in any refinement, the dominance regions that appear at the extremes in Figure 1 imply that regardless of what strategies the others agents play, a dominant response exists for player i: linking to no one if $x < c/[1 + \alpha + (N - 1)\beta]$ and to everyone if $x > c/\alpha$.

B. Equilibrium Selection Using the GG Approach

Assuming that the game is one of the incomplete information in the payoff structure. The amount of incomplete information is parameterized by a scale factor $\sigma > 0$; hence, we call this game G_σ. Let $\text{BNE}(G_\sigma)$ denote the set of Bayesian Nash equilibria. Player i's payoff function depends now on a private value x_i, observed only by i. The private value is given by $x_i = x + \sigma\epsilon_i$, where x is drawn with uniform

3. It appears natural to assume that $0 < \alpha < 1$, $0 < \beta < 1$, as benefits are scaled relative to those obtained from reciprocity x.

4. The fact that we need a direct connection in order to obtain indirect benefits relates our game to the weakest link connection game of Van Huyck et al. (1990). We thank an anonymous referee who pointed out this relation.

density from the compact set $\left[\underline{X}, \overline{X}\right]$ such that $\underline{X} < (c/1 + \alpha + (N-1)\beta) < (c/\alpha) < \overline{X}$, and ϵ_i is a realization of a random variable with density ϕ and a support within $[-(1/2), (1/2)]$. We assume that ϵ_i is $i.i.d.$ across individuals.[5]

This noise structure has been used in the GG literature to provide a simple model of conditional distribution of opponents' values x_{-i}, given that player i's own value is x_i.[6] A pure strategy for player i in G_σ is a function $s_i : \left[\underline{X} - \sigma/2, \overline{X} + \sigma/2\right] \to A_i$. The set of all these functions is denoted by S_i. Let $S_{-i} \equiv \times_{j \neq i} S_j$, such that a complete strategy profile is given by $s = (s_i, s_{-i}) \in S \equiv S_i \times S_{-i}$. Accordingly, if player i has a private value x_i, then her *interim* expected payoff for action a_i when facing an opposing strategy profile s_{-i} is $E^\sigma[\pi_i(a_i, s_{-i}, x_i)]$.

Let us define an essentially unique switching strategy between zero and one with threshold θ_i as a pure strategy $s_i^{\theta_i}(\cdot)$, satisfying the following[7]:

$$s_i^{\theta_i}(x_i) = \begin{cases} 1 & \text{if} \quad x_i > \theta_i \\ 0 & \text{if} \quad x_i < \theta_i \end{cases}$$

The following proposition, which is an extension of the main results of Harrison and Muñoz (2008), constitutes the main theoretical result of this article.

PROPOSITION 1. *For any $\sigma > 0$, consider the game G_σ. The essentially unique switching strategy profile $s^* = (s_i^{\theta^*}(\cdot))_{i \in \mathcal{N}}$ is the only strategy profile that survives iterated elimination of strictly dominated strategies in* G_σ, *where $\theta^* = c/(\alpha + 1/2 + (N-1)\beta/3)$.*

Proof. See Appendix A. ∎

This result demonstrates that the perturbed connection model G_σ has an essentially unique strategy profile s^* played in equilibrium, which is independent of the amount of noise σ.[8] In this profile, every player uses a switching strategy $s_i^{k^*}(x_i)$.

Although s^* is independent of σ, the network formed depends on σ. Figure 2 shows the network configurations that player i is able to predict based on her private value x_i when $N = 2$. If $x_i < k^* - 2\sigma$, then player i can be certain that the signals received by all other players are also lower than k^*, and that all other players will play action 0, given the equilibrium strategies $s_i^{k^*}$.[9] An analogous situation occurs when $x_i > k^* + 2\sigma$. Then, all the players will select action 1. However, if the signal that is received satisfies the condition $k^* - 2\sigma < x_i < k^* + 2\sigma$, then x_j and x_k can be higher or lower than k^*, such that different networks can arise. When σ approaches zero (i.e., when incomplete information tends to disappear), the middle area in Figure 2 is reduced to an arbitrarily small bandwidth.

C. Equilibrium Selection Using Cooperative Refinements

As an alternative hypothesis, we consider cooperative refinements. The network literature (Dutta et al. 1998) has generally advocated for the use of traditional cooperative approaches, such as SNE or CPNE, to solve this equilibrium selection problem. More recently, other cooperative concepts, such as PSNE, have also been applied. However, PSNE reduces but does not eliminate the multiplicity problem in this particular game (Harrison and Muñoz 2008), and its predictions are difficult to compare with those obtained using the GG approach.[10]

A strategy profile is called an SNE if it is a Nash equilibrium and if there is no coalition of players that can strictly increase the payoffs of all of its members by jointly deviating from it (Aumann 1959; Dutta and Mutuswami 1997).[11]

Another commonly used coalitional refinement is CPNE. A strategy profile is a CPNE if no coalition can deviate to a profile that strictly improves the payoffs of all players in the coalition. However, the set of admissible deviations is now smaller because coalitions must withstand

5. Note that ϕ does not need to be symmetric around the mean or even have a mean zero.

6. Players make decisions at an *interim* stage when the uncertainty regarding the players' types is partially resolved. Thus, players know only their own type and confront uncertainty with regard to their opponents' types.

7. The essentially unique qualification arises because any action may be played if the private value is exactly equal to θ_i (Morris and Shin, 2003).

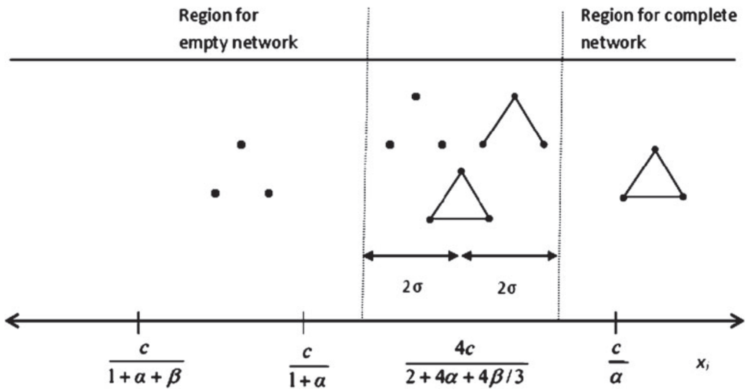
8. Note that s^* is also independent of the noise structure ϕ. In addition, we assume that the parameter x has a flat prior distribution, but it could be proved that any prior can be treated as a flat prior when σ approaches zero.

9. This assumption is possible because the support for the conditional distribution of x_j given x_i is $[x_i - 2\sigma, x_i + 2\sigma]$.

10. The multiple networks supported by PSNE can be refined using the stochastic stability concept (SSN) introduced by Jackson and Watts (2002).

11. A stronger notion of SNE is provided by Jackson and van den Nouweland (2005) and denoted SNE_{JV}. However, in the current example, the two notions coincide.

FIGURE 2
Networks Predicted by Player i Given x_i



possible further deviations by sub-coalitions (Dutta and Mutuswami 1997).[12]

In the three-player game G_x, the set of SNE(G_x) coincides with the set of CPNE(G_x). For a formal definition of PSNE, we refer the reader to Gilles and Sarangi (2010).

The application of all these coalitional refinements is direct, and we refer the reader to Harrison and Muñoz (2008) for the case of $N=2$. Figure 3 contains a summary of the predicted network configurations in such a case. Part (a) shows the networks supported by the NE in the connection model. Part (b) shows the networks supported by SNE or, equivalently, CPNE. Part (c) contains the networks supported by PSNE. Finally, part (d) shows the networks supported by the GG approach when σ approaches zero. Notice that when $N=2$, implies $\theta^* = 4c/[2+4\alpha+4\beta/3]$. A general result is established in Proposition 2.

PROPOSITION 2. *Consider the link formation game G_x with an arbitrary number of players, $N+1$. The formation of the complete network can be uniquely predicted when x is higher than a trigger value. This value differs across refinements. Specifically, it is $c/[1+\alpha+(N-1)\beta]$ for SNE and CPNE, $c/[1+\alpha]$ for PSNE, and $c/[\alpha+1/2+(N-1)\beta/3]$ for GG.*

Proof. See Appendix B. ■

The differences in the threshold values that provide the basis for the formation of a complete network constitute a clearly testable hypothesis.[13] In addition, although the SNE and CPNE prediction is consistent with Pareto-efficient outcomes and Payoff-dominant equilibria, the GG approach is not, showing a conflict between efficiency and stability. Comparative statics are also conducted and tested as a function of the problem's parameters.

III. EXPERIMENTAL DESIGNS

A. Structure of the Network Formation Game

Our experimental design considers the outcomes of the Myersonian link formation game under mutual consent, as described in the previous section. We first implement our experimental design for this link formation game under complete information for different parameter values of alpha (α), connection cost (c), and group size ($N+1$). This design allows us (i) to determine whether subjects are able to coordinate their actions around different switching thresholds for either requesting or not requesting links to other members of their own group, (ii) to observe how close the actual switching thresholds are to theoretical predictions, and (iii) to eliminate the possibility that our results arises as an artifact of our experimental design.

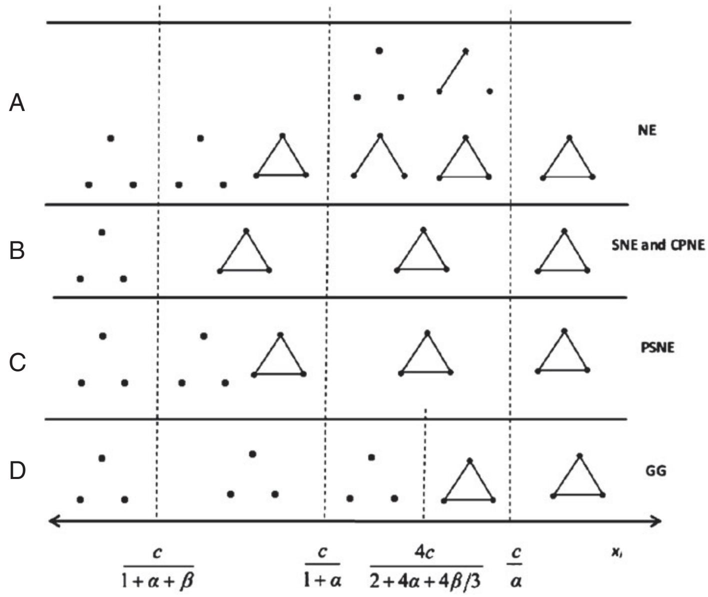
We also report additional treatments in which the same group of subjects is allowed to play

12. The following relationship exists between the sets of strategy profiles for a general game G: $\mathrm{SNE}_{JV}(G) \subseteq \mathrm{CPNE}(G)$.

13. Note that Proposition 2 does not establish a specific trigger value for SSN (see footnote 9) because SSN is a refinement of the networks supported by PSNE. However, the experimental evidence will permit us to reject any structure supported by PSNE.

FIGURE 3

Networks Supported by Nash Equilibria (NE), Strong Nash Equilibria (SNE), Coalition-Proof Nash Equilibria (CPNE), Pairwise Stable Nash Equilibria (PSNE), and the Global Games (GG) Approach



repeatedly for five rounds (r) within a given time period. Our conjecture is that repeated interaction among players would allow them to improve coordination around the efficient network configurations.

Finally, we also implement our experimental design under incomplete information for different levels of perturbation in the payoff function. The GG approach provides a rationale to refine the multiplicity arising in the complete information game. In this sense, the exercise with a sigma equal to zero is the most relevant case. When sigma is greater than zero, the Bayesian Nash equilibrium is unique, and then no refinement is needed. But the signals received by players could lead to different actions and network configurations (Figure 2). Accordingly, our goal here is to measure how different amounts of incomplete information in the payoff function (σ) affect the outcome of the game. In particular, we wish to test the theoretical prediction that the switching threshold must be independent of σ but that the network formed still depends on it.[14]

Table 1 summarizes the parameter values for the proportions of connection benefits (α), the connection costs (c), the group size ($N+1$), the number of round of repeated interaction (r), and the amount of perturbation in the payoff function (σ). The table also shows the predicted switching thresholds under each of our alternative theoretical models and the number of sessions per treatment. All these treatments permit us to determine the predictive power of each solution concept and to examine the comparative statics derived from the link formation game.[15]

B. Design Parameters

This section describes the general experimental procedure.

Participants and Venue. Subjects were drawn from a wide cross-section of undergraduate and graduate students at Pontificia Universidad Católica de Chile (PUC) in Santiago, Chile. Each subject participated in only one session and had no previous experience in similar

14. In one session of treatment 3, the system broke down, and only 30 periods of the scheduled 50 periods could be run.

15. The parameter values were chosen to guarantee the presence of the dominance regions (as the GG structure requires) and allow us to construct unique predictions for the different refinements in particular regions, in order to facilitate the empirical testing.

TABLE 1
Experimental Design

Treatment	Parameters	Predicted Thresholds			Number of Sessions
	$(\alpha, c, N+1, r, \sigma)$	GG(k^*)	PSNE(x^*)	SNE$\left(\underline{x}\right)$	
1	(0.6,120,3,1,0)	103	75	67	3
2	(0.4,120,3,1,0)	124	86	75	3
3	(0.6,180,3,1,0)	154	113	100	3
4	(0.6,120,5,1,0)	92	75	55	5
5	(0.6,120,3,5,0)	103	75	67	3
6	(0.4,120,3,5,0)	124	86	75	3
7	(0.6,180,3,5,0)	154	113	100	3
8	(0.4,120,3,1,10)	124	86[a]	75[a]	2
9	(0.4,120,3,1,50)	124	86[a]	75[a]	1

Notes: The predicted thresholds are theoretically supported in the static game (one round). For a dynamic game (five rounds), the predicted thresholds are only benchmark cases. In all these treatments, the parameter β is equal to 0.2.

[a]Strictly speaking, these thresholds do not apply for σ greater than 0.

experiments. The experiment was conducted using computers.

Number of Periods and Rounds. For the one-round interaction treatments, the agents participated in ten practice periods prior to the 50 periods that were played for money. In the five-round interaction treatments, the agents participated in two practice periods (of five rounds each) and ten periods (of five rounds each) that were played for money.

Matching Procedure and Group Size. At the beginning of each period, the computer randomly grouped the participants into teams of size $N+1$, such that each participant joined a new group in each period. The participants did not know the identity of the other group members for any given period. There were 15 participants in each of the 23 sessions, for a total of 345 participants.

Link Procedure and Payoff Structure. The participants were informed that in each period, they would need to decide whether to link-request or not to link-request members of their own group. The participants were also told that for each linking request, the monetary payoff would be equal to the sum of the following three components: (i) the independent connection component $(= \alpha \times x - c)$, that is, the payoff that a participant would receive if she requested a link to another participant; (ii) the direct (or complete) connection component $(= x)$, that is, the payoff that a participant would receive if the link were formed, which occurs when both parties request a link to one another; and (iii) the indirect connection component $(= \beta \times x)$, that is, the payoff that a participant would receive if the agent with whom she has linked has also linked with another agent from the group. Finally, the subjects were informed that if a participant decided not to request any links, then her monetary payoff would be zero for that period.

Valuation Distribution. In the complete information setup $(\sigma = 0)$, the participants were informed that in each round, every group would receive a connection value that would be randomly generated from the interval 50 to 310 and that all values were equally likely. In the incomplete information setup $(\sigma > 0)$, the participants were informed that each member of their group would privately receive a connection value x_i in every period and that this value would be generated in the following manner: (i) In each period and for every group, a number x_i from 50 to 310 would be drawn randomly. Any value in this interval would have an equal probability of being drawn. (ii) Each group member would receive a private connection value x_i, which is independently selected within the interval $[x_0 - \sigma, x_0 + \sigma]$, such that all values would be equally likely to be drawn. Furthermore, the participants did not know the values of x_0 or the private value of any of the other participants in their group.

Parameter Values. At the beginning of each section, all participants were informed of the values of alpha (α), beta (β), the connection cost (c), the group size ($N+1$), the number of rounds of repeated interactions (r) within the same group of players per period, and the level of perturbation (σ).

Minimum Capital and Payoff Procedure. Each participant received an initial balance of 9,000 points. After each round, points were added or subtracted from the initial balance. At the end of the experimental session, total accumulated points were multiplied by 0.33 Chilean pesos per point to calculate the final payoff in Chilean pesos. The average payoff per participant for the entire session was 5,250 Chilean pesos, approximately 11.00 US dollars.

Information Feedback. In every period, each participant had access to only her own payoff, which could be divided into each of the three payoff components mentioned above. Throughout all the sessions, the participants were prevented from communicating or viewing one another's screens. All players were labeled as Player 1 on the screens. In the repeated interaction treatment, other agents' positions were fixed on the screen such that any of the participants could observe which subject actually decided to link back to her in previous interactions.

IV. EXPERIMENTAL RESULTS

We first concentrate our analysis on measuring how different vectors of parameters (proportions of connection benefits [α], connection costs [c], and group size [$N+1$]) affect subjects' decisions to link with other members of their group. We focus on three types of linking requests: linking to everyone (termed "linking-all"), linking to only some participants ("linking-some"), and linking to no one ("linking-none").

Figure 4 presents a set of histograms representing the absolute number of individual linking decisions for different connection values; for different parameter values of α, c, and $N+1$; and for only one-interaction treatments ($r=1$). For example, the first row shows three charts, each presenting the number of subjects linking-none, linking-some, and linking-all with respect to members of their group, for different intervals of connection values, for α equals .6, c equals 120, and $N+1$ equals 3.

By contrast, Figure 5 shows a similar set of histograms representing the absolute number of individual decisions to link with other members of a given group over five rounds ($r=5$), for given connection values, varying parameter values of α and c, and for the same group size ($N+1=3$).

Because the subjects played the game for multiple periods, the actions of individuals over time are clearly not independent. Thus, in what follows, we present the results of the statistical analysis using a multinomial logit model with random effects (Hole 2007). For the single-round interaction treatments, we use the following model to estimate the individual likelihood of linking to other members of one's group:

$$\begin{aligned}&\Pr\left(\text{Links}_{it}=m\right)\\&\quad=F\left(\text{Intercept}_{m|M}+\beta_{x,m|M}x_{it}+\beta_{\alpha,m|M}d_{\alpha}\right.\\&\qquad\left.+\beta_{c,m|M}d_c+\beta_{n,m|M}d_n+\beta_{p,m|M}\text{per}\right).\end{aligned}$$

In this model, x_{it} represents the connection value that each individual i receives at time period t; d_α is a dummy variable that equals one when α is .4 and zero otherwise; d_c is a dummy variable that equals one when c is 180 and zero otherwise; d_n is a dummy variable that equals one when $N+1$ equals 5 and zero otherwise; per represents the time period (time trend), treated as a continuous variable; $F(.)$ is the cumulative logistic distribution function; Links_{it} equals the response category m of individual i at time period t, where m equals zero when agent i decides to request a link to no one, m equals one when she decides to request a link to some participants, and m equals two when she decides to request a link to everyone ($m=0,1,2$); and M indicates the reference category with which all other response categories are compared.

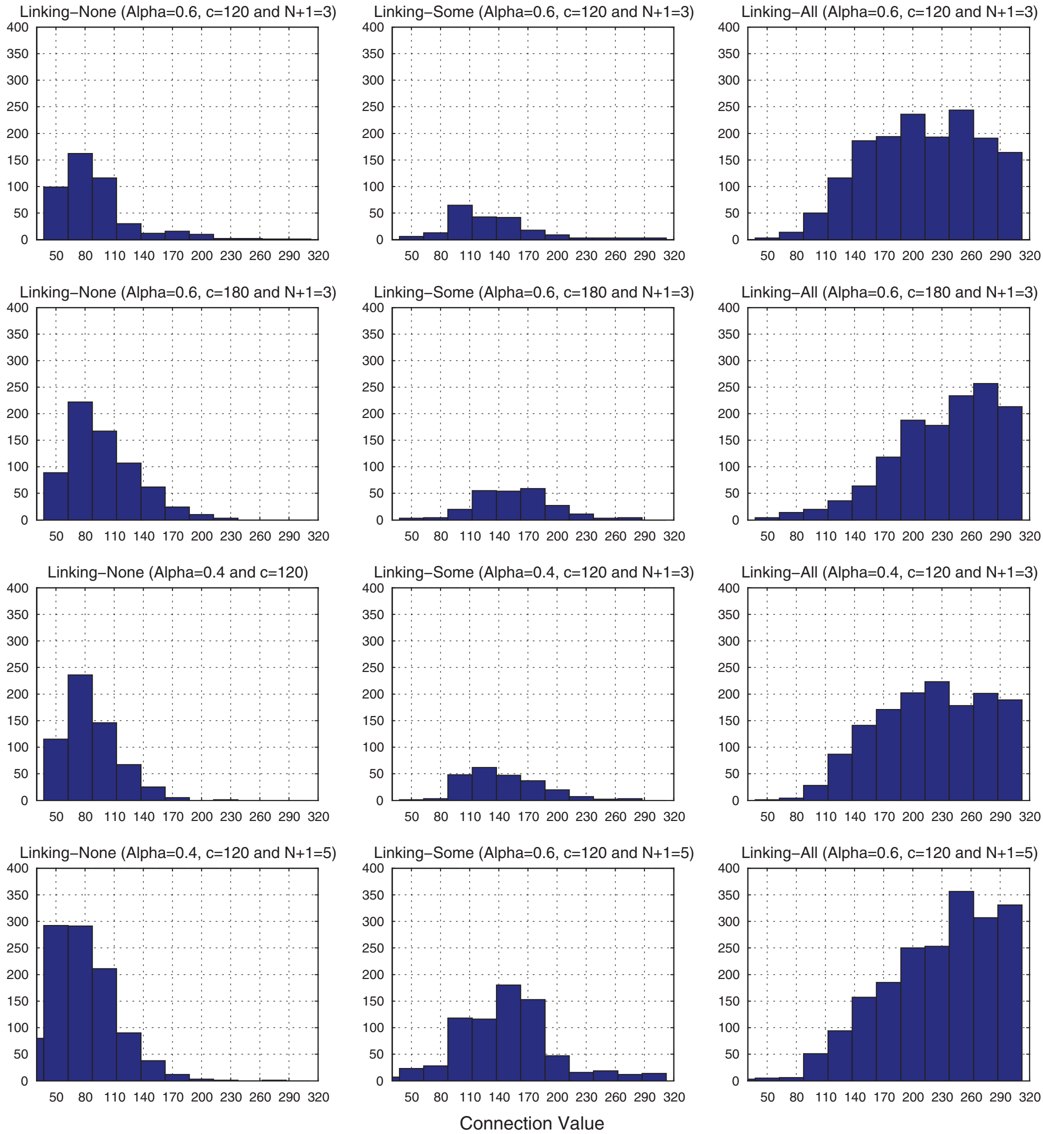
For the five-round interaction treatments, we consider the following model:

$$\begin{aligned}&\Pr\left(\text{Links}_{it}=m\right)\\&\quad=F\left(\text{Intercept}_{m|M}+\beta_{x,m|M}x_{it}+\beta_{\alpha,m|M}d_{\alpha}\right.\\&\qquad\left.+\beta_{c,m|M}d_c+\beta_{p,m|M}\text{per}+\beta_{r,m|M}\text{round}\right)\end{aligned}$$

where all variables have the same meaning as in the previous model and round represents the time trend of repeated interaction within a time period, with round treated as a continuous variable.

In Tables 2 and 3, we present the parameter estimates representing all contrasts among the three linking request categories for the one- and five-round interaction treatments, respectively. A χ^2 test for each estimation indicates that the null hypothesis that all estimated coefficients equal zero can be rejected, with $p<0.0001$. The null hypothesis that alternative categories can be combined is rejected at the same significance threshold.

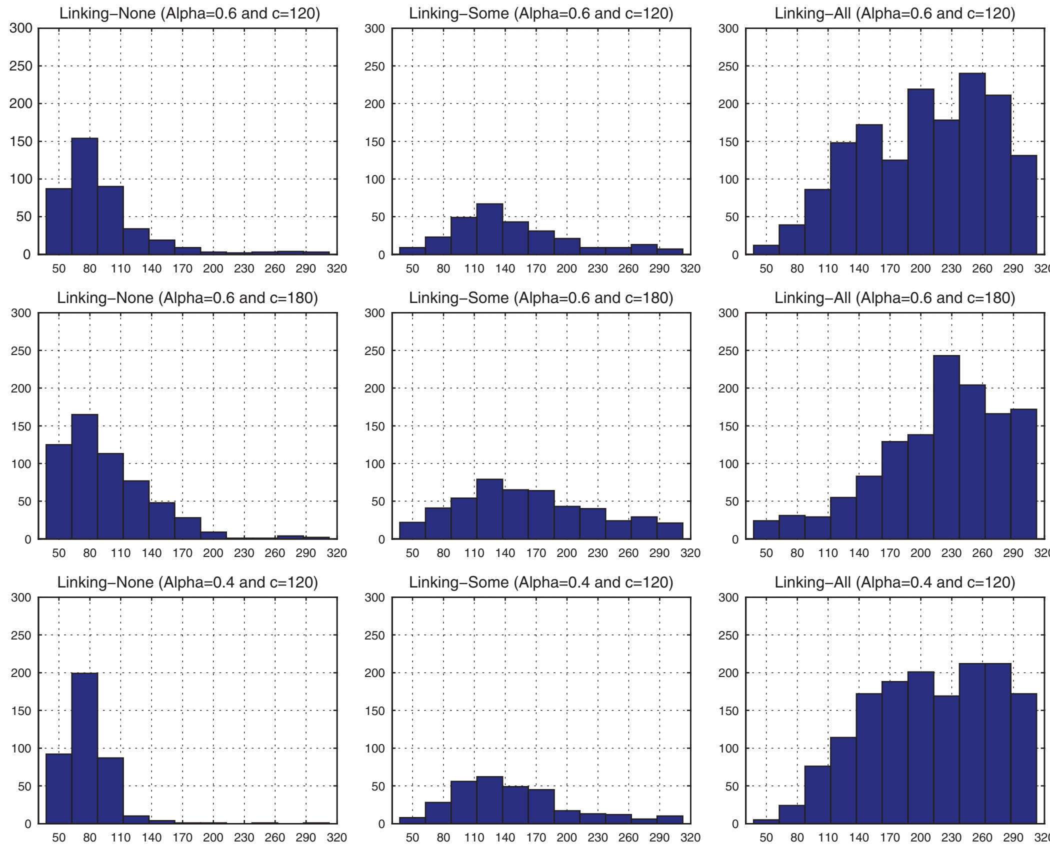
FIGURE 4
Individual Decision Histogram for Link Requests as Function of x (One-Round Interaction Treatments)



A. Result 1: Link-request Probability

First, higher connection values increase the likelihood of individual linking requests. Second, a lower proportion of connection benefits (α) has a negative (as expected) and significant effect on the likelihood of linking to everyone in the single-round interaction treatments, *ceteris paribus*. For the five-round interaction treatments, we did not observe a significant effect. Third, a higher connection cost (c) increases the likelihood of either linking-none or linking-some for all interaction treatments. Fourth, a larger group of potential participants ($N+1$) in a network induces a lower likelihood of linking-all and a higher likelihood of linking-some. Fifth, over time, there is an increased likelihood of either linking to everyone or linking to no one. Finally,

FIGURE 5
Individual Decision Histogram for Link Requests as Function of *x* (Five-Round Interaction Treatments)



we could not find any time trend effect for the repeated interaction treatments.

Support for Result 1. First, the connection value coefficients ($\beta_{x,1|2}$, $\beta_{x,0|1}$, and $\beta_{x,0|2}$) are negative and significant, as expected. This finding indicates that an individual's likelihood of making linking requests increases with higher connection value.

Second, for the one-round interaction treatments, we find a positive effect on the likelihood of linking requests to no one or to some participants in a group for lower proportions of connection benefits (α). In particular, the coefficients associated with lower alpha ($\beta_{\alpha,1|2}$ and $\beta_{\alpha,0|2}$) are positive and significant, as expected. In contrast to our expectations, we could not find an individual effect on the likelihood of a linking request for the coefficients associated with lower alpha when the subject interacted repeatedly for five rounds in each period.

Third, all three of the coefficients associated with a higher connection cost (c) ($\beta_{c,1|2}$, $\beta_{c,0|1}$, and $\beta_{c,0|2}$) for the single-round interaction are positive and significant, as expected. The same is true for two of the coefficients associated with a higher connection cost ($\beta_{c,1|2}$ and $\beta_{c,0|2}$) for the five-round interaction. These results suggest that higher connection costs are generally associated with a lower individual likelihood of linking to everyone in one's group and a higher likelihood of linking to some or none of the other participants. Because an increase in the connection cost is associated with a decrease in the upper dominance region, it may be more difficult for agents to coordinate linking requests with others in their groups.

TABLE 2
Multinomial Logit Model for Individual Link-Request Probability (One-Round Interaction Treatments)

Coefficients	Linking-Some vs. Linking-All	Linking-None vs. Linking-Some	Linking-None vs. Linking-All
Intercept	2.432***	4.297***	6.729***
	(0.315)	(0.305)	(0.404)
x_{it}	−0.025***	−0.036***	−0.061***
	(0.002)	(0.002)	(0.003)
d_α	0.563**	0.068	0.495*
	(0.220)	(0.256)	(0.206)
d_c	1.149***	0.532*	1.680***
	(0.233)	(0.267)	(0.259)
d_n	1.502***	−0.630*	0.873***
	(0.253)	(0.259)	(0.245)
per	−0.014***	0.022***	0.008*
	(0.003)	(0.003)	(0.004)
Number of observations	11,700	Number of individuals	240

Note: The numbers in parentheses below each coefficient represent the standard errors.
*$p < .05$, **$p < .01$, and ***$p < .001$.

TABLE 3
Multinomial Logit Model for Individual Link-Request Probability (Five-Round Interaction Treatments)

Coefficients	Linking-Some vs. Linking-All	Linking-None vs. Linking-Some	Linking-None vs. Linking-All
Intercept	1.017***	2.996***	4.013***
	(0.311)	(0.414)	(0.496)
x_{it}	−0.015***	−0.028***	−0.042***
	(0.002)	(0.003)	(0.004)
d_α	0.109	−0.138	−0.030
	(0.313)	(0.326)	(0.256)
d_c	0.834**	0.249	1.083***
	(0.295)	(0.397)	(0.335)
per	−0.038*	0.064***	0.026
	(0.016)	(0.018)	(0.016)
round	0.026	0.042	0.068*
	(0.027)	(0.029)	(0.029)
Number of observations	6,750	Number of individuals	135

Note: The numbers in parentheses below each coefficient represent the standard errors.
*$p < .05$; **$p < .01$, and ***$p < .001$.

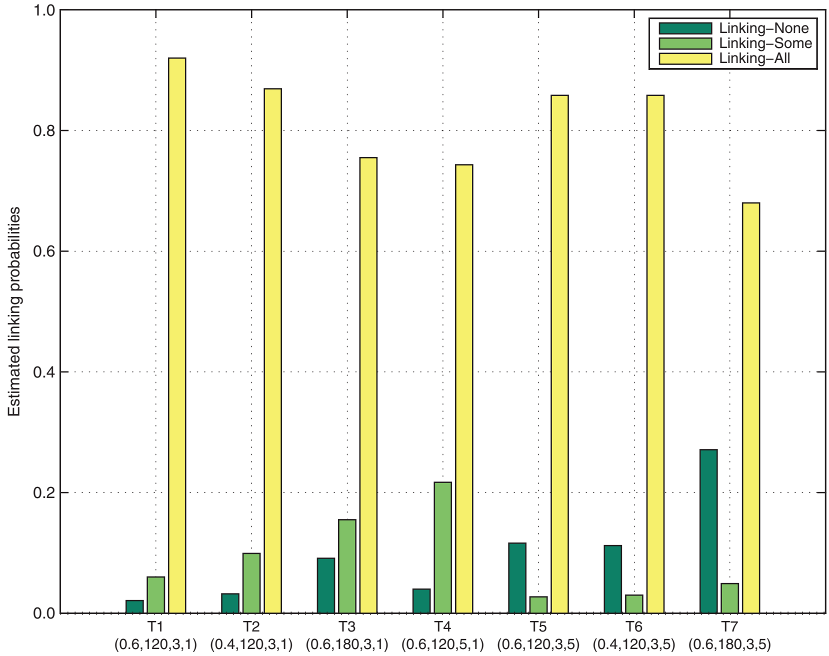
Fourth, our estimates suggest that both time period coefficients ($\beta_{p,1|2}$ and $\beta_{p,0|1}$) are significant. The negative sign of the first coefficient ($\beta_{p,1|2}$) and the positive sign of the second coefficient ($\beta_{p,0|1}$) suggest that over time, participants are more often willing to request links with either everyone or no one, rather than with only some members of their own group. This tendency could be the result of an individual learning process. For the five-round estimation, we could not find a joint significant effect of round in the likelihood of linking requests across all categories, although the coefficient $\beta_{r,0|2}$ was significant, with $p < 0.05$.

Figure 6 shows the estimated linking probabilities for different parameter values of α, c, $N + 1$, and r for the average connection value of $x = 180$. The estimations for each treatment are represented by three bars. The first bar represents the probability of linking to no one (linking-none); the second bar shows the probability of linking to some other players (linking-some); and the third bar shows the probability of linking to everyone (linking-all). In this figure, we observe significant differences between the results of the one- and five-round interaction treatments. In particular, the proportion of subjects linking to some members of a group is higher under the first set of treatments than under the second set. This pattern is even stronger if we compare the results of treatments T3 and T7. The repeated interaction in T7 creates conditions for better coordination among members of a group while members decide whether to link to no one or to everyone in their own group. Meanwhile, in the one-shot interaction of T3, there is an increase in the proportion of individuals who are also willing to link to some members of their group but fail to link to one another. This finding is a strong indication of a coordination failure resulting from a lack of repeated interaction.[16]

All the models examined assume that optimal responses take the form of cutoff strategies (i.e., connection values above which players are willing to link to all other players and below which they will link to no one). For each subject, we estimate the cutoff strategy, following the statistical procedure used by Palfrey and Prisbrey (1997): For each subject i and treatment j, we have W_{ij} observations of connection values and

16. It is worthy to remark that in the finitely repeated version of the game, when we keep the groups playing for some rounds, we expected to obtain more coordination than in the static game and, as a result, a significant movement of the thresholds toward the efficient levels. Although this prediction is supported by the experiment, the empirical thresholds under repeated interaction are, not surprisingly, different from the static theoretical predictions under both non-cooperative and cooperative refinements (Table 4), which were used just as reference values given that we do not have theoretical predictions for the repeated game.

FIGURE 6
Estimated Linking Probabilities for Different Parameter Values of $(\alpha, c, N+1, r)$



decisions (x_t, d_t). We begin by fixing a cutoff point $50 \leq x_{ij} \leq 310$. For observation t in this sample of W_{ij} observations, we count the following cases:

$$x_t < x_{ij} \text{ and } d_t = \text{linking} - \text{none}$$

$$x_t > x_{ij} \text{ and } d_t = \text{linking} - \text{all}$$

$$x_t = x_{ij}.$$

It is stated that observation t is consistent with the cutoff point x_{ij}. Otherwise, it is stated that observation t is an error with respect to x_{ij}. The estimated cutoff point x_{ij} is the threshold strategy that minimizes the number of errors.

Next, we compare the predicted switching thresholds, k^*, x^*, and $\underline{x}$, and the estimated mean switching thresholds $\widehat{x}$ across subjects for each treatment. We then determine how the estimated switching thresholds change relative to our comparative static predictions. In Table 4, we report the estimated mean switching threshold for each treatment $(\widehat{x})$, together with the estimated standard errors $(\widehat{s.e.})$ and the average number of minimal errors $(\widehat{err})$. In Table 4, we also show the equilibrium switching thresholds predicted by GG, k^*, PSNE, x^*, and SNE, $\underline{x}$. In addition, Figure 7 plots the individual cutoff point cumulative distribution functions for each of the experimental treatments.

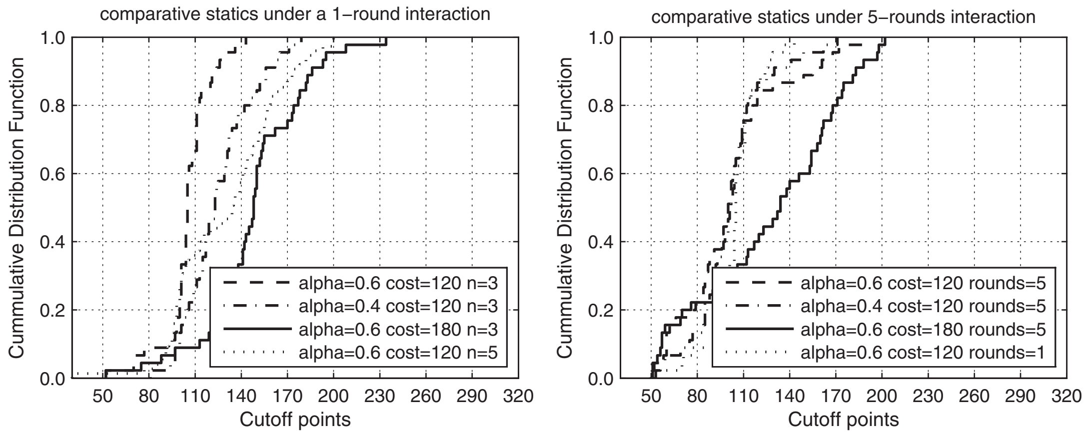
TABLE 4
Estimated Mean Switching Thresholds and Their Standard Errors

Treat-ment	$(\alpha, c, N+1, r, \sigma)$	$\widehat{x}$	$\widehat{s.e.}$	$\widehat{err}$	**GG** (k^*)	**PSNE** (x^*)	**SNE** $(\underline{x})$
1	(0.6,120,3,1,0)	105	2.4	1.8	103	75	67
2	(0.4,120,3,1,0)	125	3.3	0.9	124	86	75
3	(0.6,180,3,1,0)	148	3.0	1.0	154	113	100
4	(0.6,120,5,1,0)	130	3.9	0.4	92	75	55
5	(0.6,120,3,5,0)	102	4.8	1.2	103	75	67
6	(0.4,120,3,5,0)	102	3.6	0.6	124	86	75
7	(0.6,180,3,5,0)	127	6.9	1.0	154	113	100

B. Result 2: Equilibrium Selection on the Switching Threshold

First, the estimated switching thresholds do not significantly differ from the GG predictions for different α and connection costs under the single-round interaction treatments. In addition, as expected, either a reduction in

FIGURE 7
Individual Cutoff Points Cumulative Distribution Functions



α or an increment in the connection cost produces an increment in the estimated switching thresholds. Moreover, the estimated switching thresholds' cumulative distribution for a high α and a low connection cost (T1) is first-order stochastically dominated by similar distributions for a low α (T2) and a high connection cost (T3).

Second, the estimated switching threshold under the five-round interaction treatment does not differ from the equivalent one-round interaction treatment only when α is high and the connection cost is low (T5). Under this treatment, when there is a reduction in the α parameter (T6), we do not obtain the expected reduction in the estimated switching threshold. Meanwhile, under the treatment in which there is an increment in the connection cost (T7), we obtain the expected increment in the switching threshold, but it is lower than that predicted by the GG approach and significantly higher than those predicted by PSNE and SNE. In addition, although we do not observe any change in the cumulative distribution of the estimated switching thresholds for a lower α (T6), the same distribution for a higher connection cost (T7) first-order stochastically dominates the similar distribution for a lower connection cost (T5).

Third, the estimated switching threshold rises under the treatment in which the group size is increased (T4). This result is the opposite of the predictions for all the theoretical models that we consider. In particular, the cumulative distribution of the estimated switching thresholds for a larger group (T4) first-order stochastically dominates that for a smaller group (T1).

Support for Result 2. Table 3 shows that the predicted k^* is within two standard errors of the estimated mean switching thresholds for treatments T1, T2, T3, and T5.

For treatments T6 and T7, the estimated thresholds are between the predicted values of k^* and x^*. If we compare treatment T6 to treatment T5, then we do not observe a significant change in the estimated switching thresholds after reducing the parameter value of α. If we compare treatment T7 and T5, then we indeed observe an increase in the estimated mean switching thresholds after increasing the connection cost parameter; however, this change is not large, as was predicted by the models being examined.

After increasing the number of players in treatment T4, we expect a reduction in the estimated switching threshold because each individual should be receiving higher payoffs, as there are more potential participants in the group. Although additional gains arise from forming a larger network with more agents, the coordination problem among individuals also increases.

For the single-period treatment, we test the null hypothesis that the cumulative distribution function of individual cutoff points for high cost and lower alpha first-order stochastically dominates the original cumulative function. Using a Kolmogorov-Smirnov test, we reject the null hypothesis, with $p < 0.001$, concluding that all three distributions are significantly different. For the five-round treatments, a similar test indicates an effect on the cumulative distribution ($p < 0.05$) following an increase in the cost parameter. We do not obtain a similar result for the reduction in the alpha parameter.[17]

We now focus our analysis on measuring the effects of the main variables on the final structure of the network in the link formation game. Similar to our individual behavior analysis, we use a multinomial logit random effect model. For the single-round interaction treatments, we consider the following model to estimate the likelihood of network structures:

$$\Pr\left(\text{Structure}_{it} = s\right) = F\left(\text{Intercept}_{s|S} + \delta_{x,s|S}x_{it} + \delta_{\alpha,s|S}d_\alpha + \delta_{c,s|S}d_c + \delta_{n,s|S}d_n + \delta_{p,s|S}\text{per}\right).$$

For the five-round treatments, we consider the following model:

$$\Pr\left(\text{Structure}_{it} = s\right) = F\left(\text{Intercept}_{s|S} + \delta_{x,s|S}x_{it} + \delta_{\alpha,s|S}d_\alpha + \delta_{c,s|S}d_c + \delta_{p,s|S}\text{per} + \delta_{r,s|S}\text{round}\right).$$

In these models, x_{it} represents the connection value that each group i receives at time period t; d_α is a dummy variable that equals one when α equals .4 and zero otherwise; d_c is a dummy variable that equals one when c equals 180 and zero otherwise; per represents the period (time trend), which is treated as a continuous variable; round represents the time trend interaction effect within a time period, with round treated as a continuous variable; $F(.)$ is the cumulative logistic distribution function; Structure_{it} is the response category s of group i at time period t, where s equals zero when the network is empty (Empty), equals one when the network is partially connected (Partial), and equals two when the network is fully connected (Complete) ($s = 0, 1, 2$); and S indicates the reference category with which all other response categories are compared.

In Tables 5 and 6, we present the parameter estimates representing all the contrasts among all four categories for the one- and five-round interactions, respectively. A χ^2 test indicates that the null hypothesis that all estimated coefficients equal zero can be rejected, with $p < 0.0001$. Furthermore, the null hypothesis that alternative categories can be combined is rejected at the same significance threshold.

17. The equilibrium payoffs in Chilean pesos for each treatment were: 5,568 (GG) and 5,647 (SNE) for T1, 4,503 (GG) and 4,493 (SNE) for T2, 3,812 (GG) and 3,994 (SNE) for T3, 11,157 (GG) and 11,318 (SNE) for T4. The actual average payoff per subject in Chilean pesos was approximately 5,556 for T1, 4,366 for T2, 3,864 for T3, 10,696 for T4, 5,573 for T5 4,479 for T6, and 3,972 for T7.

TABLE 5
Multinomial Logit Model for Network Structure Probability for One-Round Interaction

Coefficients	Partial vs. Complete	Empty vs. Partial	Empty vs. Complete
Intercept	6.308***	7.534***	13.841***
	(0.350)	(0.441)	(0.568)
x_{it}	−0.036***	−0.074***	−0.110***
	(0.002)	(0.004)	(0.004)
d_α	0.627***	0.600**	1.228***
	(0.179)	(0.234)	(0.277)
d_c	1.369***	2.589***	3.958***
	(0.195)	(0.291)	(0.335)
d_n	2.356***	−0.345	2.011***
	(0.200)	(0.228)	(0.296)
per	−0.029***	0.032***	−0.003
	(0.004)	(0.006)	(0.007)
Number of observations	3,000	Number of groups	2,464

Note: The numbers in parentheses below each coefficient represent the standard errors.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE 6
Multinomial Logit Model for Network Structure Probability for Five-Round Interaction

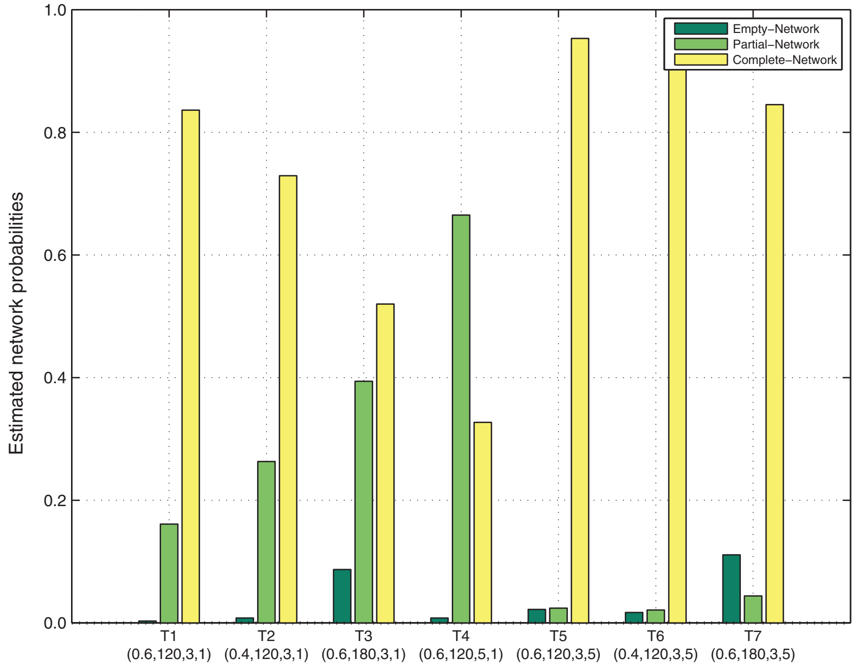
Coefficients	Partial vs. Complete	Empty vs. Partial	Empty vs. Complete
Intercept	3.325***	4.410***	7.735***
	(0.297)	(0.411)	(0.504)
x_{it}	−0.018***	−0.047***	−0.064***
	(0.001)	(0.003)	(0.004)
d_α	−0.150	−0.111	−0.261
	(0.196)	(0.219)	(0.261)
d_c	0.713***	1.020***	1.732***
	(0.198)	(0.296)	(0.332)
per	−0.077**	0.071*	0.006
	(0.028)	(0.036)	(0.043)
round	0.001	0.069	0.070
	(0.033)	(0.053)	(0.056)
Number of observations	2,250	Number of groups	450

Note: The numbers in parentheses below each coefficient represent the standard errors.
$^*p < .05$; $^{**}p < .01$, and $^{***}p < .001$.

C. Result 3: Network Structure

First, higher connection values increase the likelihood of more connected networks. Second, for the same connection values, a higher connection cost decreases the likelihood of more

FIGURE 8
Estimated Network Probabilities for Different Parameter Values of (α, c, n, r)



connected networks. Similarly, a lower alpha decreases the likelihood of fully connected networks compared with any other network structure for the same connection values. Third, over time and for the same connection values, there is an increased likelihood that networks will be either fully connected or empty. Finally, the repeated interaction of the same group of participants for a finite number of periods induces an increment in the proportion of networks that are fully connected.

Support for Result 3. As expected, the connection value coefficients ($\delta_{x,1|2}$, $\delta_{x,0|1}$, and $\delta_{x,0|2}$) for both estimations are negative and significant. This finding indicates that the likelihood of more connected networks increases as the connection value increases. Likewise, all coefficients that are associated with a higher connection cost ($\delta_{c,1|2}$, $\delta_{c,0|1}$, and $\delta_{c,0|2}$) are positive and significant. This result indicates that over the support of the connection value distribution, the proportion of highly connected networks decreases when the connection cost increases. Coefficients that are associated with lower values of alpha, which enable us to contrast partially connected or non-connected networks with fully connected networks ($\delta_{\alpha,1|2}$, $\delta_{\alpha,0|1}$, and $\delta_{\alpha,0|2}$), are all positive and significant for the one-round interaction treatments. This finding indicates that for lower values of alpha, the proportion of complete or partially connected networks decreases for the whole support of the connection value distribution. We did not observe a similar result for the five-round interaction treatments.

Our estimation also shows that the time period coefficients $\delta_{p,1|2}$ and $\delta_{p,0|1}$ are individually significant for both the one- and five-round interaction treatments. The negative sign of the first coefficient ($\delta_{p,1|2}$) and the positive sign of the last coefficient ($\delta_{p,0|1}$) indicate that the proportion of complete and empty networks tends to increase over time. This result arises from the increased likelihood of individuals requesting a link to either everyone or no one as time passes.

Finally, examining Figure 8, we can appreciate how the proportion of fully connected networks increases after imposing the structure of a finite repeated game over the link formation game (T5–T7). In particular, we can observe that this result arises from the reduction in the proportion of partially connected networks caused by the coordination failure of players linking to one another that we observed in the one-shot interaction treatments (T1–T4).

To confirm the robustness of our experimental results, we assess how different amounts of incomplete information (σ) in the payoff function affect the outcome of the game. In particular, our main objective is to check the theoretical prediction that the switching threshold is independent of σ but that the final network structure nevertheless depends on it. We proceed as in the first estimations, considering the following multinomial logit model with random effects to estimate the individual likelihood of requesting links with others:

$$\Pr\left(\text{Link}_{it} = m\right) = F\left(\text{Intercept}_{m|M} + \beta_{x,m|M} x_{it} + \beta_{\sigma>0,m|M} d_{\sigma>0} + \beta_{\sigma>10,m|M} d_{\sigma>10} + \beta_{p,m|M}\text{per}\right).$$

In this model, x_{it} represents the connection value that individual i receives at period t; $d_{\sigma>0}$ is a dummy variable that takes a value of one when the perturbation parameter $d_{\sigma>0}$ is greater than zero; and $d_{\sigma>10}$ is a dummy variable that takes a value of one when σ is greater than 10. Thus, whereas $\beta_{\sigma>0,m|M}$ measures the effect of $\sigma > 0$ compared with $\sigma = 0$, $\beta_{\sigma>10,m|M}$ measures the effect of $\sigma = 50$ compared with $\sigma = 10$. The variable per represents the period (time trend), treating time as a continuous variable; $F(.)$ is the cumulative logistic distribution function; Links_{it} is the response category m of individual i at time period t, where m equals zero when agent i decides to link to no one, equals one when she decides to link to some participants, and equals two when all participants decide to link one another ($m = 0, 1, 2$); and M indicates the reference category with which all other response categories are compared.

In Table 7, we present the parameter estimates representing all the contrasts among all three link-request categories. A χ^2 test indicates that the null hypothesis that all of the estimated coefficients equal zero can be rejected, with $p < 0.0001$. The null hypothesis that alternatives categories can be combined is also rejected, with $p < 0.0001$.

D. Result 4: Perturbation Effect on the Link-request Probability

Similar to our previous results, under complete information, higher connection values induce a higher individual likelihood of making a link-request. For the same connection values,

TABLE 7
Multinomial Logit Model for Individual Link-Request Probability for Different Levels of Perturbation (σ)

Coefficients	Linking-Some vs. Linking-All	Linking-None vs. Linking-Some	Linking-None vs. Linking-All
Intercept	3.918***	7.250***	10.990***
	(0.761)	(0.653)	(1.211)
x_{it}	−0.033***	−0.058***	−0.093***
	(0.004)	(0.006)	(0.010)
$d_{\sigma>0}$	0.669	−0.313	1.923**
	(0.414)	(0.455)	(0.683)
$d_{\sigma>10}$	0.680	−1.893***	−0.947
	(0.614)	(0.518)	(0.948)
per	−0.020**	0.020**	0.0001
	(0.006)	(0.007)	(0.008)
Number of observations	4,500	Number of individuals	90

Note: The numbers in parentheses below each coefficient represent the standard errors.
$^*p < .05$, $^{**}p < .01$, and $^{***}p < .001$.

larger perturbations produce mixed results with respect to the individual likelihood of making a link-request. Finally, for the same connection values, there is a time trend in favor of a higher individual likelihood of link-requesting either everyone or no one.

Support for Result 4. The connection value coefficients $\beta_{x,1|2}$, $\beta_{x,0|1}$, and $\beta_{x,0|2}$ are negative and significant, as expected. For a perturbation parameter greater than zero ($\sigma > 0$), the coefficient for linking-none versus linking-all ($\beta_{\sigma>0,0|2}$) is positive and significant. Thus, the likelihood of linking to everyone decreases as the perturbation becomes positive. However, larger perturbations do not produce similar effects. For instance, as the perturbation increases from 10 to 50, the coefficients for linking-none or linking-some versus linking-all ($\beta_{\sigma>10,0|2}$ and $\beta_{\sigma>10,1|2}$, respectively) are not significant. However, the coefficients for linking-none versus linking-some ($\beta_{\sigma>10,0|1}$) is negative and significant. This result indicates that the likelihood of individuals linking some other players increases as the perturbation size increases from 10 to 50. Similar to the results in the previous section, the negative sign of the first coefficient ($\beta_{p,0|2}$) and the positive sign of the second coefficient ($\beta_{p,0|1}$) suggest that over time, participants are more willing to request links to either everyone or to no one, rather than to only some members of their own group.

TABLE 8
Estimated Mean Switching Threshold and Standard Errors

Treatment	σ	$\hat{x}$	$\widehat{s.e.}$	$\widehat{err}$	GG(k^*)	PSNE(x^*)	SNE$(\underline{x})$
2	0	125	3.3	0.9	124	86	75
8	10	130	4.8	7.8	124	86[a]	75[a]
9	50	120	12.7	11.6	124	86[a]	75[a]

[a]Strictly speaking, these thresholds do not apply for $\sigma > 0$.

E. Result 5: Perturbation Effect on the Switching Threshold

The estimated mean switching threshold when sigma equals zero cannot be statistically distinguished from that when sigma is greater than zero. Moreover, the estimated mean switching thresholds for different perturbation levels do not differ significantly from the GG prediction.

Support for Result 5. In Table 8, we present the estimated switching threshold using the methodology explained above. This table shows that the predicted k^* is within two standard errors of the estimated switching strategies $\hat{x}$, for all values of σ, within 95% confidence intervals around the experimental switching threshold. Again, this result provides strong support for the GG approach.

We now assess how different levels of incomplete information (σ) in the payoff function affect the final structure of the network in the link formation game. We use the following model to estimate the network structure likelihood:

$$\Pr\left(\text{Structure}_{it} = s\right) = F\left(\text{Intercept}_{s|S} + \delta_{x,s|S}x_{it} + \delta_{\sigma>0,s|S}d_{\sigma>0} + \delta_{\sigma>10,s|S}d_{\sigma>10} + \delta_{p,s|S}\text{per}\right).$$

In this model, x_{it} represents the connection value that group i receives at time t; $d_{\sigma>0}$ is a dummy variable that takes a value of one when the perturbation parameter σ is greater than zero; $d_{\sigma>10}$ is a dummy variable that takes a value of one when σ is greater than 10; and per represents the period (time trend). $F(.)$ is the cumulative logistic distribution function; Structure_{it} is the response category s when s-connections are formed. Accordingly, s equals zero if there is an empty network, equals one if there is a partially connected network, and equals two if there is a complete (or fully connected) network; and S indicates the reference category with which other response categories are compared.

TABLE 9
Multinomial Logit Model for Network Structure Probability for Different Sigma Values

Coefficients	Partial vs. Complete	Empty vs. Partial	Empty vs. Complete
Intercept	7.593***	6.991***	15.254***
	(0.523)	(0.661)	(0.836)
x_{it}	−0.039***	−0.057***	−0.104***
	(0.002)	(0.005)	(0.006)
$d_{\sigma>0}$	0.612**	0.903	1.580***
	(0.189)	(0.281)	(0.301)
$d_{\sigma>10}$	1.644***	−1.135**	0.536
	(0.310)	(0.406)	(0.491)
per	−0.036***	0.014	−0.023**
	(0.006)	(0.008)	(0.010)
Number of observations	1,500	Number of groups	1,157

Note: The numbers in parentheses below each coefficient represent the standard errors.
$^*p < .05$, $^{**}p < .01$, and $^{***}p < .001$.

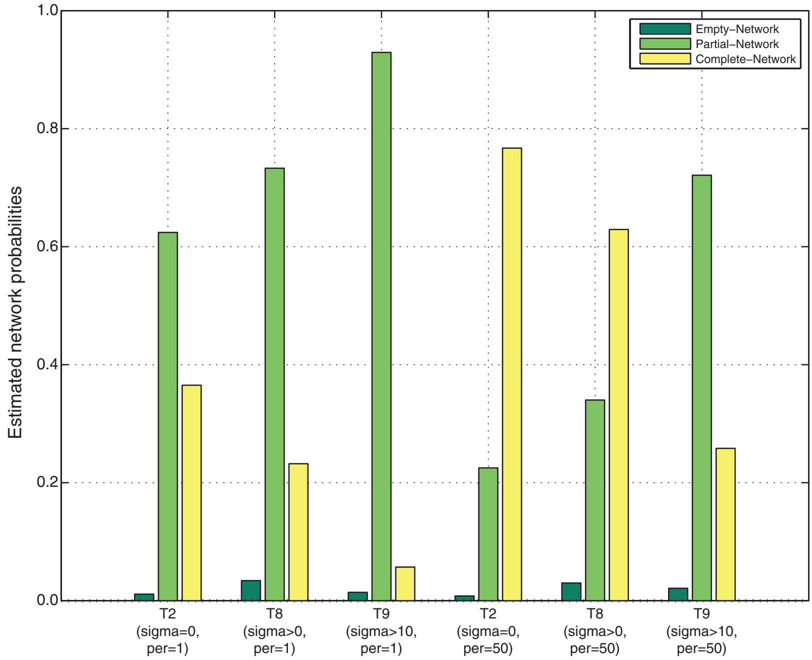
In Table 9, we present the parameter estimates representing all the contrasts among all three categories. A χ^2 test indicates that the null hypothesis that all estimated coefficients equal zero can be rejected, with $p < 0.0001$. Furthermore, the null hypothesis that alternative categories can be combined is also rejected at the same significance threshold.

G. Result 6: Perturbation Effect on the Network Structure

Consistent with our previous results, higher connection values are found to indicate a greater likelihood of connected networks. For the same connection values, larger perturbations are found to reduce the likelihood of fully connected or empty networks. Finally, over time, there is a higher likelihood of fully connected networks.

Support for Result 6. The coefficients that are associated with positive perturbations $\delta_{\sigma>0,1|2}$ and $\delta_{\sigma>0,0|2}$ are positive and significant. This finding indicates that the proportion of networks with complete connections decreases when the perturbation becomes positive. By contrast, the positive sign of $\delta_{\sigma>10,1|2}$ and the negative sign of $\delta_{\sigma>10,0|1}$ indicate that the proportions of complete and empty networks tend to decrease when the perturbation size increases from 10 to 50. Together, these results show that incomplete information generates greater variability in network formation than complete information does. Finally, our estimate shows that the time period coefficients $\delta_{p,1|2}$ and $\delta_{p,0|2}$ are individually significant. The

FIGURE 9
Estimated Network Probabilities for Different Levels of Perturbation (σ) and Time Period (per)



negative signs of these coefficients indicate that the proportion of complete networks tends to increase over time.

Finally, examining Figure 9, we can appreciate, first, how the proportion of partially connected networks increases after increasing the level of perturbation. This observation confirms our conjecture that even though the switching threshold does not depend on σ, the network structure nevertheless depends on the level of perturbation. Second, we can also appreciate how the proportion of complete networks tends to increase as subjects' experience increase.

In sum, we have shown that the GG approach offers a good description of behavior in the Myersonian consent game under study. In particular, the GG predictions were accurate under complete and incomplete information, within 95% confidence intervals around the experimental switching threshold. Moreover, the comparative statics outcomes also support the use of the GG approach as a robust refinement, as it eliminates the possibility that our results are an artifact of our experimental design. However, some of the GG predictions appear to break down either when there is some repetition or when the group size increases. Elucidating these findings may require further exploration.

V. CONCLUSIONS

In this article, we use an experiment to evaluate the accuracy of the GG approach to predict network configurations in a link formation game under complete and incomplete information. Our results indicate that the GG approach provides a good approximation of the observed behavior in a static game (single-round interaction) with three players under different information sets. In particular, the GG approach pointwise predicts the switching thresholds above which individuals are willing to link-request other players in a Myersonian link formation game. In general, the GG approach generates predictions that match the estimated switching thresholds within 95% confidence interval.

We also determined the robustness of our results through comparative static analysis. First, we found that higher connection values induce a higher proportion of agents to link-request other players and, consequently, increase the likelihood of more connected networks. Second, higher connection costs induce a smaller proportion of agents to link-request other members of their own groups and, consequently, decrease the proportion of fully connected networks. Third, lower returns from connections decrease the likelihood of complete networks; however, at an individual level, we could not find an effect on the proportion of agents requesting connections with repeated interaction. Fourth, for the same connection values, we found that over time, a higher proportion of agents link-request either everyone or no one, such that there is a lower proportion of partially connected networks, likely as a result of a learning process.

Contrary to expectations, we also found that participants tend to link with fewer members of their own group when group size increases. It appears that in such a scenario, the subjects in this study are unable to consider the positive effects of building larger networks. It is possible that the participants were unable to foresee the indirect benefits that would arise from having more individuals in the network or that they considered the strategic uncertainty that could result from having to coordinate with more individuals in a group (Heinemann et al. 2009). To eliminate the first possibility one could increase the value of the beta parameter while keeping the group size constant.

With the goal of testing the robustness of our results against repeated interaction, we permitted the groups of players to remain together for five rounds. In this case, the switching thresholds slightly decreased, showing better coordination and consequently a higher proportion of fully connected networks. Although GG predictions generally fail, so do alternative coalitional refinements.[18]

The main practical implication of this experiment is that coordination problems are present even in contexts in which win-win, pairwise relationships are feasible. For example, consider a start-up incubator in which people learn business practices from one another. An entrepreneur could be willing to discuss her ideas when the return is high but inefficiently high.[19] From a social perspective, individuals in this scenario should share ideas, with a lower trigger value in terms of returns. It is possible to conceive an institutional arrangement that promotes the sharing of ideas, thus lowering the empirical switch point and, in turn, fostering the success of incubators. Such a design, however, is a matter for future research.

APPENDIX A

Proof of Proposition 1

The strategy of the proof follows closely the proof of proposition 1 in the study by Harrison and Muñoz (2008) and it is based on successive "extensions" of the dominance regions. Each extension is obtained through a round of elimination of strictly dominated strategies. In round t, there exist $\underline{x}^t > \underline{x}^{t-1}$ and $\overline{x}^t < \overline{x}^{t-1}$ such that each surviving strategy satisfies $s_i(x_i) = \mathbf{0}$ if $x_i < \underline{x}^t$ and $s_i(x_i) = \mathbf{1}$ if $x_i > \overline{x}^t$. The iteration starts with $\underline{x}^0 \equiv \underline{x}$ and $\overline{x}^0 \equiv \overline{x}$. Formally, let us define S_i^t as player i's set of strategies that survive t rounds of deletion of interim strictly dominated strategies in the link formation game $G(\sigma)$. It will be shown that the set S_i^t is given by:

(A1) $$S_i^t = \left\{s_i \in S_i^{t-1} : s_i\left(x_i\right) = \mathbf{0} \text{ if } x_i < \underline{x}^t \text{ and } s_i\left(x_i\right) = \mathbf{1} \text{ if } x_i > \overline{x}^t\right\}$$

$$\text{where } S_i^0 = \left\{s_i \in S_i : s_i\left(x_i\right) = \mathbf{0} \text{ if } x_i < \underline{x} \text{ and } s_i\left(x_i\right) = \mathbf{1} \text{ if } x_i > \overline{x}\right\}.$$

In what follows we focus on the first round of extension of the lower dominance region to the right, $\underline{x}^1 > \underline{x}$ (the extension of the upper dominance region is analogous). The procedure for the next rounds is the same.

Given the complementarities involved in the payoff function, the worst scenario arises when the other players are using the same switching strategy with threshold in $\underline{x}$. In other words if $a_i = 0$ is a best response action for signals $x_i < \underline{x}^1$ when player i is facing the profile $s_{-i}^{\underline{x}}$, then $a_i = 0$ must also be a best response action to any other profile $s_{-i} \in S_{-i}^0$.

When the others use $s_{-i} = s_{-i}^{\theta}$ player i's expected payoff at action a_i is denoted by $\Pi_i^{\sigma}\left(a_i, x_i, \theta\right) \equiv E^{\sigma}\left[\pi_i\left(a_i, s_{-i}^{\theta}, x_i\right)\right]$ The goal is to characterize Π_i^{σ} as a function of x_i for given $\theta \in \underline{X} - \sigma/2, \overline{X} + \sigma/2]$. The following definitions are useful.

DEFINITION 1. *A_i^h is player i's set of homogenous actions, i.e., $A_i^h \equiv \{0, 1\} \subset A_i$. If $a_i \in A_i^h$, then we say that a_i is a homogenous action.*

DEFINITION 2. *$A_{-i}^{h,l}$ is a strict subset of $A_{-i}^h \equiv \times_{j \neq i} A_j^h$ such that its elements are action profiles where exactly $l \in \{0, 1, 2, ..., N\}$ individuals are playing the homogenous action 1 and the rest, $N-1$ individuals, are playing the homogenous action 0.*[20]

18. To be precise, the predictions fail in treatments 6 and 7, but provide a prediction within the 95% confidence intervals in treatment 5.

19. The decision to expose and discuss an idea with a counterpart (requesting a link) involves the risk of losing property rights, which constitutes a cost even if the other party is unwilling to share his/her idea (i.e., even if the link is not formed). The model is strongly reflective of players' consideration of such a risk. In the model, discussing an idea with a partner could be profitable, but it would be better to discuss the partner's idea as well, which is itself enriched by the partner's experiences with third parties.

20. Given this definition it is clear that $\left\{A_{-i}^{h,l}\right\}_{l=0}^{N}$ is a partition of A_{-i}^h.

Let $\Pr(a_{-i}|s_{-i}, x_i)$ denote i's beliefs about the others' action profile a_{-i} conditional on the others' strategy profile s_{-i} and the private value x_i.

Player i's interim expected payoff $\Pi_i^\sigma(a_i, x_i, \theta)$ can be written as:

$$\sum_{a_{-i}\in A_{-i}^h} \pi_i(a_i, a_{-i}, x_i) \Pr(a_{-i}|s_{-i}^\theta, x_i)$$

$$= \sum_{l=0}^{N} \sum_{a_{-i}\in A_{-i}^{h,l}} \pi_i(a_i, a_{-i}, x_i) \Pr(a_{-i}|s_{-i}^\theta, x_i).$$

Note that, by symmetry, if a_{-i} and $a'_{-i} \in A_{-i}^{h,l}$ then $\Pr(a_{-i}|s_{-i}^\theta, x_i) = \Pr(a'_{-i}|s_{-i}^\theta, x_i)$. Consequently, let $\Pr(a_{-i}^l|s_{-i}^\theta, x_i)$ denote i's beliefs about an action profile among the others that has exactly l agents choosing the homogeneous action **1**, conditional on the others' switching strategy profile s_{-i}^θ and the private value x_i.

Accordingly $\Pi_i^\sigma(a_i, x_i, \theta) = \sum_{l=0}^{N} \Pr(a_{-i}^l|s_{-i}^\theta, x_i) \sum_{a_{-i}\in A_{-i}^{h,l}} \pi_i(a_i, a_{-i}, x_i)$ and using the payoff defined in Equation (1), we have:

$$\text{(A2)}\qquad \Pi_i^\sigma(a_i, x_i, \theta) = \left(\sum_{j\neq i} a_{ij}\right) \sum_{l=0}^{N} \Pr(a_{-i}^l|s_{-i}^\theta, x_i)$$
$$\left[(\alpha x_i - c)\binom{N}{l} + \binom{N-1}{l-1} x_i + \binom{N-1}{l-1}(l-1)\beta x_i\right]$$

LEMMA 1. *If* $x_i = \theta$, *then* $\Pr(a_{-i}^l|s_{-i}^\theta, x_i) = 1/[(N+1)\binom{N}{l}] > 0$ *for all* $\theta \in \underline{X} - \sigma/2, \overline{X} + \sigma/2]$ *and all* $a_{-i}^l \in A_{-i}^{h,l}$ *for all* $l = 0, 1, 2, ..., N$.

Using Lemma 1 and the definition of $\underline{x} = c/(1 + \alpha + (N-1)\beta)$, if $x_i = \theta = \underline{x}$, we have:

$$\Pi_i^\sigma(a_i, \underline{x}, \underline{x}) = -\left(\sum_{j\neq i} a_{ij}\right)\left(\frac{c}{1+\alpha+(N-1)\beta}\right)$$
$$\times\left[\frac{1}{2} + \frac{2(N-1)\beta}{3}\right] < 0.$$

However, if player i receives a private value $x_i = \underline{x} + \sigma$, then he is receiving a sufficiently high value such that $\Pr\left(a_{-i}^l|s_{-i}^{\underline{x}}, \underline{x} + \sigma\right) = 0 \quad \forall l \in \{0, 1, ..., N-1\}$ and $\Pr\left(a_{-i}^N|s_{-i}^{\underline{x}}, \underline{x} + \sigma\right) = 1$, then $\Pi_i^\sigma(a_i, \underline{x} + \sigma, \underline{x}) = \left(\sum_{j\neq i} a_{ij}\right)\sigma(1 + \alpha + (N-1)\beta) > 0$.

Given the continuity of the expected utility function and using the *intermediate value theorem* then $\forall\sigma > 0$, $\exists\, x > \underline{x}$ such that $\Pi_i^\sigma(a_i, x, \underline{x}) = 0$. From Equation (A2), it is clear that such an x is independent of a_i, moreover, by symmetry, it is also independent of i, so we can define $\underline{x}^1 = \min\{x|\Pi_i^\sigma(\mathbf{1}, x, \underline{x}) = 0\}$. The analogous procedure for the upper dominance region permit us to define $\overline{x}^1 = \max\{x : \Pi_i^\sigma(\mathbf{1}, x, \overline{x}) = 0\}$. The set of surviving strategies for any player i is then given by:

$$S_i^1 = \left\{s_i \in S_i^0 : s_i(x_i) = 0 \text{ if } x_i < \underline{x}^1 \right.$$
$$\left. \text{and } s_i(x_i) = 1 \text{ if } x_i > \overline{x}^1\right\}.$$

Common knowledge of rationality allows players to update their information about other players' dominance regions. Using this fact, the process described above can be repeated, generating the sequences $\{\overline{x}^t\}_{t=0}^\infty$ and $\{\underline{x}^t\}_{t=0}^\infty$, with $\overline{x}^t = \max\{x : \Pi_i^\sigma(\mathbf{1}, x, \overline{x}^{t-1}) = 0\}$ and $\underline{x}^t = \min\{x : Pi_i^\sigma(\mathbf{1}, x, \underline{x}^{t-1}) = 0\}$.

The procedure guarantees that $\{\underline{x}^t\}_{t=0}^\infty$ is a strictly increasing sequence bounded above by $\overline{x}$, while $\{\overline{x}^t\}_{t=0}^\infty$ is a strictly decreasing sequence bounded below by $\underline{x}$. Therefore both sequences converge. Let us call these limit points $\underline{x}^\infty$ and $\overline{x}^\infty$, then $\Pi_i^\sigma(\mathbf{1}, \overline{x}^\infty, \overline{x}^\infty) = 0$ and $\Pi_i^\sigma(\mathbf{1}, \underline{x}^\infty, \underline{x}^\infty) = 0$.

From Equation (A2) and Lemma 1 we can see that the equation $\Pi_i^\sigma(\mathbf{1}, \theta, \theta) = 0$ has a unique solution θ^* that can be easily obtained. Therefore, we have $\overline{x}^\infty = \underline{x}^\infty = \theta^* = \frac{c}{\alpha+1/2+(N-1)\beta/3}$. Finally, we conclude that the only strategy profile that survives iterated elimination of strictly dominated strategies is given by $s^* = \left(s_i^{\theta^*}(\cdot)\right)_{i\in\mathcal{N}}$ ■

Proof of Lemma 1

Owing to the problem's symmetry, a player receiving a private value θ assigns a probability $\binom{N}{l}\Pr(a_{-i}^l|s_{-i}^\theta, \theta)$ to the scenario where exactly l individuals are receiving private values greater than θ. Then,

$$\text{(A3)}\qquad \binom{N}{l}\Pr(a_{-i}^l|s_{-i}^\theta, \theta) = \binom{N}{N-l}\int \phi(\tau)[\Phi(\tau)]^{N-l}$$
$$\times[1 - \Phi(\tau)]^l\, d\tau$$

with $\tau = \frac{\theta - x}{\sigma}$ and ϕ is the density (Φ the cumulative) of the noise ϵ_i. Integrating by parts, the right side of Equation (A3) becomes $\int_{-\infty}^{\infty}\phi(\tau)[\Phi(\tau)]^N d\tau = \frac{1}{N+1}$. Therefore $\Pr(a_{-i}^l|s_{-i}^\theta, \theta) = 1/\left[(N+1)\binom{N}{l}\right]$ for all $\theta \in \underline{X} - \sigma/2, \overline{X} + \sigma/2]$ and for all $l \in \{0, 1, 2, ..., N\}$ ■

APPENDIX B

Proof of Proposition 2

It is easy to see that the strategy profile $a = [0] \equiv (0, 0, \ldots, 0)$ is the unique profile in SNE(G_x) when $x < c/[1 + \alpha + (N-1)\beta]$, because for this range of values each agent plays 0 as a dominant strategy and, consequently, no coalition of agents can improve upon it. However, $a = [1] \equiv (1, 1, \ldots, 1)$ is the unique profile in SNE(G_x) when $x > [1 + \alpha + (N-1)\beta]$. To see this, consider any other given strategy profile $\hat{a} \neq \mathbf{1}]$ (Nash equilibrium or not). Because of the complementarities involved in the payoff function (1), the grand coalition, by playing $a = [1]$, can strictly increase the payoffs of all its members and then $\hat{a}$ would not belong to SNE(G_x). In addition, starting from $a = [1]$ which is trivially a Nash equilibrium, it is not possible to increase the payoff of any player in a deviation. Finally, if $x = c/[1 + \alpha + (N-1)\beta]$, then SNE($G_x$) = {[0], [1]}.

It is easy to show, again because of the complementarities involved, that the $\hat{a}$ from above is also rejected as a CPNE, because there is no subcoalition that can improve upon the grand coalition when the last is playing $a = [1]$. By the same argument, $a = [0]$ is the unique profile in CPNE(G_x) when $x < c/[1 + \alpha + (N-1)\beta]$, while $a = [1]$ is the unique profile in CPNE(G_x) when $x > [1 + \alpha + (N-1)\beta]$, being both feasible in the limit. As a result SNE(G_x) = CPNE(G_x).

Consider now the case of PSNE. When $c/(1 + \alpha) < x \leq c/\alpha$ any pair of agents which are not connected can profitably make a link and, consequently, only the complete network can be supported by a PSNE. Notice that when $c/[1 + \alpha + (N-1)\beta] \leq x \leq c/(1 + \alpha)$ then indirect connections are needed to make any connection profitable for these low values of x; hence, should nobody be requiring links, an agreement between two players to form a link does not suffice to set up a profitable relationship. Accordingly, different networks can be supported by PSNE in this area depending on the level of x and N. Finally, if $x < c/[1 + \alpha + (N - 1)\beta]$ then action $a_i = 0$ is a dominant strategy for player i and then the unique PSNE is [0], forming the empty network. Analogously, if $x > c/\alpha$ then action $a_i = 1$ is a dominant strategy and then the unique PSNE is [1] and the complete network is formed.

Finally, the trigger point for GG is a direct implication of Proposition 1.■

APPENDIX C

Experimental Instructions

The following is the verbatim translation (from Spanish into English) of experimental instructions administered to subjects at PUC (the Spanish original is available from the authors upon request) under treatments 1–3.

Instructions

This is an experiment about decision-making. Funding for this research has been provided by several academic institutions. Instructions are simple and if you follow them carefully and make good decisions, you can earn a CONSIDERABLE AMOUNT OF MONEY, which will be PAID WITH A CHECK that you can immediately cash in the bank office inside the campus.

General Proceedings

1. In this experiment, you will participate as a member of a group of agents with the opportunity to link each other. The experiment consists of 60 periods: 10 practice periods, which will not count for your final payoff, and 50 periods to be played for money.

2. At the beginning of every period, the computer will randomly form groups of three participants. Each of you will form part of a new group in each of the following periods. You will always be identified as agent 1 in the computer screen. Furthermore, you will never know who you are grouped with in any given period.

3. In every period, you have to decide whether to request a link to each member of your group.

4. In every period, each member of a group will receive a CONNECTION VALUE (X_0). This CONNECTION VALUE will be identical for all members of the same group and it will be generated randomly by the computer from the interval 50 to 310 points. Any value in this interval will have an equally likely chance of being drawn and it will be generated independently from previous periods.

For example, in each period, the computer will randomly form groups of three participants and it will assign a random CONNECTION VALUE, X_0, to each group. Suppose that a particular group gets an X_0 equal to 200 points. Therefore, all members of this group will have a CONNECTION VALUE of 200. That is, the CONNECTION VALUE of agent 1 (X_1) will be equal to that of agent 2 (X_2) and to that of agent 3 (X_3).

The members of each group should decide whether to connect other members in their group.

5. Then, you and every member of your group will have to decide whether to request zero, one, or two links. The connection costs and the monetary payoffs that you receive will depend on your decisions to linking request other members of your group and the decisions of the other members of your group to linking request you and among themselves. The costs and the monetary payoffs for each

FIGURE A1

Computer Screen for Participant in the Five-Group Treatment

Agent	Independent Connection	Direct Connection	Indirect Connection	Total Payoff per Connection	Total Payoff
Agent 2	ALPHA $\times X_1$ − C. COST	X_1	BETA $\times X_1$	ALPHA $\times X_1$ + X_1 + BETA $\times X_1$ − C. COST	ALPHA $\times X_1$ + X_1 + BETA $\times X_1$ − C. COST
Agent 3	0	0	0	0	

linking request you decide to make will be the sum of the following three payoff components:

5.1 Independent connection payoff: For each member of your group you decide to linking request, you will get the payment of:

$$\text{ALPHA} \times X_i - \text{CONNECTION COST}$$

The members of each group should decide whether to connect other members in their group.

For each agent you decide to NOT linking request, you will get zero as payoff, even if any other agent has decided to linking request you.

For example, if agent 1 decides to linking request agent 2 and to NOT linking request agent 3, as in the figure above, then agent 1 will get the amount of ALPHA $\times X_1$ − CONNECTION COST for linking request agent 2 and zero for NOT linking request agent 3.

5.2. Direct connection payoff: If the agent you have linking request decides to linking request you in return, then you will get the amount of your CONNECTION VALUE (X_i) as an additional payoff.

For example, if agents 1 and 2 decide to linking request each other, as in figure above, then agent 1 will get the amount of ALPHA $\times X_1$ − CONNECTION COST plus the amount of her X_i: That is, (1 + ALPHA) $\times$ X_1 − CONNECTION COST. The same will happen with agent 2.

5.3. Indirect connection payoff: If the agent you have established a direct connection has also established a direct connection with the third agent of your group, you will get the amount of BETA $\times X_1$ as an additional payoff.

For example, if agents 1 and 2 and agents 2 and 3 decide to linking request each other, as in figure above, then agent 1 will get the sum of all three payoff components: Independent, Direct and Indirect connection payoffs. That is, agent 1 will receive the amount of

$$\text{ALPHA} \times X_1 - \text{CONNECTION COST} + X_1 + \text{BETA} \times X_1$$

That is, (1+ALPHA+BETA) $\times X_1$ − CONNECTION COST Notice that agent 1 will get her payoff for having an indirect connection with agent 3 through agent 2 even if she has an independent connection with agent 3. Likewise, the amount an agent can get might be negative or positive depending on her CONNECTION VALUE.

According to the last figure above, agent 1 would get the following payoff.

Payoff Table for Agent 1

Exercise: Just for clarification and as an exercise, fill the table indicating how much agent 1 will get given the following graph of connections.

Fill up the following table assuming that the individual CONNECTION VALUE is X_1

Agent	Independent Connection	Direct Connection	Indirect Connection	Total Payoff per Connection	Total Payoff
Agent 2					
Agent 3					

6. Initial Capital Balance, Capital Accumulation, and Minimum Capital Balance.

Each agent will begin the experiment with a capital balance of 9,000 points. Total gains (or loses) in each period will be added (or subtracted) from the previous accumulated capital. If your capital balance in any period is lower than 4,500 point, you will not be able to continue participating in the experiment. You will get your capital balance and will have to leave the room.

7. Payment Procedure

Your final payoff will be equivalent to the final capital balance multiplied by 0.33 plus your participation fee. You will receive the amount in check that you can immediately cash at the bank office inside the campus.

Are there any questions?

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