Behavioral Attenuation in Networks*

Fulin Guo† Syngjoo Choi‡ Sanjeev Goyal§ Frédéric Moisan¶

November 6, 2024

For the latest version, click here.

Abstract

Social networks shape individual behavior and public policy increasingly leverages networks to enhance effectiveness. It is therefore important to understand how individuals behave in network interactions. This paper uses lab experiments to examine behavior in games on networks involving strategic substitutes and strategic complements. Theory suggests that an individual's choice is proportional to their (Bonacich) centrality. Our experiments, however, find that while choices increase with centrality, the relationship is weaker than predicted. The total action levels individuals choose and the total payoff they achieve are higher than the Nash outcomes in some cases while lower in others. We find that these results can be coherently explained by individuals' behavioral attenuation: they have incomplete adjustments to the strategic differences across network positions, exhibiting a bias toward generally high-payoff choices in complex networks—even when these choices are not optimal for their specific network positions.

JEL: C92, D83, D85, Z13.

*The paper was supported by the Keynes Fund (University of Cambridge), the Center for Behavioral Institutional Design (NYUAD) and Tamkeen under the NYU Abu Dhabi Research Institute Award CG005, and the Creative-Pioneering Researchers Program (Seoul National University). We thank Antonio Cabrales, Dan Friedman, Andrea Galeotti, Edoardo Gallo, Christian Ghiglino, Moritz Janas, Karl Schlag, Simon Weidenholzer, Michael Xu, Zheng Wang, and participants at a number of seminars and conferences for helpful comments. This paper was previously circulated under the title "Experimental evidence on the relation between network centrality and individual choice".

†Faculty of Economics, University of Cambridge. Email: fg400@cam.ac.uk

‡Department of Economics, Seoul National University. Email: syngjooc@snu.ac.kr

§University of Cambridge and New York University Abu Dhabi. Email: sg472@cam.ac.uk

¶Emlyon Business School & GATE. Email: moisan@em-lyon.com

1 Introduction

Social interactions influence individual behavior. An individual's investment in public goods, collaborative efforts in scientific research, and participation in criminal activities are affected by the actions of their neighbors (the people they interact with), whose actions, in turn, depend on the actions of their own neighbors, and so on. The outcome for the entire population ultimately depends on both the nature of the interactions and the structure of these interactions.

The economic theory of networks shows that the action profile of the population can be summarized in a single network measure – Bonacich centrality (Ballester, Calvó-Armengol, and Zenou [2006], Bramoullé, Kranton, and D'Amours [2014], Bonacich [1987]; for an early contribution in this spirit see Leontief [1941]). Network centrality measures are being applied in areas related to the design of policy interventions, where resources are allocated to individuals based on their network location, e.g. target special lessons to students, concentrate monitoring on specific criminals, offer subsidies to specific business sectors, and seed some rural households (Beaman, BenYishay, Magruder, and Mobarak [2021], Bandiera and Rasul [2006], Banerjee, Chandrasekhar, Duflo, and Jackson [2013], Galeotti, Golub, and Goyal [2020], Jackson, Rogers, and Zenou [2017], Zenou [2016]).

However, it is far from clear whether individuals embedded in a network will actually play the equilibrium, given the complex strategic reasoning required for each individual to reach the theoretical prediction (the Bonacich centrality). It is uncertain what behavioral tendencies individuals exhibit in network interactions and how these tendencies will shape the overall network outcome. If the theoretical prediction is not empirically valid then interventions may be less effective or may even have counterproductive effects. Laboratory experiments with human subjects offer the ideal environment to test this prediction as we can control the main parameters – the payoffs and the networks. Our paper offers the first experimental evidence on the relation between network centrality and individual choice covering a range of networks and classical economic environments within a common design.

In a wide range of circumstances – a prominent example is local public goods (Bramoullé and Kranton [2007]) – an increase in others' efforts lowers an individual's incentive to exert effort: this is the case of *strategic substitutes*. In others – examples include school performance, scientific collaboration and crime (Ballester, Calvó-Armengol, and Zenou [2006]) – an increase in others' efforts raises an individual's returns from their action: this is the case of *strategic complements*. Figure 1 illustrates the rich implications of the theory for two well known networks (core-periphery network and Erdos-Renyi network) and for games of strategic substitutes and strategic complements. The core-periphery structure is a stylized network (see Farboodi [2023] and Everett and Borgatti [1999]) that represents inequality in connections. It consists of two types of nodes: highly connected core nodes and less connected periphery nodes, which allows us to test whether individuals can play the equilibrium in a network with minimal node-type diversity. In contrast, the Erdős-Rényi network is a random graph model (see Newman [2018], Jackson [2008], and Goyal [2023]) that generates more diversity in node types: the degrees follow a binomial distribution, and nodes typically have different set of neighbors, etc., allowing us to study how the complexity of network structures influences individual choices.

Our *first* finding summarizes the relation between subjects' choices and equilibrium predictions. We find that, across all the four treatments, subjects' choices are positively correlated with their centrality but the rate of increase is not as steep as predicted by equilibrium. Regarding the role of network complexity: we find that subjects' choices in the Erdos-Renyi network are less responsive to centrality than in the core-periphery network, especially in the case of strategic substitutes.

In a network, an individual's centrality is typically highly correlated with their degree—the number of connections they have. We note that as long as there are non-negligible distinctions between centrality and degree in the network, even when controlling for degree, the above finding (a positive but flat relationship between subject choice and centrality) still holds.

Our *second* finding is that subject effort levels display rich departures from equilibrium across treatments. Consider the core-periphery network: under strategic substitutes, choices are (weakly) larger than the equilibrium; under strategic complements, choices are (weakly) smaller than the equilibrium. Next consider the Erdos-Renyi network: choices are larger than the equilibrium for both games of strategic complements and games of strategic substitutes.

These departures from equilibrium have significant effects on subjects' earnings. Due to positive deviations of action in the case of strategic substitutes (which also has negative spillovers), subjects' total payoff is smaller than the equilibrium prediction. In the case of strategic complements (which also has positive spillovers), the total payoff subjects earn is lower (higher) than the predicted earnings in the case of core-periphery (Erdos-Renyi) network due to negative (positive) deviations in action level.

This leads us to examine decision rules that can explain these departures from theoretical predictions. We show that classic behavioral features cannot account for the observed outcomes across treatments. The positive deviations of choice in the case of strategic substitutes (negative spillovers) are inconsistent with efficiency seeking and other-regarding preferences. We show that subjects do not achieve more equitable payoffs than the Nash equilibrium, which contradicts the notion of inequity aversion. Also, level-k reasoning (Charness and Rabin [2002] and Stahl and Wilson [1995]) and best response to the average effort (instead of neighbors' efforts) cannot generate the consistent flat relationships between choice and centrality.

Following the literature on behavioral attenuation, which suggests that individual behavior tends to show less sensitivity to parameter changes than would be optimal (Enke and Graeber [2023] and Enke et al. [2024]), we model an individual's choice as a convex combination of their position-specific best response and a position-independent "default" level. The default level is modeled as a weighted average of the network's mean choice and the highest-payoff choice, with the latter representing a tendency to imitate high-payoff choices, which we term the "imitation tendency". We find that the weight on the default value is significantly positive in both networks, with this tendency being larger in the more complex Erdos-Renyi network compared to the simpler core-periphery network. The weight on the highest-payoff choice is significantly positive in the Erdos-Renyi network but not in the core-periphery network. These results suggest that subjects exhibit behavioral attenuation: they only partially account for strategic differences across network positions and tend to anchor on certain effort levels chosen by others in the network, with a bias toward high-payoff choices in complex situations.

We show that behavioral attenuation and the imitation tendency interact in influencing the action profile of the network—specifically, the relationship between choice and centrality, as well as the overall action level. A stronger imitation tendency can mitigate the flattening effect of behavioral attenuation on the choice-centrality slope, particularly in the case of strategic complements. Strategic complements are generally more sensitive to individual behavioral biases than strategic substitutes. These findings explain the aggregate network outcomes across different networks and strategic contexts.

In the above setting, individuals' network positions are randomly reassigned each period, and they receive information on all participants' choices and payoffs. We hypothesize that these position reassignments, which require individuals to determine the optimal choice in each new position, demand high cognitive ability, contributing to behavioral attenuation.

Regarding the payoff information, note that the equilibrium payoff increases with centrality, suggesting that individuals with higher choices tend to earn more than those with lower choices, which may drive the positive deviations in action levels in the Erdos-Renyi network under both strategic substitutes and complements. To test these conjectures we designed two variations in the experimental setting: a fixed-position setting, where individuals keep the same network position throughout the game, and a limited information setting, where no information on others' payoffs is provided. We find that, compared to the baseline setting, fixed positions increase the sensitivity to centrality in three out of four treatments, with significant and largest effects observed in the Erdos-Renyi complements case. Limited information reduces average effort across all treatments, with significant and largest effects also in the Erdos-Renyi complements case. These results align with our conjecture: in the fixed-position setting, individuals only need to determine the choice for their own position rather than for different positions, which reduces decision complexity and thus behavioral attenuation. In the limited information setting, the unavailability of others' payoffs prevents individuals from being biased toward high choices that generally yield high payoffs, thus lowering the overall choice level in the network. Changes of experimental setting have the largest effect on the ER complements case because individuals exhibit larger behavioral biases in the baseline under ER than CP and strategic complements are more sensitive to behavioral biases compared to strategic substitutes.

Our paper is a contribution to the experimental studies of games on networks (Cassar [2007], Hoelzemann and Li [2021], Choi, Galeotti, and Goyal [2017], Gale and Kariv [2009], Charness, Feri, Meléndez-Jiménez, and Sutter [2014], Gallo and Yan [2021], Rosenkranz and Weitzel [2012], Antinyan et al. [2020], Boosey and Brown [2022]). Two aspects of our experimental design make it novel. Firstly, we consider continuous actions, whereas most existing literature focuses on binary actions (e.g., Charness, Feri, Meléndez-Jiménez, and Sutter [2014], Rosenkranz and Weitzel [2012]). Secondly, we allow for both strategic complements and substitutes (through a change in a single parameter); existing papers cover only one class of games (see e.g Gallo and Yan [2021], Antinyan et al. [2020]). Consideration of continuous actions allows us to evaluate the intensive margin of individual decisions. Coverage of different games is important as subjects exhibit different types of departures from equilibrium across games of strategic complements and strategic substitutes. Our findings on the lower than equilibrium response to centrality across treatments and the different level effects on actions across different types of games and networks are novel.

An influential body of experimental research shows that individuals often exhibit lower-than-optimal sensitivity to economic fundamentals (e.g., Enke and Graeber [2023], Enke et al. [2024],**?**, Ilut and Valchev [2023], Woodford [2020]). The behavioral attenuation model suggests that due to cognitive uncertainty, individuals' choices tend to regress toward intermediate values, resulting in reduced responsiveness to changes in economic environments. Our first contribution is that we extend the behavioral attenuation model (Enke et al. [2024]) to networked strategic games and demonstrate how individual-level behavioral attenuation impacts the action profile in different networks and strategic contexts; second, while the behavioral attenuation literature does not provide a theory on the cognitive default value, we find that this value is above the network average and biased toward highly-paid choices in complex network. The result that this imitation tendency can interact with behavioral attenuation to determine the network-level flatness of the choice-centrality relationship is novel.

The rest of the paper is organized as follows. In Section 2, we describe the model of continuous action games on networks, section 3 describes the experimental design, and section 4 formulates the principal hypotheses to be tested. Section 5 presents the main experimental findings. Section 6 presents the analysis of the role of degree and centrality in subject choices. Section 7 presents behavioral analysis for the experimental data. Section 8 discusses additional treatments and the implications of our findings.

2 Theory

We consider continuous action games on networks that admit a linear best response (Ballester, Calvó-Armengol, and Zenou [2006], Bramoullé, Kranton, and D'Amours [2014]; for an overview of research in this field, see Goyal [2023]). The set of players is denoted by $N = 1, .., n$, with $n \geq 2$. Individuals make simultaneous choices, where each individual i selects an action $s_i \in \mathbb{R}_+$. The individuals are located in a network g, which has a corresponding adjacency matrix given by G. In the matrix G, the entry $g_{ij} \in \mathbb{R}_+$ reflects the strength of the relationship that individual i has with individual j. In our experimental setting, we will assume $g_{ij} \in \{0, 1\}$ for any pair of individuals $i, j \in N$. Let $N_i(g) = \{j | g_{ij} > 0\}$ denote the nodes with whom node i has a link, i.e., the *neighbors* of i. We assume that for every $i \in N$, $g_{ii} = 0$, meaning that there are no self-loops in the network g. The vector of actions chosen by players is denoted by $\boldsymbol{s} \in \mathbb{R}^n_+$. The payoffs to an individual i given a vector of actions $\boldsymbol{s}$ and a network, G, are given by

$$U_i(\boldsymbol{s}, \boldsymbol{G}) = s_i \left(b_i + \beta \sum_{j \in N} g_{ij} s_j \right) - \frac{1}{2} s_i^2. \tag{1}$$

The coefficient $b_i \in \mathbb{R}$ corresponds to the portion of i's marginal return that is independent of others' actions and is referred to as i's standalone marginal return. The contribution of others' actions to i's marginal return is given by the term $\beta \sum_{j \in N} g_{ij} s_j$. The parameter β captures strategic spillovers. If $\beta > 0$, then actions are strategic complements; and if $\beta < 0$, then actions are strategic substitutes.

The following result summarizes the theoretical prediction on the relation between networks, strategic interaction, and individual actions.

Theorem 1. *Suppose the spectral radius of $\beta\mathbf{G}$ is less than 1, i.e., the absolute value of the largest eigenvalue of $\beta\mathbf{G}$ is smaller than one, then the unique Nash equilibrium of the game is given by*

$$\boldsymbol{s}^* = [\mathbf{I} - \beta\mathbf{G}]^{-1}\mathbf{b}. \tag{2}$$

Individual equilibrium actions are proportional to their Bonacich centrality.

where $\mathbf{I}$ is the $n \times n$ identity matrix and $\mathbf{b}$ is the vector of coefficients b_i for every $i \in N$.

For easy reference, we present a definition of Bonacich centrality here.

Definition 1. *(**Bonacich [1987]**) The Bonacich centralities of a network $\mathbf{G}$ corresponding to parameter β is $[\mathbf{I} - \beta\mathbf{G}]^{-1}\mathbf{1}$*

where $\mathbf{1}$ is the n-dimensional one vector. Bonacich centrality depends both on the network structure and the spillover parameter β. In terms of network topology, the Bonacich centrality of node i counts the total number of walks in the network starting from i, discounted exponentially by the parameter β determining the content of strategic interaction. Local payoff interdependence in the payoff function is restricted to neighbors but in equilibrium spreads indirectly through the network and the spread is summarized by Bonacich centrality.

The aim of our paper is to experimentally test this prediction.

3 Experimental design

To test the theoretical prediction, we consider two standard networks (core-periphery and Erdos-Renyi random graphs) and we consider both games of strategic substitutes and games of strategic complements. We chose these two types of networks because the core-periphery network is a simple network (Figure 1 (a) and (b)) consisting of only two types of nodes: core nodes, which have eight neighbors, and periphery nodes, which have one core neighbor. The core-periphery network's minimal variation, with only two distinct centrality values, allows us to test whether individuals can play the equilibrium in a network with minimal node type diversity. In contrast, the Erdos-Renyi network exhibits greater complexity (Figure 1 (c) and (d)). It has nodes with degrees ranging from one to seven, and even nodes with the same degree have different sets of neighbors, leading to distinct centrality values for each node. The Erdos-Renyi network allows us to study how the complexity of network structures influences individual choices.

In our experiment, links take on binary values 1 and 0. In the case of complements, the spillover parameter $\beta = 0.1$, and for substitutes the parameter $\beta = -0.1$. For simplicity, we set the standalone parameter b to a constant value of 10 across all nodes and all treatments. These parametric values are chosen so as to satisfy the conditions of the theorem on equilibrium for all networks we consider and to ensure that there is adequate variation in equilibrium choices across nodes.

The core-periphery structure is a stylized but empirically prominent network in finance, business, and social contexts (Farboodi [2023], Everett and Borgatti [1999]). A core-periphery network features individuals in the core who are considerably more "central" compared to the periphery nodes. The equilibrium prediction in the core-periphery network, as shown in Figures 1 (a) and (b), brings out the role of complements vs substitutes: core individuals have the highest Bonacich centrality and choose the highest effort under strategic complements, and they have the lowest Bonacich centrality and choose the lowest effort under strategic substitutes (this helps us appreciate that it is the network location and the spillover that jointly determine centrality). Figure 2 presents equilibrium payoffs: they show that location in a network can have large effects on payoffs: in Figure 2 (a) for strategic substitutes we see that the payoffs of the highest centrality nodes (the periphery nodes) are more than 4 times the payoffs of the lowest centrality nodes (the core nodes), and in Figure 2 (b) for strategic complements we see that the payoffs of the highest centrality nodes (the core nodes) are more than eight times the payoffs of the lowest centrality nodes (the periphery nodes).

The core-periphery network is a natural model to formulate inequality in connections. However, in some contexts, such as classroom friendships, the distribution of number of connections across nodes is more even, with most nodes having similar numbers of connections, resulting in fewer hubs and more overlapping neighbors. A canonical mathematical model for such situations is the Erdos-Renyi random graph (see Newman [2018], Jackson [2008] and Goyal [2023] for a discussion of the wide uses of this model in the social sciences). Figure 1 (c) and (d) present the Erdos-Renyi network used in the experiment, which is generated under parameters $n = 25$ and $p = \frac{1}{6}$ (i.e., each pair of two nodes has a probability of $\frac{1}{6}$ of being connected), which results in an average degree equal to four. Figures 1 (c) and (d) and 2 (c) and (d) show that the 25 nodes in the Erdos-Renyi network are each unique in their centrality and equilibrium payoff. The ranges of efforts and payoffs are comparable to those in the core-periphery network, but the diversity is greater in the sense that the Erdos-Renyi network exhibits a richer set of intermediate values in equilibrium efforts and payoffs, rather than just the two extreme values observed in the core-periphery network.[1]

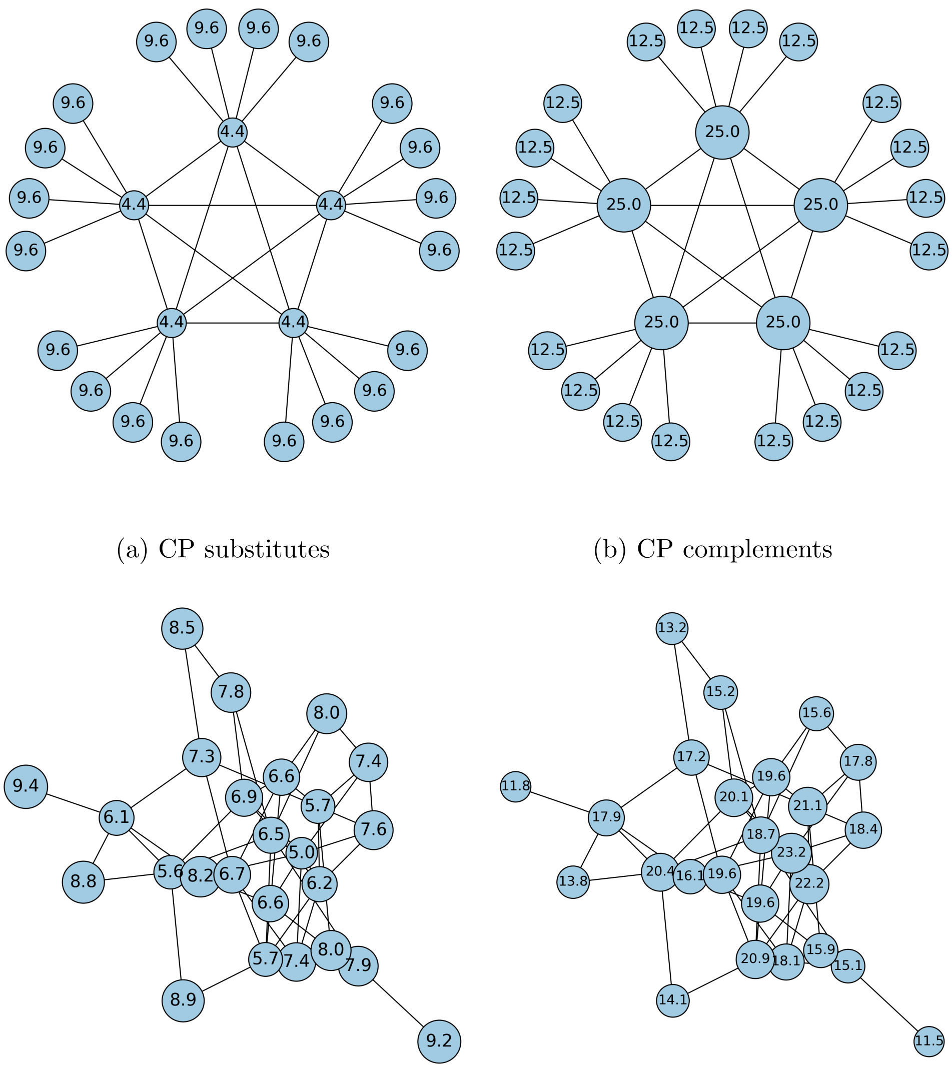
Due to the computational complexity of the decision problem and the uncertainty about what others will do, it is unlikely players will choose equilibrium actions right away: to facilitate learning our experiment involves repeated plays of the one-shot game. In each treatment, a group takes part in a session that consists of 40 periods. The group with 25 individuals is located in the same network, but participants' positions in the network are reassigned after each period randomly to mitigate potential repeated game effects. Reassignment of location in the network means that there is no persistent asymmetry across the subjects: this is important as large payoff differences could bring into play social preferences such as inequality aversion in shaping behavior. In every period, subjects choose an action lying in the interval $[0, 40]$ using a sliding scale. The granularity of the choices is 0.01.[2]

At the end of each period, participants are informed about choices and payoffs of all 25 nodes in that period. Given the great complexity of the networks we view this

[1] In the core-periphery and the Erdos-Renyi network, centrality and degree move in tandem – an increase in degrees almost always leads to a larger (lower) centrality in the case of complements (substitutes). To examine whether individuals take indirect network interactions beyond degrees into consideration, we considered a class of networks in which the relation between centrality and degree is non-monotonic; our principal findings remain unchanged and suggest that players' choices increase with centrality. These networks are discussed in Section 6.

[2] We provide subjects with a "calculator" to help them compute what they would get depending on the sum of their neighbors' actions, and their own action. See Section A in Appendix for details.

Figure 1: Equilibrium action levels



(a) CP substitutes

(b) CP complements

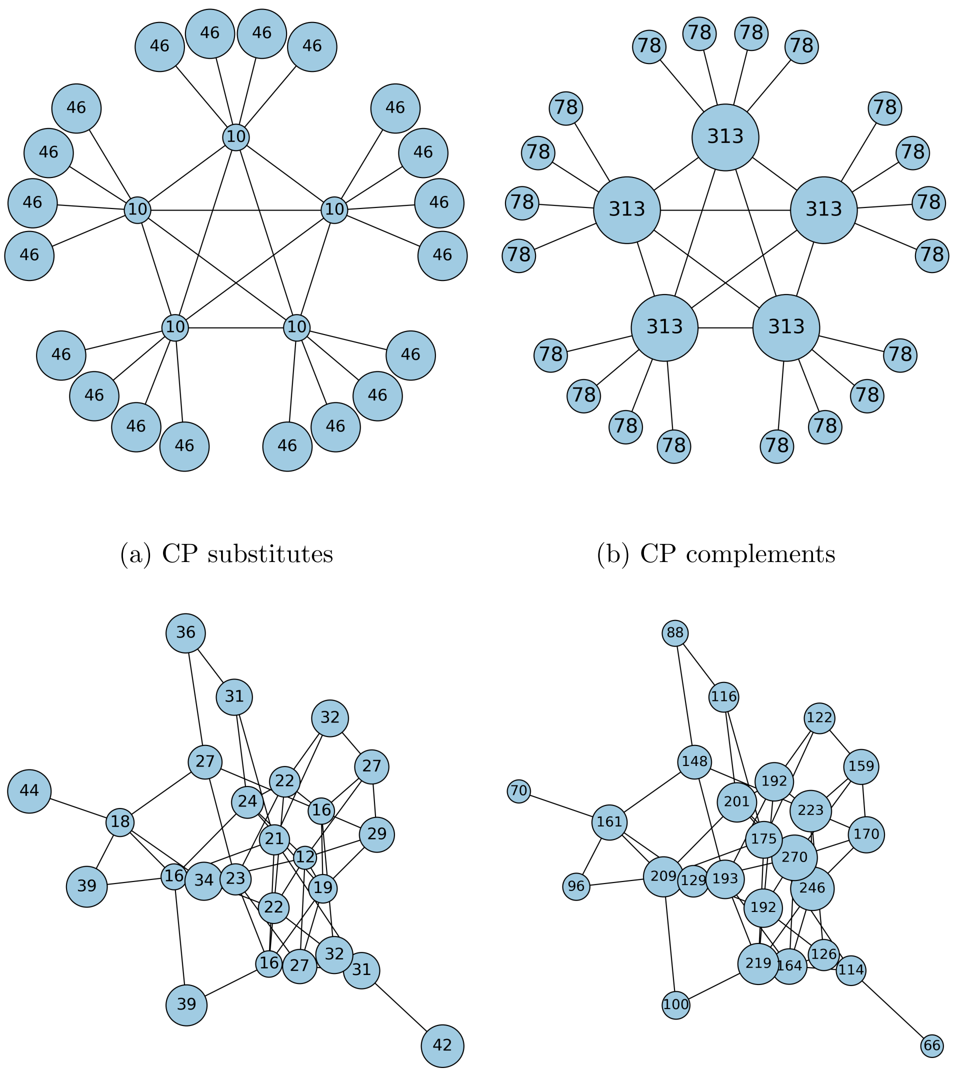
(c) ER substitutes

(d) ER complements

Notes: CP: core-periphery network; ER: Erdos-Renyi network. $b = 10$; $\beta = -0.1$ for substitutes and $\beta = 0.1$ for complements. Each number represents the equilibrium action level of a node.

detailed information as a baseline case as it should help ensure learning and convergence to equilibrium. Section A in the Appendix presents the screen interface and feedback protocol

Figure 2: Games on networks: equilibrium payoffs



(a) CP substitutes

(b) CP complements

(c) ER substitutes

(d) ER complements

Notes: CP: core-periphery network; ER: Erdos-Renyi network. $b = 10$; $\beta = -0.1$ for substitutes and $\beta = 0.1$ for complements. Each number represents the equilibrium payoff of a node.

we used in our experiment.

Subjects payments are based on the sum of payoffs of the 40 periods plus some initial endowment of points: 700 points for core-periphery network and Erdos-Renyi network under strategic complements, and 150 points for the core-periphery network and Erdos-Renyi network under strategic substitutes. The conversion rates are 700pts=£1 for core-periphery network and Erdos-Renyi network under strategic complements, and 150pts=£1 for the core-periphery network and Erdos-Renyi network under strategic substitutes. The endowments and conversion rates were chosen based on equilibrium predictions to allow subjects to recover from some bad periods with low payoffs, which can be negative (with different range across treatments, and this motivated the different endowment levels). The experiments were conduced at CeDEx (University of Nottingham). On average the subjects earned £15.

For each of the four treatments, there were 8 sessions: as there were 40 periods and 25 subjects per session, there were $8 \times 25 \times 40 = 8,000$ observations on individual choices per treatment.

4 Hypotheses

Theorem 1 provides a sharp prediction on behavior. However, the strategic interactions in large networks are complex and it is unclear if individuals will act in conformity with equilibrium, either via introspection or through learning via repeated observation of choices.

To develop a first idea of the dynamics of choice and learning, we simulate outcomes when individuals choose a myopic best response action at any period t given the choices of others at period $t-1$. In our simulation, the choices are made repeatedly over 40 periods, as in the experiment. In period 1, we assume individuals make decisions uniformly at random, and in each subsequent period $(2-40)$, they choose the best response action to the previous period's action profile of others. If the best response action falls outside the range of $[0, 40]$, the action is truncated to 0 or 40 accordingly. Figure 22 in section B of the Appendix plots the dynamics of the best response dynamics: we see that choices converge to the Nash equilibrium and the convergence is fast in all treatments. For a general discussion on the convergence of best response dynamics in such games see Bramoullé, Kranton, and D'Amours [2014]. Putting together Theorem 1 and our best response simulations we arrive at the following hypothesis:

Hypothesis: Subject choices converge to Nash equilibrium, i.e., their action is equal to their Bonacich centrality multiplied by the standalone value b at the end of the experiment.

(A). Core-periphery network: In the substitutes game, core subjects choose 4.4 and periphery subjects choose 9.6. In the complements game, core subjects choose 25 and periphery subjects choose 12.5.
(B). Erdos-Renyi network: In the substitutes game, actions range from 5 to 9.4. In the complements game, actions range from 11.5 to 23.2.

The hypothesis above assumes that individuals can play precise myopic best responses. However, the complexity of decision-making and equilibrium reasoning in networks may make such behavior challenging. Drawing on the concepts of behavioral attenuation (Enke and Graeber [2023] and Enke et al. [2024]), which demonstrate that human subjects exhibit weaker-than-optimal sensitivity to parameter variations due to cognitive uncertainty (potentially stemming from the complexity of economic environments), individuals in network interactions may show lower sensitivity in their choices to centrality compared to equilibrium predictions. This reduced sensitivity may be more pronounced in the more complex Erdos-Renyi network (which has 25 distinct centrality values) than in the core-periphery network (which has only 2 distinct centrality values). We formalize this in the following alternative hypothesis:

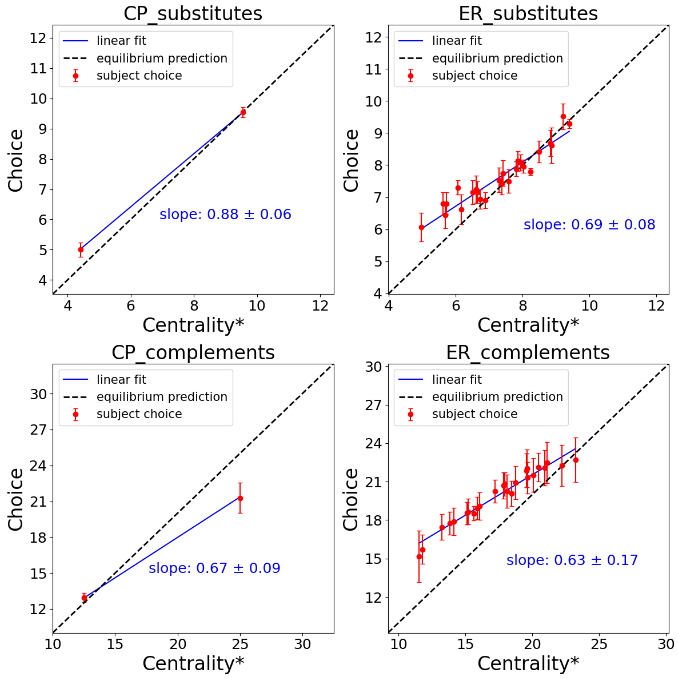
Alternative Hypothesis (Behavioral Attenuation Hypothesis):
(A) The sensitivity of subject choices to Bonacich centrality is weaker than predicted by the theory across all treatments.
(B) Subject choices are less sensitive to Bonacich centrality in the Erdos-Renyi network compared to the core-periphery network.

5 Equilibrium predictions vs subject behavior

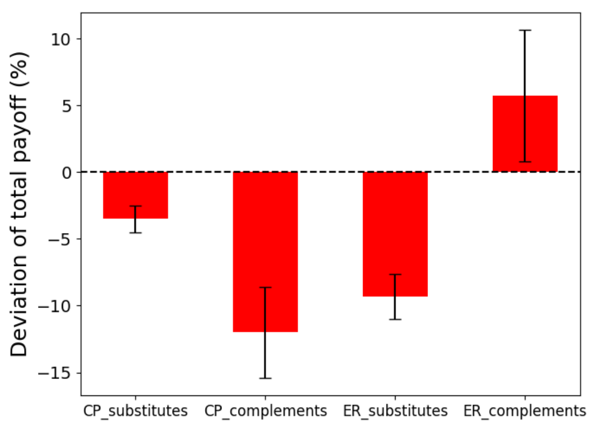
As shown in Section C.1 in Appendix, The average actions stabilize towards the end of the experiment. Therefore, our analysis will focus on the actions in the last ten rounds.

Figure 3 presents the relation between equilibrium prediction and subjects' choices (in the last ten rounds). The x-axis plots the Bonacich centrality of a subject multiplied by the standalone marginal return (denoted as centrality*) and the y-axis plots the choice of subjects (averaged per node across all sessions in the last ten periods). We recall that equilibrium effort is equal to centrality multiplied by the standalone advantage $b = 10$: we represent this on the 45-degree black dashed line.

Figure 3: Theoretical predictions and subjects' behavior



(a) Choices



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average choice chosen by subjects in the last 10 periods of a given network centrality, averaged across the eight sessions. The 95% confidence interval bars are calculated using clustered standard errors over sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the choice. The 45-degree black dashed line represents the values where the choice equals the equilibrium prediction. The blue line is the random effect panel regression fit of the subject choices on theoretical prediction, reported in Table 1. The text reports the slope coefficient and 95% confidence interval (CI). (b) This bar plot shows the percentage deviation of the total payoff across subjects from the total equilibrium payoff in the last ten periods. Error bars represent 95% CIs around the mean, calculated using clustered standard errors over sessions.

Our first observation on Figure 3 is that (on average) subjects' choices increase with centrality but that they do not increase as sharply as predicted by equilibrium.[3] In other words, the slope between choices and centrality is positive but smaller than 1 in all treatments. This is shown by the blue line which represents linear fit of subject choice on equilibrium prediction.

The flat relationship between subject choice and centrality is confirmed by the random effects regression presented in Table 1, which shows that the coefficient of centrality* is significantly less than one in all treatments. Figure 26 in Appendix C.1 shows the time series of the slope coefficient of subject choice on centrality*, which indicates that the slope coefficient is smaller than one in all periods across all treatments: there is an increasing trend in the slope coefficient during the first half (especially in the first ten periods) of the game, and the slopes plateau at values below one in the latter half of the game.

Regarding the comparison across the two networks, we can observe that for the game of strategic substitutes, the slope coefficient is much higher for core-periphery network than for Erdos-Renyi network (0.88 vs. 0.69); for the game with strategic complements, the slope coefficient in the core-periphery network is slightly higher than that in the Erdos-Renyi network (0.67 vs. 0.63). Section C.3 shows that there is greater individual-level heterogeneity and a higher proportion of individuals with low sensitivity to different network positions in the more complex Erdos-Renyi network compared to the core-periphery network. We summarize these as follows:

Finding 1: As in line with the hypothesis of behavioral attenuation,

(A). In all treatments, subjects' choices increase with centrality but the effect of centrality on subjects' choices is smaller than predicted by the equilibrium.

(B). Subjects' choices in the Erdos-Renyi network are less responsive to centrality than in the core-periphery network, especially under strategic substitutes.

We next examine the level of choices: whether they are systematically higher or lower than the equilibrium prediction. As shown in Figure 3(a), consider the core-periphery network: under strategic substitutes, choices of core agents (the lowest centrality agents) are higher and choices of periphery agents (the highest centrality agents) are (roughly) equal to equilibrium predictions; under strategic complements, core agents (the highest centrality agents) choices are lower and periphery agents (the lowest centrality agents)

[3] This pattern is robust to different ways of organizing the data including regressions with averaged data per node or with session-level data. See Tables 7 and 8 in section C.5 in the Appendix.

Table 1: Panel regression of choice on equilibrium

	CP sub	CP com	ER sub	ER com
centrality*	0.878***	0.675***	0.688***	0.631***
	(0.029)	(0.047)	(0.042)	(0.085)
constant	1.151***	4.479***	2.590***	8.927***
	(0.233)	(0.631)	(0.321)	(1.187)
N	2000	2000	2000	2000
R^2	0.712	0.562	0.234	0.286

Notes: $centrality^* = centrality \cdot b$. *** represents $p < 0.01$ (for the null hypothesis that $centrality^* = 1$ and constant = 0). Parenthesis reports standard errors clustered over sessions.

actions are (roughly) equal to equilibrium predictions. In the Erdos-Renyi network, choices of all agents are (weakly) larger than the equilibrium under both strategic complements and strategic substitutes. Figure 36 in Appendix C.5 shows that the mean choice is smaller than mean Nash action level in the case of core-periphery strategic complements while above mean Nash in the other three treatments. We summarize these observations as follows:

Finding 2: The level of average choices is heterogeneous across treatments.

A. Core-periphery: under strategic substitutes core (periphery) subjects' choices are larger than (equal to) equilibrium predictions; under strategic complements core (periphery) subjects' choices are lower than (equal to) equilibrium predictions.

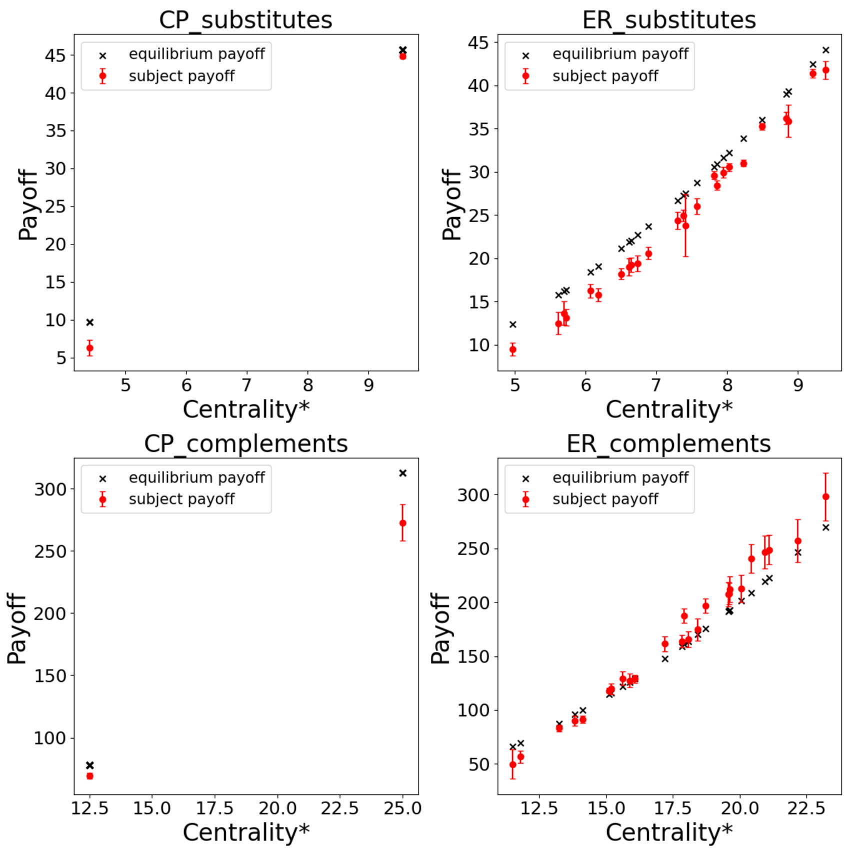
B. Erdos-Renyi network: subjects' choices are larger than the equilibrium prediction under both strategic complements and substitutes.

Section C.2 shows that these results are consistently observed in most groups (i.e., sessions), indicating that the flat relationship between choice and centrality and level effects are not merely averages from heterogeneous sessions but are generally observed in each realization of the network result (i.e., each individual session).

Figure 3(b) shows that the subjects' behavior has large effects on their payoffs: total payoffs across subjects are lower than the predicted payoffs in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments (two-sided Wilcoxon signed-rank (WSR) test, $p < 0.01$). The total payoff is larger than predicted payoff in the Erdos-Renyi network with strategic complements (two-sided WSR test, $p < 0.05$).

These observations are supplemented with data on how payoffs vary with centrality. Figure 4 summarizes how our treatments affect subjects with different centrality. Consider

Figure 4: Payoff vs. centrality



Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average payoff of subjects in the last 10 periods of a given network centrality, averaged across the eight sessions. The 95% confidence interval bars are calculated using clustered standard errors over sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the payoff.

the core-periphery network: in both strategic substitutes and complements, the core nodes earn significantly less than equilibrium, while the peripheral nodes earn close to equilibrium. Next consider the Erdos-Renyi network: in strategic substitutes all nodes earn slightly below equilibrium payoffs. In strategic complements, the low centrality nodes earn close to equilibrium payoffs, while the high centrality nodes earn higher than equilibrium payoffs consistently.

6 Centrality vs. degree

The results from the previous section show that there is a positive but flat relationship between subject choice and centrality. Since centrality and degree are highly correlated in both networks, there is also a significantly positive (negative) — yet weaker than predicted — relationship between subject choice and degree under strategic complements (substitutes) across both networks.

Do subject choices increase with centrality, holding degree constant?

This raises a question whether centrality has an impact on subject choice when degree is held constant. In the core-periphery network, degree and centrality are perfectly correlated (as there are only two distinct degree and centrality values), making it impossible to distinguish their individual effects on subject choice. In the Erdos-Renyi network, there are 25 distinct centrality values but only 7 distinct degree values, which provides an opportunity to examine the impacts of centrality on subject choice for nodes with the same degree. Table 2 presents the panel regression of subject choice in the last ten periods on centrality and dummy variables for each degree value. As shown in columns (2) and (5), the coefficient of centrality is no longer significant under ER strategic substitutes, but remains significantly positive under strategic complements. This suggests that subject choices tend to increase with centrality, even when holding degree constant, under strategic complements, whereas centrality does not significantly influence subject choice for same-degree nodes under ER strategic substitutes.

Do subject choices align more closely with centrality when centrality and degree are less correlated?

The results in the ER network suggest that centrality does not significantly impact choice once degree is held constant for strategic substitutes, while it still plays a significant role in strategic complements. Section C.4 in Appendix shows that in both strategic sub-

Table 2: Panel regression of choice on centrality* and degree in the ER network

Variable	ER sub (1)	ER sub (2)	ER sub (3)	ER com (4)	ER com (5)	ER com (6)
Centrality*	0.69***	-0.16		0.63***	0.36***	
	(0.04)	(0.17)		(0.09)	(0.09)	
Constant	2.59***	10.94***	9.43***	8.93***	11.34***	15.57***
	(0.32)	(1.70)	(0.13)	(1.19)	(1.28)	(0.46)
Degree 2		-0.96***	-0.87***		1.42**	2.18***
		(0.19)	(0.15)		(0.46)	(0.54)
Degree 3		-1.65***	-1.44***		1.81***	3.24***
		(0.33)	(0.13)		(0.46)	(0.55)
Degree 4		-2.17***	-1.87***		2.56***	4.83***
		(0.43)	(0.15)		(0.60)	(0.75)
Degree 5		-2.79***	-2.35***		2.98***	5.74***
		(0.61)	(0.15)		(0.60)	(0.81)
Degree 6		-3.39***	-2.82***		3.10***	6.56***
		(0.72)	(0.15)		(0.71)	(0.98)
Degree 7		-3.89***	-3.19***		2.99***	7.19***
		(0.86)	(0.20)		(0.89)	(1.14)
N	2000	2000	2000	2000	2000	2000
Overall R^2	0.23	0.25	0.25	0.29	0.30	0.29

Notes: This table represents random effects regression of subject choice on centrality* and/or degree dummy variables. Standard errors are calculated clustered over sessions. Notes: *** p<0.01, ** p<0.05, * p<0.1

stitutes and strategic complements, the ranking of choices aligns with degree rather than centrality in the (rare) cases where the ranking between centrality and degree is reversed.

However, we should note that the differences in these centrality values are very small, and the relationship between centrality and degree is highly correlated and monotonic (with few exceptions of limited economic importance). One question is whether centrality plays a more significant role if the correlation between degree and centrality is weaker and the non-monotonicity between centrality and degree is more pronounced.

To study this, we create two tree networks depicted in Figure 5, which shows that there exists apparent non-monotonicity between centralities and degrees. Under strategic substitutes, the equilibrium action does *not* monotonically decrease with degrees: degree-3 nodes have lower equilibrium effort levels than degree-4 nodes. Conversely, under strategic complements, centrality and hence equilibrium action does *not* monotonically increase with degrees: degree-3 nodes have higher equilibrium effort levels than degree-4 nodes. We investigate whether agents will follow centralities or degrees.

We set the parameters for strategic substitutes to $b = 40$ and $\beta = -0.3$, and for strategic complements to $b = 0.15$ and $\beta = 0.39$. These parameters are designed to generate non-monotonicity in the relationship between centrality and degree.

Figure 6 shows the average subject choice in the last ten periods for each network position in the tree treatments. Similar to the CP and ER networks, we observe a positive relationship between subject choice and centrality, but the relationship is flatter than the theory suggests. Again, this finding is in line with the hypothesis of behavioral attenuation.

Regarding the question of whether choice increases with centrality for the same degree nodes, Table 3 presents the regression of subject choice on centrality and dummy variables for each degree. In contrast to the Erdős-Rényi network, we find that the coefficient of centrality is significantly positive, even when holding degree constant, for both strategic substitutes and strategic complements.[4]

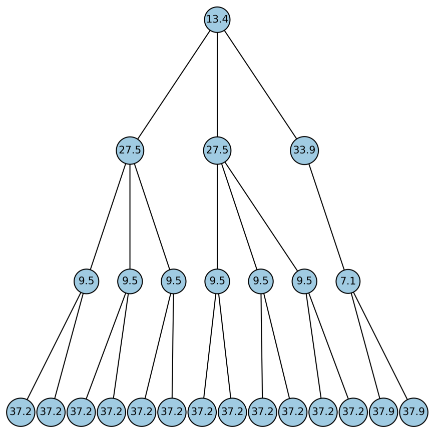
Table 3: Panel regression of choice on centrality* and degree in the Tree networks

Variable	Tree Sub (1)	Tree Sub (2)	Tree Sub (3)	Tree Com (4)	Tree Com (5)	Tree Com (6)
Centrality*	0.64***		0.54***	0.71***		0.20***
	(0.04)		(0.18)	(0.04)		(0.05)
Constant	10.18***	35.08***	14.88**	3.34***	9.74***	7.82***
	(0.92)	(0.54)	(6.36)	(0.43)	(0.36)	(0.53)
Degree 2		-10.90***	-9.04***			
		(0.71)	(0.78)			
Degree 3		-17.99***	-3.03		15.94***	11.25***
		(0.99)	(4.39)		(0.94)	(0.82)
Degree 4		-14.98***	-9.68***		12.54***	9.64***
		(0.51)	(1.81)		(0.43)	(0.62)
N	2000	2000	2000	2000	2000	2000
Overall R^2	0.62	0.69	0.70	0.70	0.74	0.74

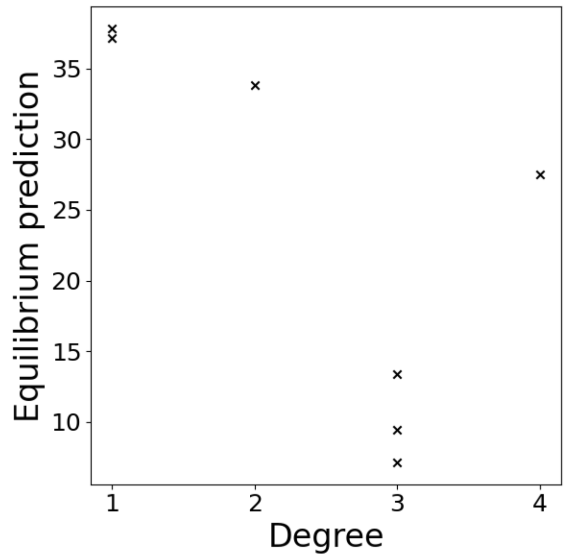
Notes: This table represents random effects regression of subject choice on centrality* and/or degree dummy variables. Standard errors are calculated clustered over sessions. Notes: *** p<0.01, ** p<0.05, * p<0.1

[4]Tables 10 and 11 in Section C.5 of the appendix shows that these results hold if using a linear model of degree (instead of dummy variables) in both the Erdos-Renyi and the tree networks.

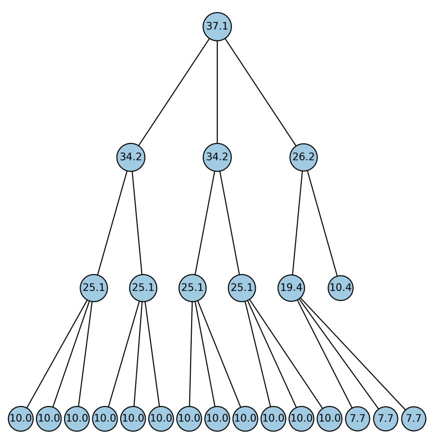
Figure 5: Equilibrium in tree networks



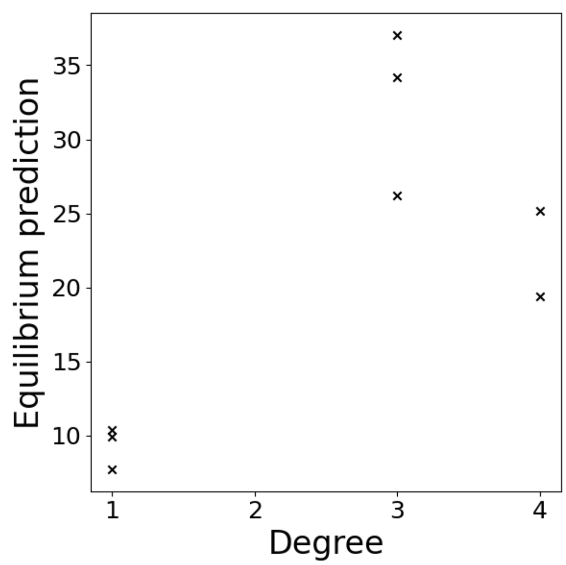
(a) Strategic substitutes: network



(b) Strategic substitutes: equilibrium prediction vs. degree

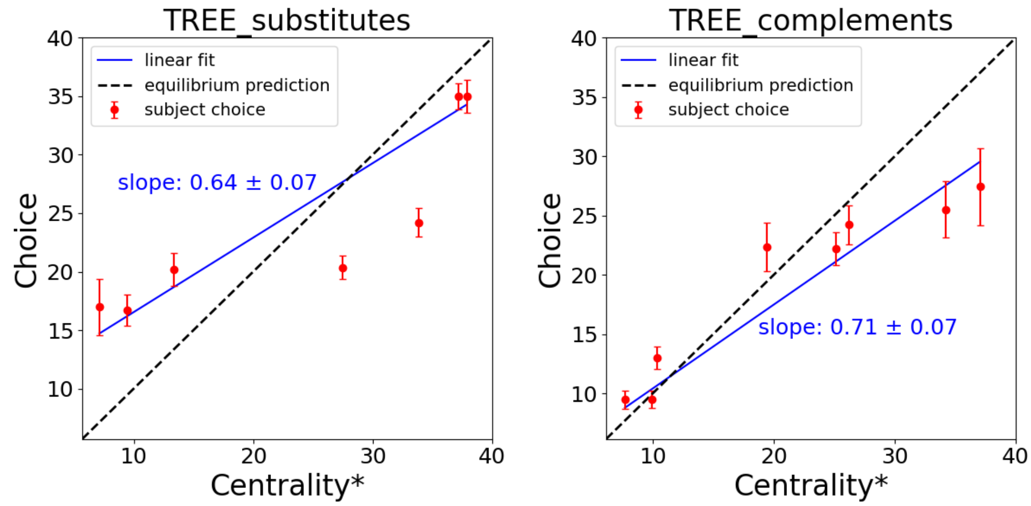


(c) Strategic complements: network



(d) Strategic complements: equilibrium prediction vs. degree

Figure 6: Choices vs. equilibrium prediction

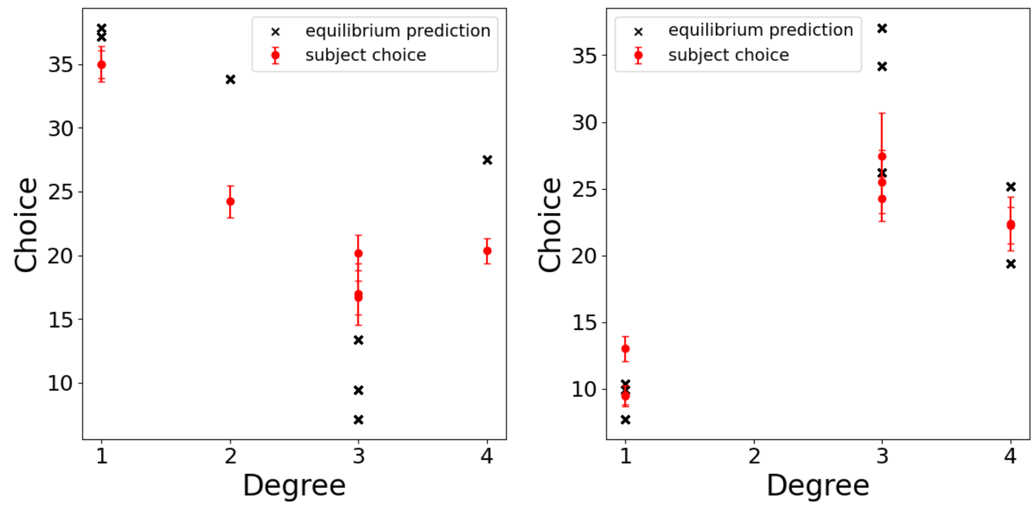


(a) Tree substitutes (b) Tree complements

Section C.4 in the Appendix shows that, in contrast to the ER network, the ranking of subject choices in the last ten periods aligns with centrality rather than degree for the nine non-monotonic pairs of reversed nodes, with eight out of nine being statistically significant (one-sided Wilcoxon Signed-Rank test, $p < 0.05$, $n = 8$).

The results in the tree networks suggest that when centrality and degree are less correlated and the non-monotonic relationship between the two is more pronounced, centrality plays a significant role in shaping subject choices, which indicate that degree alone is insufficient to explain subject behavior in such networks.

Figure 7: Choices vs. degree



(a) Tree substitutes

(b) Tree complements

7 Behavioral Explanations

This section presents behavioral models to explain the experimental results. In Part 7.1, we consider the behavioral attenuation model, where an individual's choice is a convex combination of their best response and a position-independent default effort level. Part 7.2 presents the results of alternative behavioral models, including efficiency-seeking, other-regarding preferences, inequity aversion, level-k, and best response to the average effort (instead of neighbors' efforts). We will show that these behavioral models cannot explain the experimental results.

7.1 Behavioral Attenuation

Following the spirit of Enke and Graeber [2023] and Enke et al. [2024], suppose an individual's choice is a convex combination of best response choice ($s_{i,br}$) and a "default value" (s_{def}) depending on the overall action levels of the network.

$$
\begin{aligned}
& s_i = \lambda s_{i,br} + (1-\lambda) s_{def} \\
\textit{where} \quad & s_{i,br} = b_i + \beta \sum_{j \in N} g_{ij} s_j \\
& s_{def} = \alpha \hat{s} + (1-\alpha)\overline{s} \\
& \hat{s} = argmax_{s_i \in \boldsymbol{s}} \pi_i(s_i, \boldsymbol{s}_{-i}), \;\; \overline{s} = \frac{\sum_i s_i}{N}
\end{aligned}
\tag{3}
$$

where $\lambda \in [0,1]$ is the weight on best responses and $1-\lambda$ is the weight on the default value. When $\lambda = 1$, the model corresponds to everyone making best responses to others' choices. A value of $\lambda < 1$ suggests that individuals exhibit behavioral attenuation, meaning that they only partially account for the differences in optimal choice among various network positions and tend to regress toward a position-independent value.

We model the default value depends on the average network choice $\overline{s}$ and the highest-paid choice $\hat{s}$. We model in this way because individuals can observe the choices of all participants in the network, and when they are uncertain about how to differentiate their choices based on network position, it is conceivable that they may imitate what others are doing (e.g., Apesteguia, Huck, and Oechssler [2007] and Huck, Normann, and Oechssler [1999]). In addition, as shown in Figure 27 in the Appendix C.1, the average deviations of subject choices from best responses are consistently non-negative across treatments. This pattern indicates a bias toward higher choices, which generally yield higher payoffs (as equilibrium payoffs increase with centrality across all treatments – see Figure 4).

From direct calculations, we define the behavioral equilibrium as follows:

Definition 2. *An action profile* $\mathbf{s^{be}}$ *is a behavioral equilibrium under behavioral parameters* (λ, α) *for a network game* $(G, \beta, \mathbf{b})$ *if*

$$
\begin{aligned}
& \mathbf{s}^{be} = \left[\mathbf{I} - \lambda\beta \left(\mathbf{G} + \frac{(1-\alpha)(1-\lambda)}{\lambda\beta} \mathbf{M} \right) \right]^{-1} (\lambda \mathbf{b} + (1-\lambda)\alpha \hat{s} \mathbf{1}) \\
& \textit{and } \hat{s} = argmax_{s_i \in \mathbf{s^{be}}} \pi_i(s_i, \mathbf{s^{be}_{-i}})
\end{aligned}
\tag{4}
$$

where $\mathbf{M} = \frac{1}{n}\mathbf{1}\mathbf{1}^T$ is a $n \times n$ matrix with each entry equal to $\frac{1}{n}$ for calculating the average action level. Recall that the Nash equilibrium (Theorem 1) is given by $(\mathbf{I} - \beta\mathbf{G})^{-1}\mathbf{b}$. When $\lambda = 1$, it is straightforward to see that the behavioral equilibrium (4) is equal to the Nash equilibrium. For $\lambda \in [0, 1)$, the impacts of behavioral attenuation on the equilibrium can be decomposed into three parts. First, it reduces the effective magnitude of the spillover effect from β to $\lambda\beta$. Second, it changes the effective magnitude of the standalone benefit from $\mathbf{b}$ to $(\lambda\mathbf{b} + (1-\lambda)\alpha\hat{s}\mathbf{1})$. Third, it changes the effective interaction network from $\mathbf{G}$ to $\left(\mathbf{G} + \frac{(1-\alpha)(1-\lambda)}{\lambda\beta}\mathbf{M}\right)$.

To explore how the behavioral parameters impact the behavioral equilibrium (BE), we calculated the BE for different pairs of $(\lambda,\ \alpha)$ and the corresponding slope coefficient of BE choices on Nash equilibrium. Figure 8 presents the heatmap where each cell shows the slope for a specific pair of $(\lambda,\ \alpha)$. This figure reveals three findings: (1) Given α, the slope of BE choices on NE decreases as λ decreases, indicating a higher behavioral attenuation leads to a flatter relationship between choice and centrality; (2) Given $\lambda < 1$, the slope of BE choices on NE increases with α, indicating that the flat relationship between BE choices and centrality becomes less pronounced when individuals have a higher imitation tendency; and (3) The slope is more sensitive to the imitation parameter α in the complements cases compared to the substitutes cases. Figure 9 shows that behavioral biases have a larger effect on the overall choice level in strategic complements than in strategic substitutes (see Section D of the Appendix for more analysis of how behavioral attenuation (λ), imitation tendency (α), networks, and strategic contexts jointly affect the flat relationship between subject choice and centrality, as well as the level effects).

Estimation: We estimate the parameters by minimizing the mean absolute deviation from subject choice in the last ten periods and the behavioral equilibrium under (λ, α). As previously mentioned, the CP and ER networks exhibit starkly different levels of complexity, which may influence individual behavioral features; therefore, we estimate parameters separately for the CP and ER networks. We estimate common parameters across the strategic substitutes and strategic complements cases, as the only difference between them is a single parameter change in the payoff function—β from -0.1 to 0.1—which we assume has minimal impact on individuals' intrinsic behavioral traits (λ, α). We will report how fixing the parameters across strategic contexts can fit the experimental data.

$$\begin{aligned}
MAE(\lambda, \alpha; treat) &= \frac{\sum_{g=1}^{8}\sum_{t=31}^{40}\sum_{i=1}^{25} |s_{g,t,i}(treat) - \boldsymbol{s}_i^{be}(\lambda, \alpha; treat)|}{8 \times 10 \times 25} \\
(\hat{\lambda}_{CP}, \hat{\alpha}_{CP}) &= argmin_{\lambda,\alpha}\ MAE(\lambda, \alpha; CP_sub) + MAE(\lambda, \alpha; CP_com) \\
(\hat{\lambda}_{ER}, \hat{\alpha}_{ER}) &= argmin_{\lambda,\alpha}\ MAE(\lambda, \alpha; ER_sub) + MAE(\lambda, \alpha; ER_com)
\end{aligned} \tag{5}$$

Figure 8: Slope of BE on NE for different (λ, α)

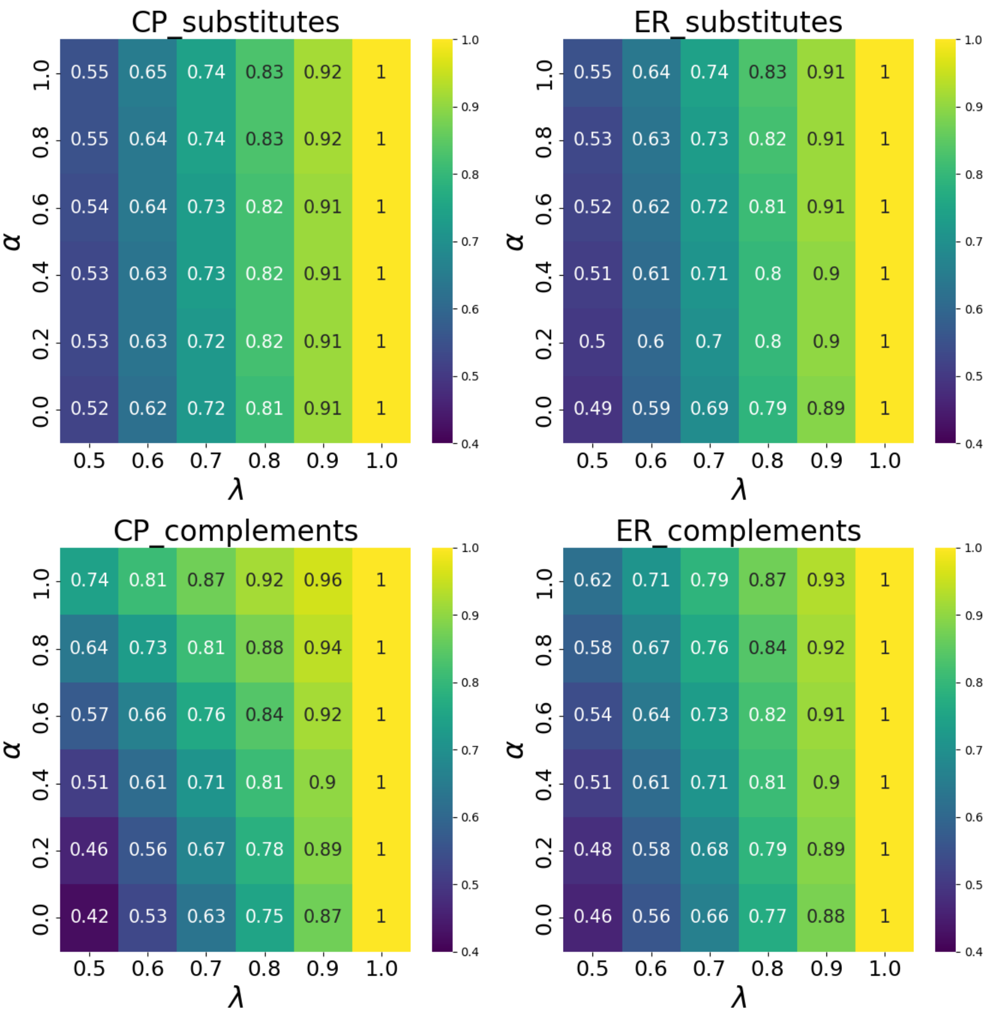
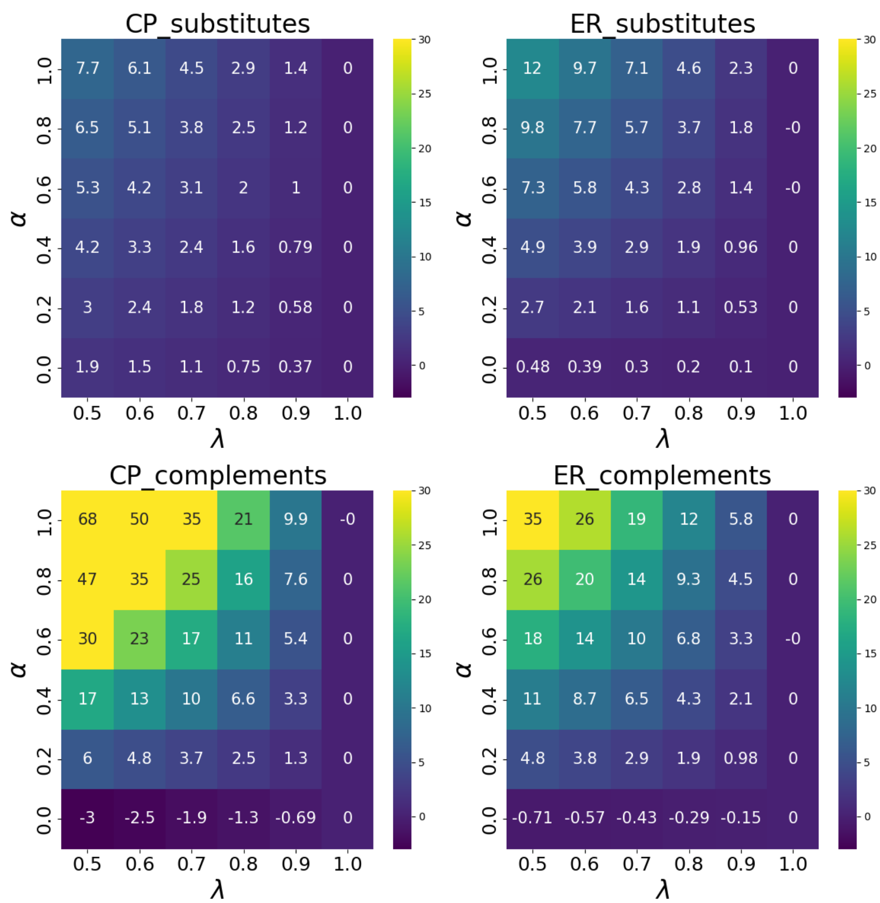


Figure 9: Deviation of average action for different (λ, α)



where $s_{g,t,i}$ represents the choice of session g, period t, and network position i, under treatment = treat. To account for within-group correlations, we calculate bootstrap standard errors by sampling at the session level.

Table 4: Estimated parameters for the behavioral model

	Core-periphery	Erdos-Renyi
λ	0.82***	0.63***
	(0.04)	(0.07)
α	0.00	0.66***
	(0.00)	(0.17)
N	4000	4000
Obj.	2.43	3.38

Notes: *** represents $p < 0.01$ for the null hypothesis that $\lambda = 1$ and $\alpha = 0$, respectively. Parentheses show bootstrap standard errors based on 100 bootstrap samples at the session level.

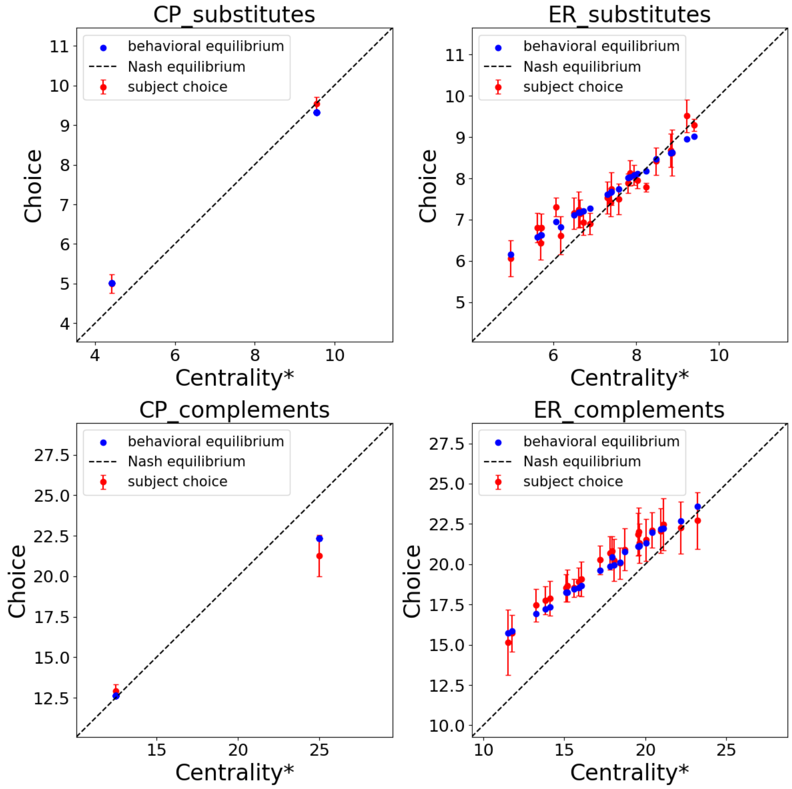
Table 4 shows that the estimated parameter λ is significantly less than one in both networks. The imitation parameter α is significantly positive in the ER network but not in the CP network. The value of λ being less than one suggests that individuals only partially differentiate across network positions, exhibiting attenuation toward some default value in both networks. λ is also much smaller in the Erdos-Renyi network than in the core-periphery network, in line with the hypothesis regarding the impacts of network complexity on behavioral attenuation. α being significantly positive in the ER network but not in the CP network suggests that individuals tend to imitate highly-paid choice in the more complex ER network but not in the simpler CP network.

Figure 10 shows that the behavioral attenuation model replicates the patterns of subject choices well across different treatments.[5]

From individual behavioral attenuation to network-level flat relationships. We observe that the gap in behavioral attenuation between CP complements and ER complements (0.82 vs. 0.63) is much larger than the gap in the slope of choices on centrality* (0.67 vs. 0.63). In addition, we note that while CP substitutes and CP complements have very different slope coefficient (0.88 vs. 0.67), the aggregate outcome can be fitted

[5]Table 12 in Appendix D shows that the estimated behavioral parameters in the tree networks are $\hat{\lambda}_{Tree} = 0.87$ and $\hat{\alpha}_{Tree} = 0.28$. As in the ER network, individuals in the tree networks exhibit both significant behavioral attenuation and an imitation tendency, but the extent of each is much smaller than in the ER network. Figure 41 shows that the behavioral attenuation model can match subject choices well in the tree networks under both strategic substitutes and strategic complements.

Figure 10: Behavioral Equilibrium with Estimated Parameters



reasonably well under common behavioral parameters.

To explain these, note that individual behavioral attenuation interacts with the imitation tendency, network structure, and strategic contexts in determining the aggregate action pattern (e.g., Figure 8): (1) Individuals in the ER network tend to imitate highly-paid choices while they do not in the CP network, which can mitigate the flattening of the choice-centrality relationship caused by behavioral attenuation and thus narrows the choice-centrality flatness gap between ER complements and CP complements. (2) When $\alpha = 0$ (no bias toward high-payoff choices), behavioral attenuation has the largest effect on the network-level flatness of choice-centrality sensitivity in the CP complements case and the smallest in the CP substitutes case, among all four treatments (see also Figure 39 in Section D of the Appendix).

7.2 Alternative behavioral models

This part shows that the experimental results cannot be explained by some classic behavioral models: efficiency seeking, other-regarding preference, inequity aversion, level-k, and best response to the network average effort (instead of neighbors' efforts).

7.2.1 Efficiency seeking

Consider the problem of maximizing the aggregate payoffs:

$$\sum_i U_i(\boldsymbol{s}, \boldsymbol{G}) = \sum_i \left[s_i \left(b_i + \beta \sum_{j \in N} g_{ij} s_j \right) - \frac{1}{2} s_i^2 \right] \tag{6}$$

The first-order condition is given by: for each i

$$\left(b_i + \beta \sum_{j \in N} g_{ij} s_j \right) + \sum_{j \in N} \beta g_{ij} s_j - s_i = 0 \tag{7}$$

That is, the socially optimal choice $\tilde{\boldsymbol{s}}$ is

$$\tilde{\boldsymbol{s}} = [\mathbf{I} - 2\beta \mathbf{G}]^{-1} \mathbf{b}. \tag{8}$$

This would suggest that (1) subjects' average behavior should be below equilibrium in the case of strategic substitutes and above equilibrium under strategic complements, and (2) the sensitivity of choice to centrality should be larger than the equilibrium prediction. However, neither of these holds: (1) we have shown in Figure 3(a) that subjects have a positive deviation in CP and ER substitutes and a negative deviation in CP complements, (2) we observe a flatter relationship between choice and centrality than predicted by theory, which contradicts the socially optimal outcome.

In addition, as shown in Figure 3(b), (average) payoffs are lower than the equilibrium payoffs in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments (two-sided Wilcoxon signed-rank (WSR) test, $p < 0.01$). These indicate that the experimental results cannot be explained by individuals' efficiency seeking tendency.

7.2.2 Other-regarding preferences

Suppose an individual has other-regarding preferences (Cooper and Kagel [2016]), which can be represented by a weight $\gamma < 1$ placed on the average payoffs of the population:

$$\tilde{U}_i(\boldsymbol{s}, \boldsymbol{G}) = U_i(\boldsymbol{s}, \boldsymbol{G}) + \gamma \frac{\sum_{j \neq i} U_j(\boldsymbol{s}, \boldsymbol{G})}{n-1} \tag{9}$$

Using similar derivations as for the efficient seeking outcome, the solution to maximizing (9) is

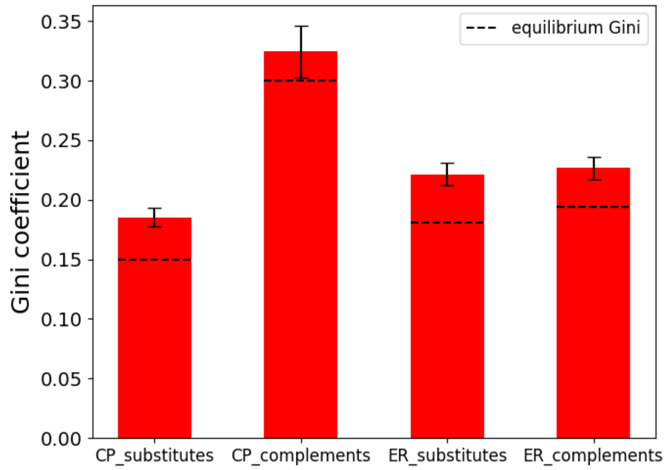
$$\tilde{\boldsymbol{s}} = [\mathbf{I} - (\beta + \frac{\beta\gamma}{n-1})\mathbf{G}]^{-1}\mathbf{b}. \tag{10}$$

We can see that the efficient outcome in (8) is a special case of (10) where an individual takes equal weight to all individuals. The implications for (10) are the same as those for (8): average choices should be larger (smaller) than the Nash equilibrium under strategic complements (substitutes) and choices should be more sensitive to centrality than the theory suggests. Thus, the directions of deviations of choices and the flat relationship between choice and centrality indicate that other-regarding preferences cannot explain the observed results.

7.2.3 Inequity aversion

A potential explanation for the flatter relationships between actions and centrality could be that subjects care about equity: not only own payoff but also the comparison of own payoff and others' payoffs (Fehr and Schmidt [1999]). However, In our experiment players are being reassigned locations across rounds. As individuals have an equal chance of occupying different positions, if they took a long run view of the game then there would be no *a priori* reason to shade efforts to obtain more egalitarian outcomes: from an ex-ante perspective in equilibrium all subjects expect the same payoffs aggregated across rounds. In addition, considering inequality of payoffs across different network positions, the Gini coefficient of payoffs is higher than the theory predicts in all the treatments, as shown in Figure 11.

Figure 11: Gini coefficient



7.2.4 Level-k model

We examine whether the level-k reasoning model (Nagel [1995], Stahl and Wilson [1995], Crawford et al. [2013]) can explain the key patterns of our data. Consider the level-k model:

level 0: $\mathbf{s}^{l_0} = m \cdot \mathbf{1}$, where $m \in [0, 40]$ is the level-0 action.

level 1: $\hat{\mathbf{s}}^{l_1} = \mathbf{b} + \beta G \mathbf{s}^{l_0}$ and $\mathbf{s}_i^{l_1} = \max(\min(\hat{\mathbf{s}}_i^{l_1}, 40), 0)$ for each $i \in N$.

We can define the level-k action vector iteratively as follows:

level k: $\hat{\mathbf{s}}^{l_k} = \mathbf{b} + \beta G \mathbf{s}^{l_{k-1}}$ and $\mathbf{s}_i^{l_k} = \max(\min(\hat{\mathbf{s}}_i^{l_k}, 40), 0)$ for each $i \in N$.

In the level-k model, each individual makes a best response to the level-(k-1) action profile, represented by $\mathbf{b} + \beta G \mathbf{s}^{l_{k-1}}$.

Figure 12 shows the slope coefficient of choice on Nash for each value of k and the level-0 action. For a given cell, we assume that all agents have the same level k and the same level-0 action. We can see that the level-k model does not consistently generate flat relationship between choice and Nash equilibrium. In particular, when k is large, the slope is close to one as the level-k action profile becomes close to Nash equilibrium.

7.2.5 Best response to the average

It may be plausible to assume that instead of making best response to the choices of the exact neighbors, individuals make best response by anticipating that each neighbor

Figure 12: Slope for different k and level-0 action

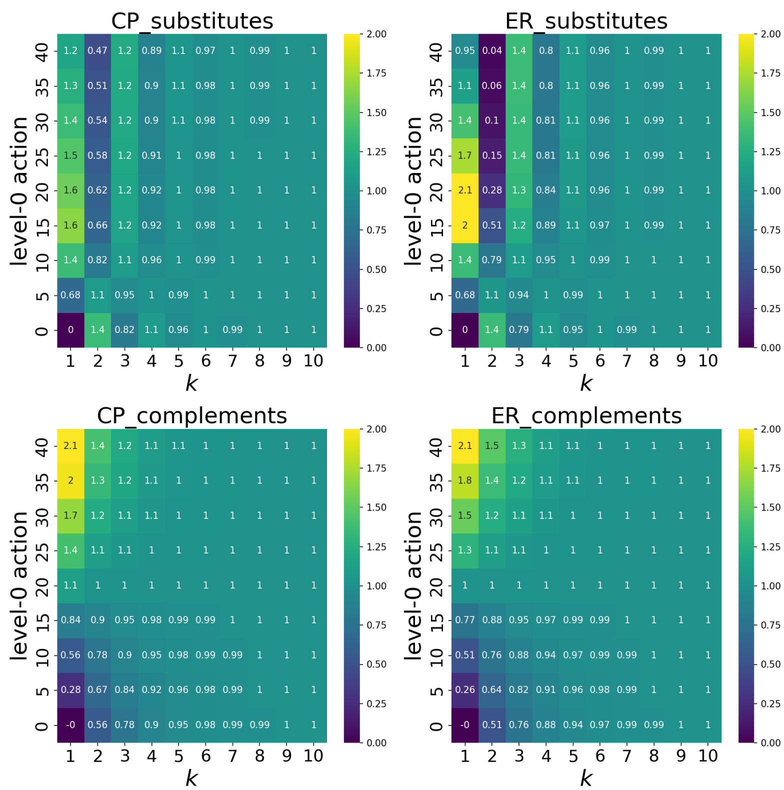
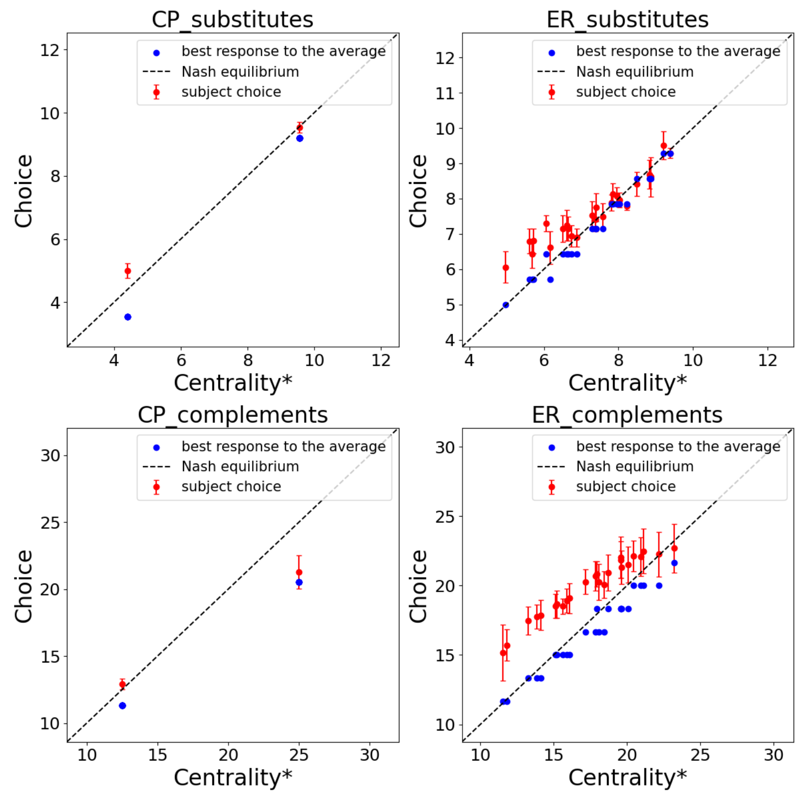


Figure 13: Choice vs. centrality for best response to the average



plays the average choice level of the population, represented by $\mathbf{s} = \mathbf{b} + \beta G\overline{\mathbf{s}}$. This could be because subjects are unable to remember the choices made by individuals in different network positions. We can write the equilibrium vector for this model as $\mathbf{s}^*_{BA} = \mathbf{b} + \beta GM\mathbf{s}^*_{BA}$, which gives

$$\mathbf{s}^*_{BA} = (I - \beta GM)\,\mathbf{b} \tag{11}$$

where M is a 25×25 matrix with each element equal to $\frac{1}{25}$ for calculating the average action.

The blue dots in Figure 13 show the choice of best response to the average for each centrality value. It shows that this model, while results in the same choice for nodes with the same degree, does not consistently generate flat relationship between choice and centrality overall.

8 Discussion

This article has demonstrated that subjects exhibit behavioral attenuation in network games, as they cannot fully differentiate the strategic differences across different network positions and have the tendency to imitate highly-paid choices in complex networks. This behavioral tendency leads to reduced sensitivity of choices to equilibrium predictions and generates level effects in aggregate choice outcomes and payoffs. We now consider how these results might be influenced if individuals do not have to determine choices for different network positions or lack information about which choices yield high payoffs for others. Following this, we discuss the broader implications of our findings.

8.1 What if subjects do not need to make decision for different network positions?

In the baseline setting, subjects' network positions are reshuffled each period to reduce repeated game effects and potentially large payoff inequality among subjects participating in the experiment. We considered a design where agents were assigned a fixed position that remained unchanged throughout the 40 periods of the experiment. Since subjects only needed to determine the choice for a particular network position, without needing to figure out a mapping from network position to choice, our primary conjecture is that fixed positions would increase the sensitivity of choice to centrality. The results of this experiment are reported in section E.1 in the Appendix.

We find that the sensitivity of choices to centrality is greater in the fixed position setting compared to the baseline in three out of four treatments, except in the core-periphery substitutes case,[6] despite it being still less than the theoretical prediction in three out of the four treatments (except in the case of ER complements). The increase in the choice-centrality slope is statistically significant ($p < 0.05$) and is largest in the ER network with strategic complements among the four treatments. Overall, consistent with the conjecture based on behavioral attenuation, a fixed network position reduces the severity of behavioral attenuation and tends to increase the sensitivity of choice to centrality, with the most pronounced effect in the ER network with strategic complements (as the ER network exhibits larger behavioral attenuation than the CP network in the baseline, and strategic

[6] In the CP substitutes case under the fixed position setting, some subjects are persistent outliers in the sense that they consistently choose very high or very low effort. The slope coefficient of choice to centrality is not significantly different from one in CP substitutes.

complements are more sensitive to behavioral biases than strategic substitutes).

8.2 What if subjects do not know which choices generate high payoffs for others?

We also considered the scenario where each player can observe the choices of all individuals but do not observe others' payoffs. They did however observe their own payoffs. This is in contrast to the baseline setting, where individuals have access to information about both the choices and payoffs of all players. Without information on others' payoffs, players will be unable to learn what choices typically lead to high payoffs in the network, and this might affect the average choice level in the network. The results of this experiment are reported in section E.2 in the Appendix.

We find that the total effort level is lower than that in the baseline across all four treatments, with this effect statistically significant ($p < 0.01$) and largest in the ER network with strategic complements. In the baseline setting under ER complements, subjects' choices tend to exceed the equilibrium across different centralities, whereas low centrality nodes choose above equilibrium while high centrality nodes choose below equilibrium when no payoff information about others is presented. As a consequence, in the baseline, subjects' total payoff positively deviates from the total equilibrium payoff in ER complements, whereas it now deviates negatively from the total equilibrium payoff (Figure 44(b)). The behavioral model (Table 17) shows that the imitation parameter is much lower in the ER network when payoff information is limited (0.23 vs. 0.66). This suggests that limiting information about others' payoffs prevented subjects from placing greater weight on those highly-paid high choices of others in the complex ER network, thereby reducing consistent positive deviations of actions from equilibrium in the ER complements.

8.3 Implications of the findings

Our study has broad implications for the literature on networks. While the economics of networks literature often focuses on analyzing how network structures impact equilibrium outcomes with payoff-maximizing agents, our findings suggest that strategic reasoning plays only an imperfect role in determining network outcomes, and individual behavioral attenuation can lead to flat relationship between individual choices and equilibrium predictions.

The literature on behavioral attenuation generally does not specify the default cognitive value toward which individuals tend. Our findings suggest that in environments involving network interactions, that value can depend on the observed actions of others and is sometimes biased toward choices with higher payoffs in the population. Thus, in addition to other possible determinants of the default value, such as salient choices or the anchoring effect (Enke and Graeber [2023]), imitation may be a source of individuals' non-strategic default choices in social network interactions.

This paper also highlights the value of combining behavioral economics with the economics of networks. We find that behavioral attenuation can interact with the tendency to imitate highly-paid choices in shaping the overall network action profile and payoff distributions. The impact of behavioral features on network outcomes varies across different network structures and economic contexts. Future research could further explore the mapping from behavioral biases to aggregate network results.

The behavioral attenuation individuals exhibit also suggest that, in the case of strategic substitutes with negative spillovers, payoff information about others is not conducive to achieving socially beneficial outcomes due to positive deviations from equilibrium predictions. However, in the case of strategic complements with positive spillovers, payoff information about others may "leverage" individuals' behavioral biases to achieve more efficient outcomes than those predicted by Nash equilibrium. Future research could investigate how information design and network structures influence individual behavioral traits and aggregate outcomes.

References

A. Antinyan, G. Horvath, and M. Jia. Positional concerns and social network structure: An experiment. *European Economic Review*, 129:103547, 2020.

J. Apesteguia, S. Huck, and J. Oechssler. Imitation—theory and experimental evidence. *Journal of Economic Theory*, 136(1):217–235, 2007.

C. Ballester, A. Calvó-Armengol, and Y. Zenou. Who's who in networks. wanted: The key player. *Econometrica*, 74(5):1403–1417, 2006.

O. Bandiera and I. Rasul. Social networks and technology adoption in northern mozambique. *The economic journal*, 116(514):869–902, 2006.

A. Banerjee, A. G. Chandrasekhar, E. Duflo, and M. O. Jackson. The diffusion of microfinance. *Science*, 341, 2013.

L. Beaman, A. BenYishay, J. Magruder, and A. M. Mobarak. Can network theory-based targeting increase technology adoption? *American Economic Review*, 111(6):1918–43, 2021.

P. Bonacich. Power and centrality: A family of measures. *American Journal of Sociology*, 92:1170–1182, 1987.

L. Boosey and C. Brown. Contests with network-based externalities: Experimental evidence. Technical report, Working Paper, 2022.

Y. Bramoullé and R. Kranton. Public goods in networks. *Journal of Economic theory*, 135 (1):478–494, 2007.

Y. Bramoullé, R. Kranton, and M. D'Amours. Strategic interaction and networks. *American Economic Review*, 104(3):898–930, 2014.

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

G. Charness, F. Feri, M. A. Meléndez-Jiménez, and M. Sutter. Experimental games on networks: Underpinnings of behavior and equilibrium selection. *Econometrica*, 82(5): 1615–1670, 2014.

G. B. Charness and M. Rabin. Understanding social preferences with simple tests. *Quarterly Journal of Economics*, 117:817–869, 2002.

S. Choi, A. Galeotti, and S. Goyal. Trading in networks: theory and experiments. *Journal of the European Economic Association*, 15(4):784–817, 2017.

D. J. Cooper and J. H. Kagel. Other-regarding preferences. *The handbook of experimental economics*, 2:217, 2016.

V. P. Crawford, M. A. Costa-Gomes, and N. Iriberri. Structural models of nonequilibrium strategic thinking: Theory, evidence, and applications. *Journal of Economic Literature*, 51(1):5–62, 2013.

B. Enke and T. Graeber. Cognitive uncertainty. *The Quarterly Journal of Economics*, 138 (4):2021–2067, 2023.

B. Enke, T. Graeber, R. Oprea, and J. Yang. Behavioral attenuation. Technical report, National Bureau of Economic Research, 2024.

M. G. Everett and S. P. Borgatti. The centrality of groups and classes. *Journal of Mathematical Sociology*, 23(3):181–201, 1999.

M. Farboodi. Intermediation and voluntary exposure to counterparty risk. *Journal of Political Economy, forthcoming*, 2023.

E. Fehr and K. M. Schmidt. A theory of fairness, competition, and cooperation. *The quarterly journal of economics*, 114(3):817–868, 1999.

D. M. Gale and S. Kariv. Trading in networks: A normal form game experiment. *American Economic Journal: Microeconomics*, 1(2):114–32, 2009.

A. Galeotti, B. Golub, and S. Goyal. Targeting interventions in networks. *Econometrica*, 88(6):2445–2471, 2020.

E. Gallo and C. Yan. Efficiency and equilibrium in network games: An experiment. *Review of Economics and Statistics, forthcoming*, 2021.

S. Goyal. *Networks: An Economics Approach.* MIT Press, 2023.

J. Hoelzemann and H. Li. Coordination in the network minimum game. Technical report, School of Economics, The University of New South Wales, 2021.

S. Huck, H.-T. Normann, and J. Oechssler. Learning in cournot oligopoly–an experiment. *The Economic Journal*, 109(454):80–95, 1999.

C. Ilut and R. Valchev. Economic agents as imperfect problem solvers. *The Quarterly Journal of Economics*, 138(1):313–362, 2023.

M. Jackson. *Social and Economic Networks.* Princeton University Press, 2008.

M. O. Jackson, B. W. Rogers, and Y. Zenou. The economic consequences of social-network structure. *Journal of Economic Literature*, 55(1):49–95, 2017.

W. Leontief. *The Structure of the American Economy: An empirical application of Equilibrium Analysis.* Cambridge, MA: Harvard University, 1941.

R. Nagel. Unraveling in guessing games: An experimental study. *The American economic review*, 85(5):1313–1326, 1995.

M. Newman. *Networks.* Oxford university press, 2018.

S. Rosenkranz and U. Weitzel. Network structure and strategic investments: An experimental analysis. *Games and Economic Behavior*, 75(2):898–920, 2012.

D. O. Stahl and P. W. Wilson. On players' models of other players: Theory and experimental evidence. *Games and Economic Behavior*, 10(1):218–254, 1995.

M. Woodford. Modeling imprecision in perception, valuation, and choice. *Annual Review of Economics*, 12(1):579–601, 2020.

Y. Zenou. Key players. In Y. Bramoulle, A. Galeotti, and B. Rogers, editors, *Oxford Handbook of the Economics of Networks.* Oxford University Press, 2016.

ONLINE APPENDIX

A Network game interface

A.1 Instructions

Instructions

Please read the following instructions carefully. **These instructions are the same for all the participants**. The instructions explain everything you need to know to participate in the experiment. If you have any questions, please raise your hand. One of the experimental assistants will answer your question.

In addition to the £5 show up fee that you are guaranteed to receive if you complete the experiment, you can earn money by scoring points during the experiment. The number of points depends on your own choices and the choices of other participants. At the end of the experiment, the total number of points that you have earned will be exchanged at the following exchange rate:

150 points = £1

The money you earn will be paid out digitally through **Paypal** after the experiment. The other participants will not see how much you earn in the experiment.

In this experiment, you will participate in **40 independent rounds** of the same form. All the 40 rounds will be counted for your payment. At the beginning of the first round, you will be grouped with **24 other participants**: there are 25 participants in your group. This group remains fixed throughout the 40 rounds.

Participants will be positioned in a network. The network is the same for all 40 rounds.

Next

(a) Screen 1

A Round

We now describe in detail the process that will be repeated in each of the **40 rounds**.

At the beginning of a round, participants in your group will be randomly assigned to one of 25 positions in the network. A line segment between any two positions indicates that they are connected. Participants connected to you are your neighbours. Your position in the network is labelled **"Me"**.

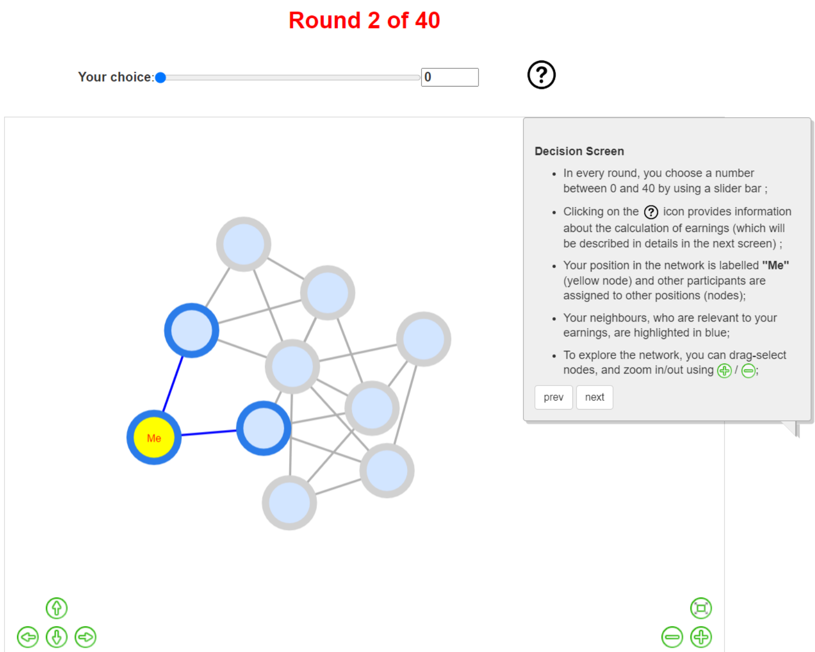
The assignment of positions in the network depends solely upon chance and is drawn afresh at the start of a round. That is, in each round, every participant is equally likely to be assigned to any position in the network.

The next screen will show you a sample decision screen illustrating the various features that will be available to you during the game. Please take time to explore it.

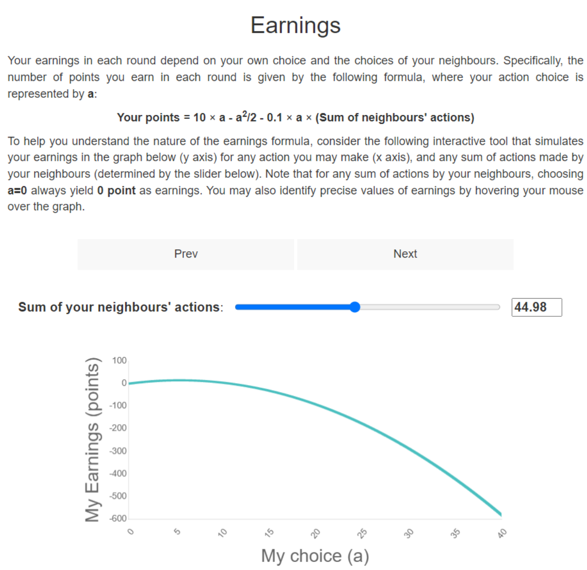
Prev | Next

(b) Screen 2

Figure 14: Main instructions (ER substitutes treatment)



(a) Screen 3



(b) Screen 4

Figure 15: Main instructions (ER substitutes treatment, Cont.)

Earnings

At the beginning of the experiment, you are given an initial balance of **150 points**. Your total earnings in the experiment will consist of the **sum of points you earn across the 40 rounds**, after the first round (which will be used to familiarize yourself with the game and will have no influence on your earnings), plus this initial balance. Note that if your total earnings (i.e., the sum of your earnings across the 40 rounds plus the initial balance) go below 0, your total earnings will be simply treated as 0. At the end of the experiment, the total earnings you earned from the experiment will be exchanged with the afore-mentioned rate. Your final earnings are the money you earned from the experiment, plus the 5 pound show-up fee.

Prev Next

(a) Screen 5

Feedback Screen

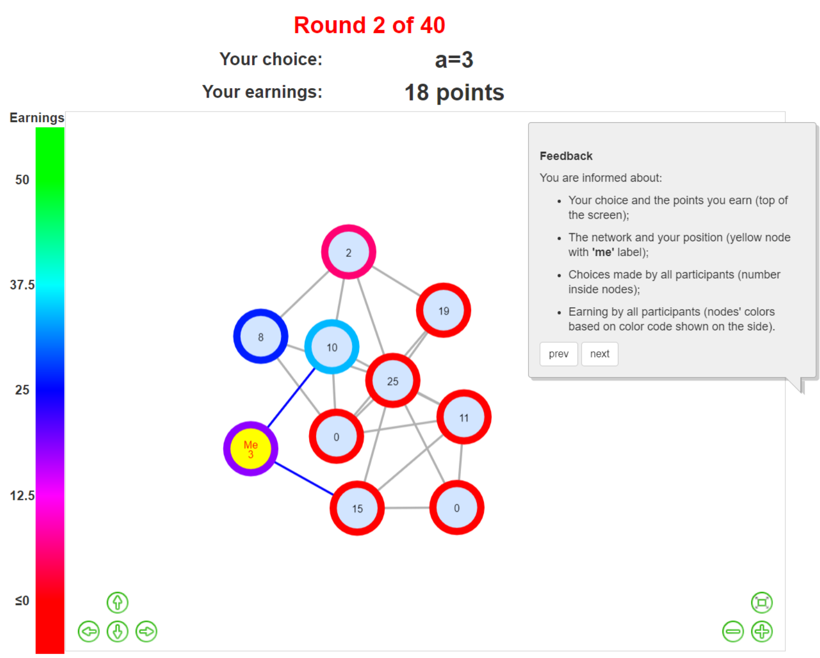
After all participants choose their actions, the computer will inform participants of the outcomes including their earnings in a round. You need to click on the 'ready' button after you confirm the outcomes. Once all participants submit the 'ready' button, the next round will start with the computer randomly assigning participants to network positions and IDs. Your network position, and the network positions and IDs of other players is likely to be different in the next round.

This process will be repeated until all **40** independent rounds are completed. At the end of the last round, you will be informed that the experiment has ended.

The next screen will show you a sample feedback screen. Please take time to explore it, and answer the related question.

Prev Next

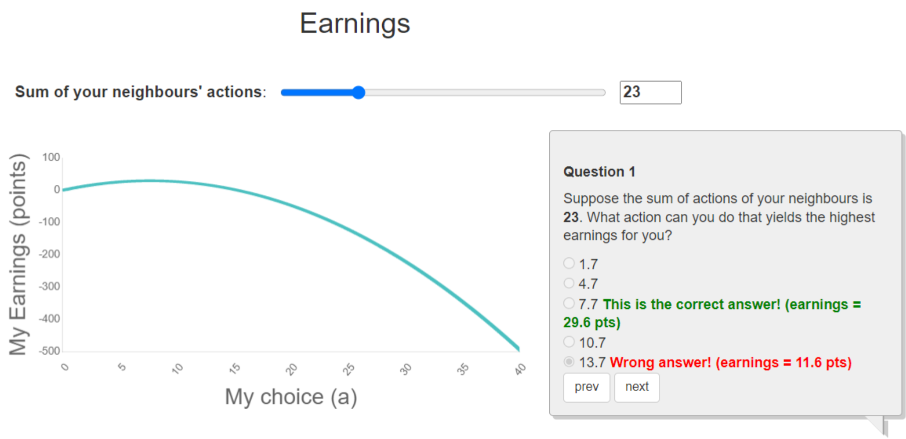
(b) Screen 6



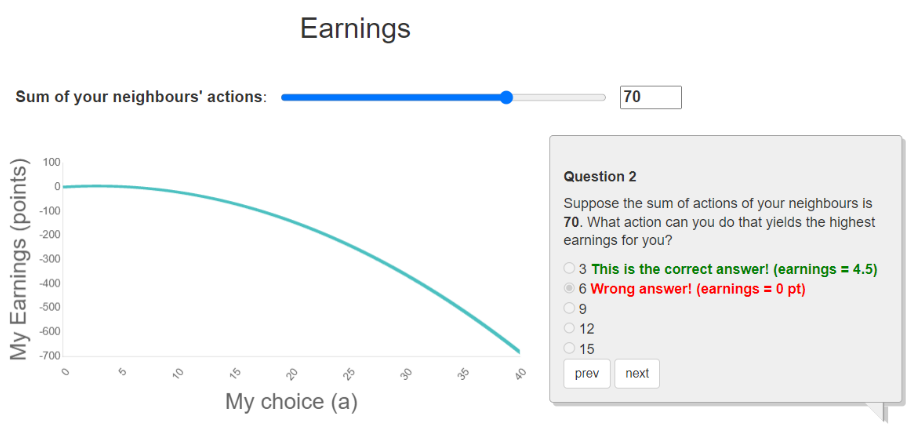
(c) Screen 7

Figure 16: Main instructions (*ER* substitutes treatment, Cont.)

A.2 Tutorial



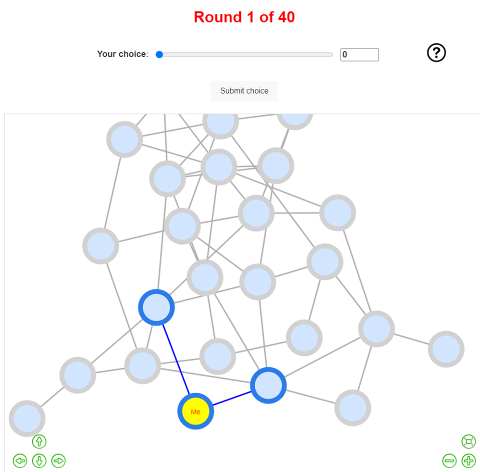
(a) Screen 1



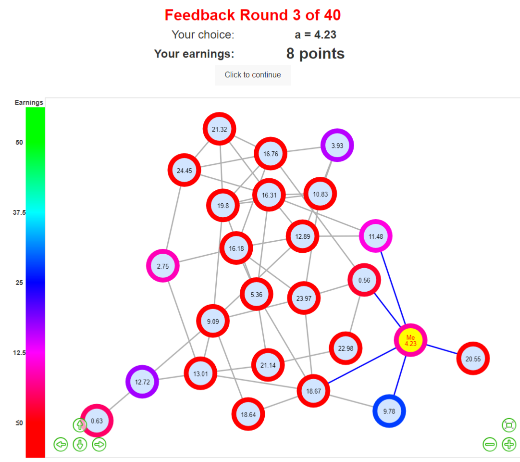
(b) Screen 2

Figure 17: Comprehension questions (ER substitutes treatment)

A.3 Game interface



(a) Decision screen



(b) Feedback screen

Figure 18: Illustrations of game interface (ER substitutes treatment)

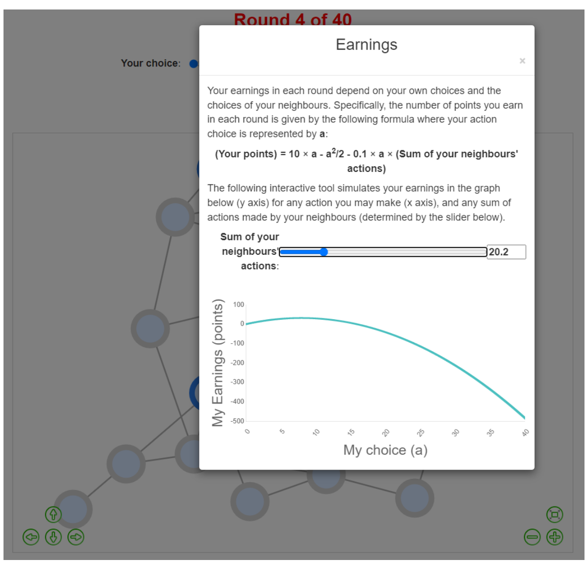
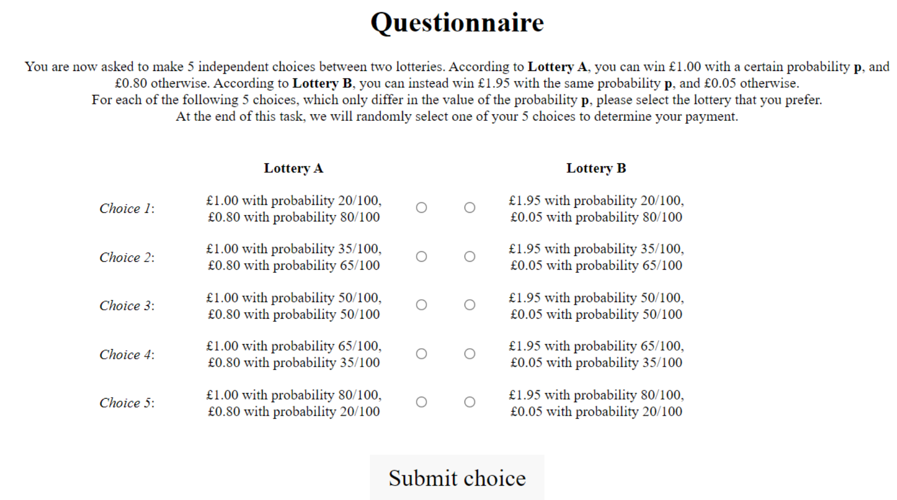


Figure 19: Help screen during the experiment

A.4 Questionnaire: Risk Aversion



Questionnaire

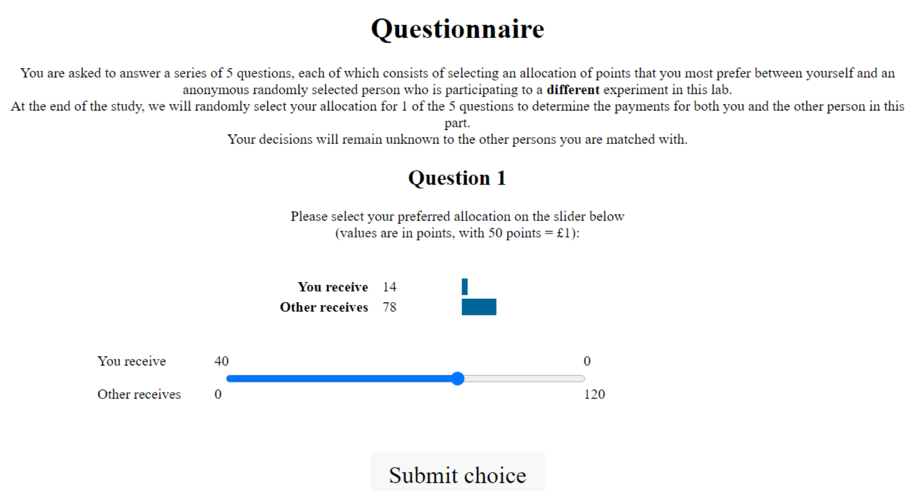
You are now asked to make 5 independent choices between two lotteries. According to **Lottery A**, you can win £1.00 with a certain probability **p**, and £0.80 otherwise. According to **Lottery B**, you can instead win £1.95 with the same probability **p**, and £0.05 otherwise.
For each of the following 5 choices, which only differ in the value of the probability **p**, please select the lottery that you prefer.
At the end of this task, we will randomly select one of your 5 choices to determine your payment.

	Lottery A	**Lottery B**
Choice 1:	£1.00 with probability 20/100, £0.80 with probability 80/100	£1.95 with probability 20/100, £0.05 with probability 80/100
Choice 2:	£1.00 with probability 35/100, £0.80 with probability 65/100	£1.95 with probability 35/100, £0.05 with probability 65/100
Choice 3:	£1.00 with probability 50/100, £0.80 with probability 50/100	£1.95 with probability 50/100, £0.05 with probability 50/100
Choice 4:	£1.00 with probability 65/100, £0.80 with probability 35/100	£1.95 with probability 65/100, £0.05 with probability 35/100
Choice 5:	£1.00 with probability 80/100, £0.80 with probability 20/100	£1.95 with probability 80/100, £0.05 with probability 20/100

Submit choice

Figure 20: Risk aversion questionnaire

A.5 Questionnaire: Social Preferences



Questionnaire

You are asked to answer a series of 5 questions, each of which consists of selecting an allocation of points that you most prefer between yourself and an anonymous randomly selected person who is participating to a **different** experiment in this lab.
At the end of the study, we will randomly select your allocation for 1 of the 5 questions to determine the payments for both you and the other person in this part.
Your decisions will remain unknown to the other persons you are matched with.

Question 1

Please select your preferred allocation on the slider below
(values are in points, with 50 points = £1):

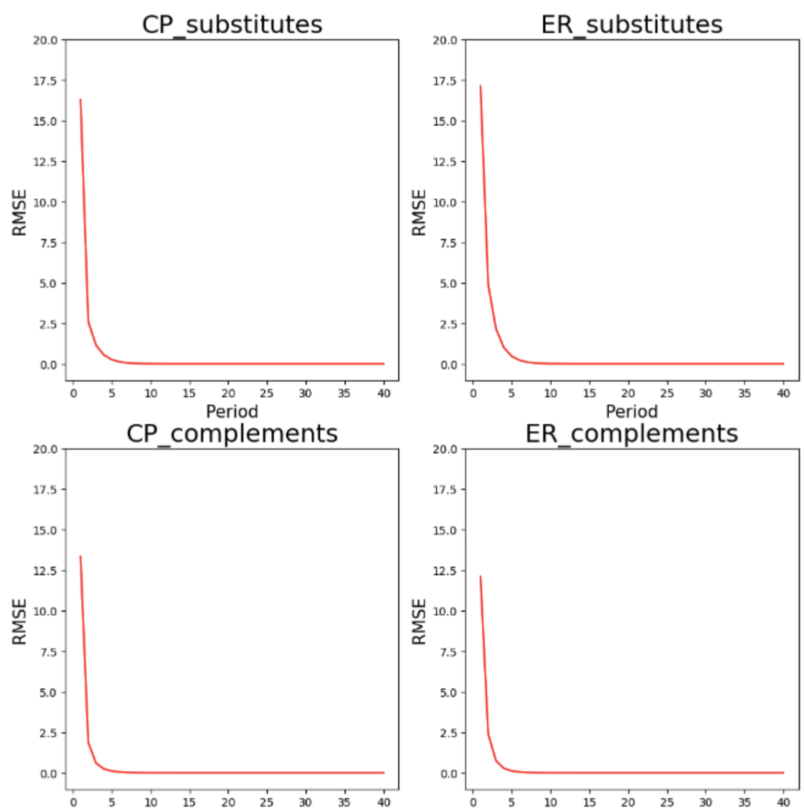
Submit choice

Figure 21: Social preference questionnaire

B Simulation of best response dynamics

We simulate outcomes when individuals choose a myopic best response action at any period t given the choices of others at period $t-1$. In our simulation, the choices are made repeatedly over 40 periods, as in the experiment. In period 1, we assume individuals make decisions uniformly at random, and in each subsequent period $(2-40)$, they choose the best response action to the previous period's action profile of others. If the best response action falls outside the range of $[0, 40]$, the action is truncated to 0 or 40 accordingly.

Figure 22: Best response dynamics



RMSE measures the distance between choices generated by best response dynamics $s_{i,t}^B$ and the theoretical prediction s_i^*: $\text{RMSE}_t = \sqrt{\frac{\sum_{i=1}^{N}(s_{i,t}^B - s_i^*)^2}{N}}$. Figure 22 plots the RMSE of best response dynamics against the Nash equilibrium based on 1000 simulations in each treatment.

We observe that the RMSE decreases sharply across periods and converge to the equilibrium within 10 periods in all the four treatments.

C Additional experimental results

C.1 Time series

Figure 23 shows the evolution of choices for the core and the periphery in the core-periphery network. Figure 24 presents the time series of choices for different positions in the ER network. The 25 network positions are grouped into five categories based on the increasing order of their Bonacich centrality. For instance, the leftmost figure on the top displays the five nodes with the five lowest Bonacich centrality under strategic substitutes in the ER network. The light red curves represent time series per session, while the dark red curve represents average outcomes across the eight sessions.

Figure 23: Time series of choices in the core-periphery network

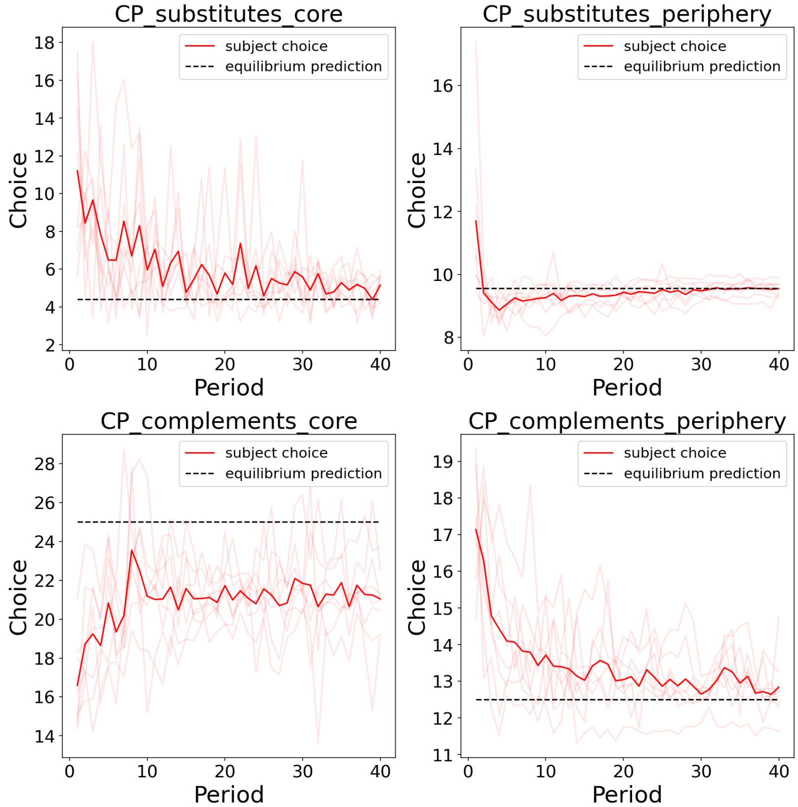
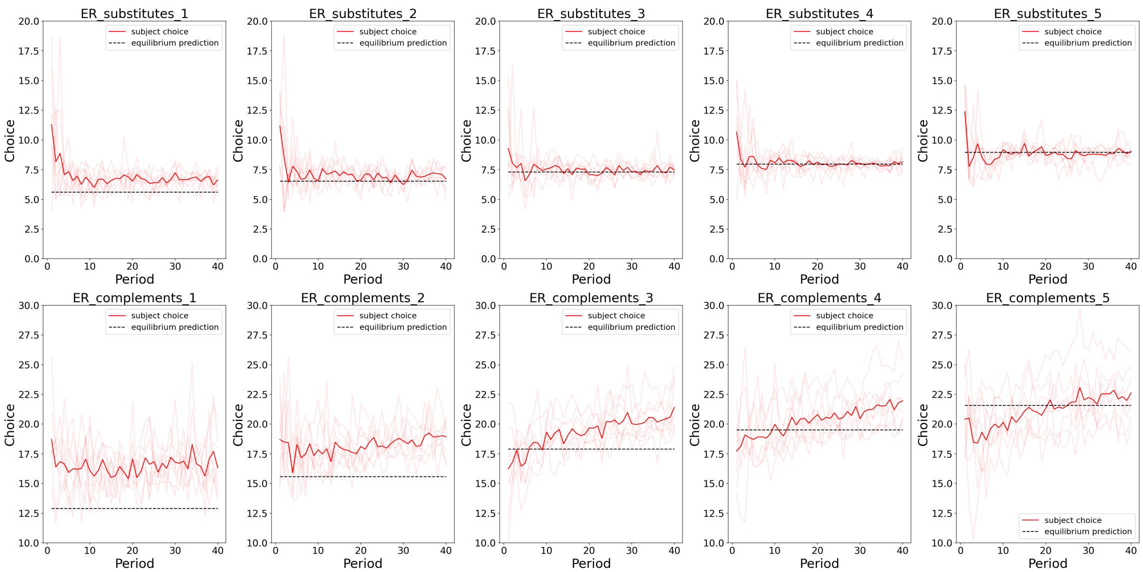


Figure 24: Time series of choices in the Erdos-Renyi network

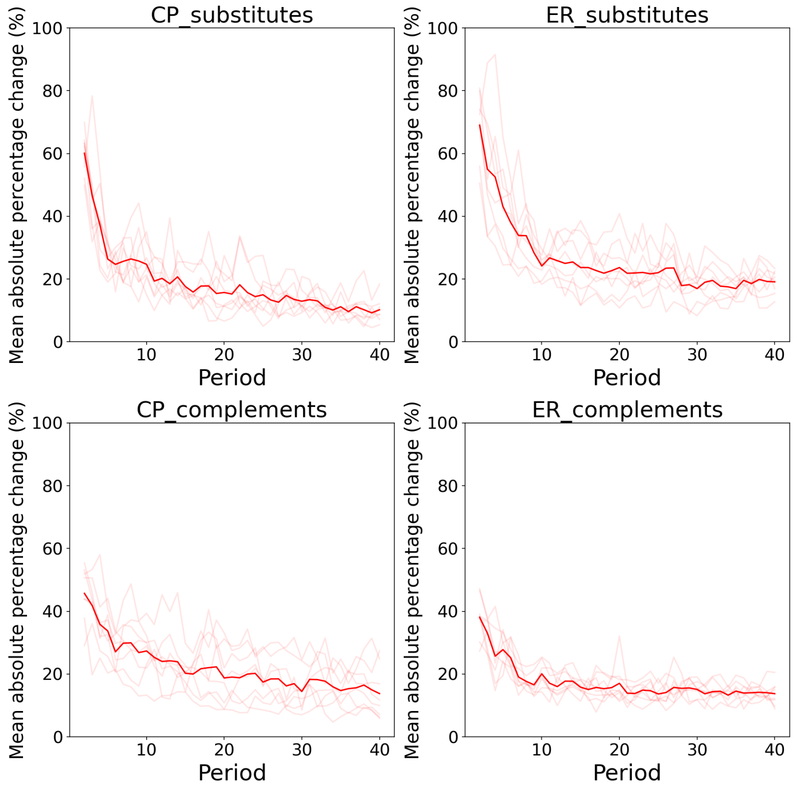


To show the magnitude of changes of choices across periods, we plot the time series of the mean absolute percentage change (MAPC) of choice for each treatment. Specifically, for each period $t \geq 2$, the $MAPC_t$ is calculated as follows:

$$\begin{aligned} MAPC_{grp,t} &= \frac{\sum_{i=1}^{25} |s_{i,grp,t} - s_{i,grp,t-1}|}{\sum_{i=1}^{25} |s_{i,grp,t-1}|} \\ MAPC_t &= \frac{\sum_{grp=1}^{8} MAPC_{grp,t}}{8} \end{aligned} \tag{12}$$

The light red curves in Figure 25 plot the time series of $MPAC$ for each group or session (i.e., $MAPC_{grp,t}$), while the bold red curves plot the MAPC averaged across all eight sessions (i.e., $MAPC_t$).

Figure 25: Change of choices



We observe that the mean absolute percentage change (MAPC) are below 20% in the last ten periods for all the treatments. Our analysis focuses on the last ten periods in the main text.

Figure 26 shows the time series of the slope coefficient of subject choice on centrality* and best response. We observe an increasing trend in the slope coefficient during the initial stages (especially in the first ten periods) of the game, and the slopes plateau at values below one in the latter half of the game.

Figure 26: Time series of the slope of subject choice on centrality* and best response

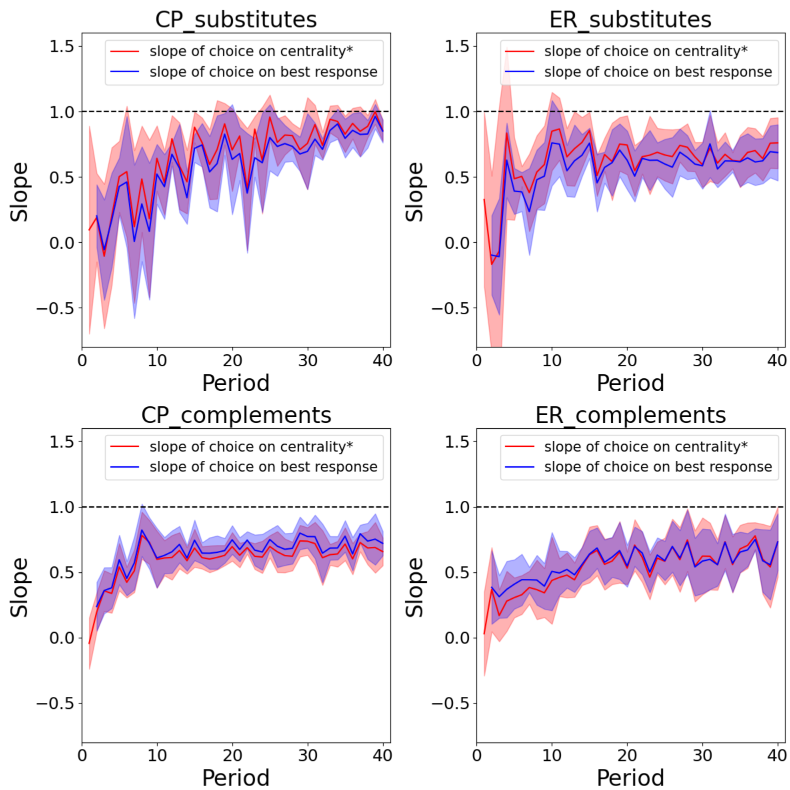
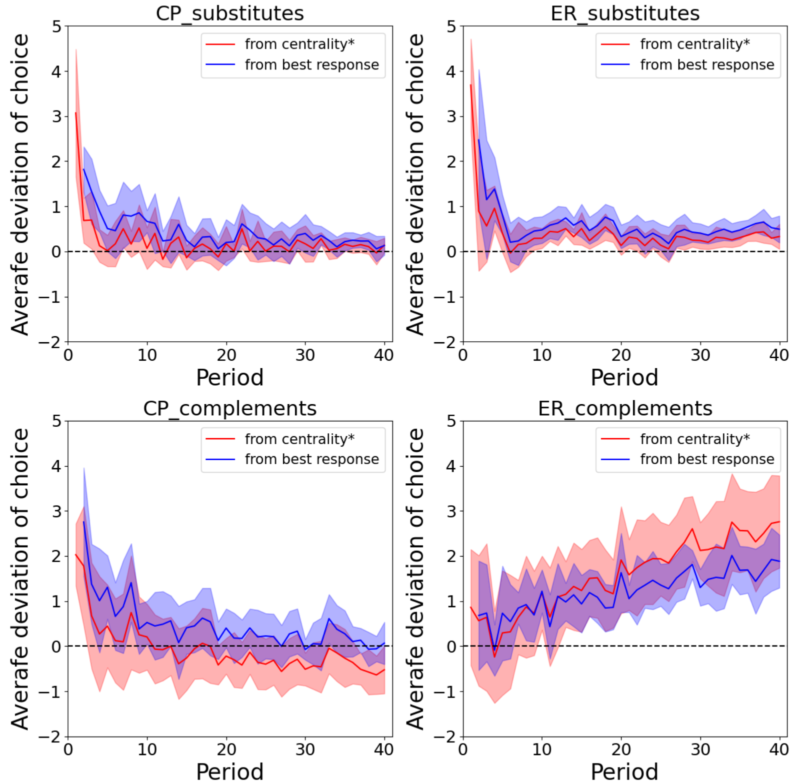


Figure 27 plots the time series of the average deviation of choice from centrality* and from best response choices. We observe a negative deviation from centrality* in the core-periphery complements during the second half of the game, while the deviation from the best response is generally positive throughout all periods across all treatments.

Figure 27: Time series of average deviation of choices



C.2 Group heterogeneity

Figures 28 - 31 present subject choices for each session separately. Each red dot represents the mean choice of a particular network node in the last ten periods. The text inside each figure reports the slope coefficient of choice on centrality* from random effects regressions and its 95% CIs. The figures reveal consistent patterns of subject behavior across groups within each treatment. In 31 out of 32 sessions, the slope coefficient of the mean choice on centrality* is less than one. Additionally, the deviation patterns from equilibrium are consistent across sessions. For instance, in CP complements, the core players' choices consistently fall below the equilibrium in all sessions, whereas in Erdos-Renyi complements, the choices tend to exceed the equilibrium in all sessions. These findings suggest that the aggregate outcomes reported in Section 5 are not merely averages from heterogeneous sessions but are generally observed in each realization of the network result (i.e., each individual session).

Figure 28: Results of CP substitutes in each session

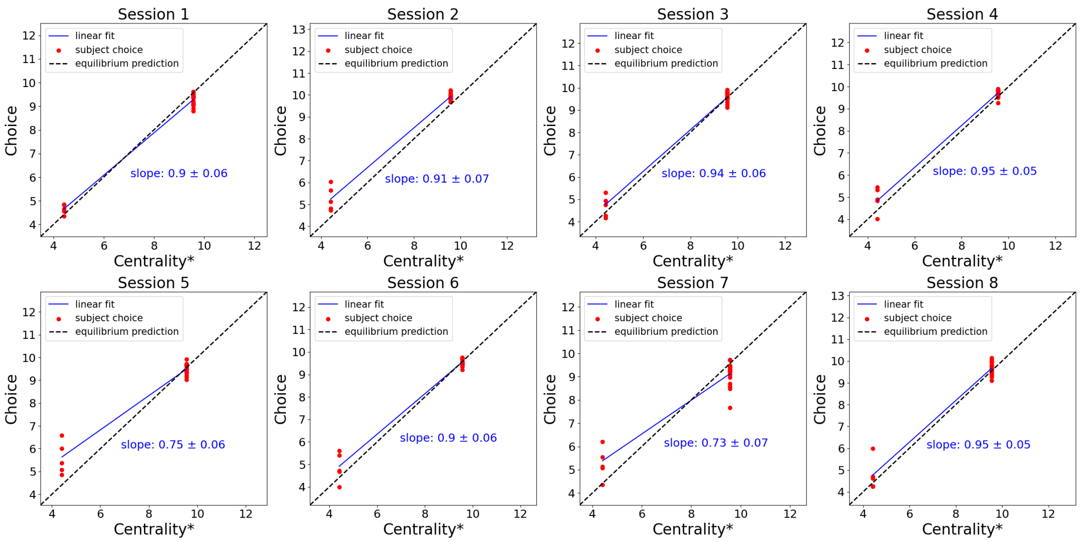


Figure 29: Results of CP complements in each session

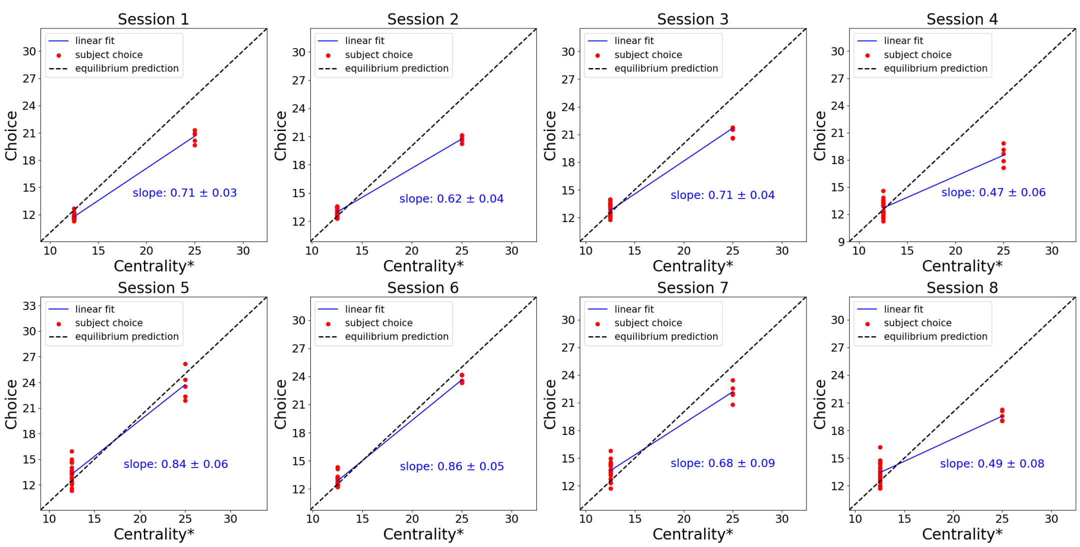


Figure 30: Results of ER substitutes in each session

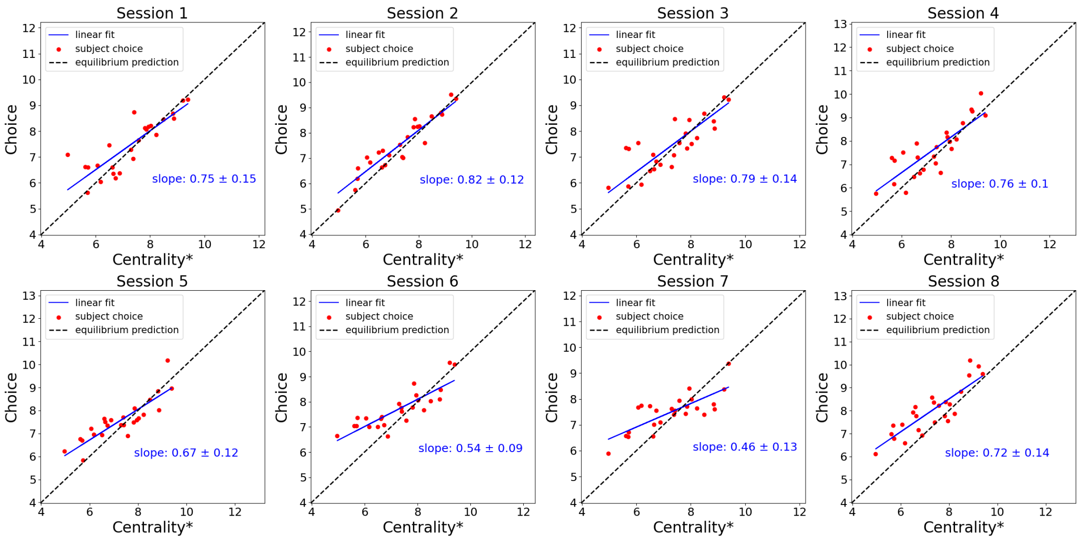
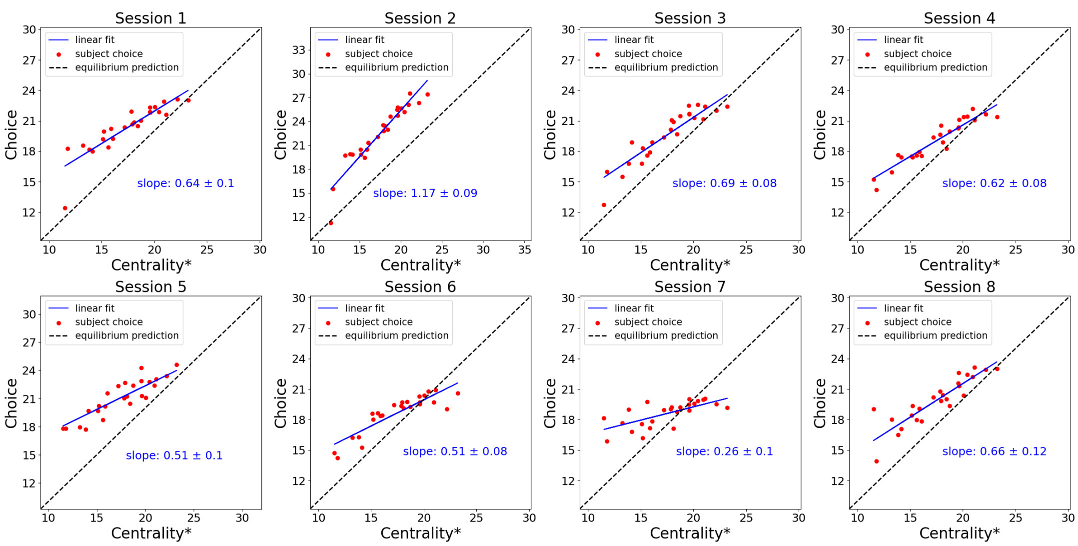


Figure 31: Results of ER complements in each session



C.3 Individual heterogeneity

To examine individual heterogeneity in decision-making across different network positions, we calculated each individual's sensitivity to the best response choices (to the action profile in the previous period), as well as their deviation from those best response choices. An individual aligning with best response behavior would have a slope close to one and deviation close to zero.

Figures 32 and 33 and Table 5 show the distribution of individual slopes (of subject choices on best response choices) in the last 10 periods. Figure 34 and 35 and Table 6 show the distribution of individual mean absolute percentage error (MAPE) from best responses over the last 10 periods. We observe that the slope distribution of the CP network roughly second-order stochastically dominates that of the ER network (i.e., the slope distribution in the ER network has a smaller mean value and is more dispersed). For MAPE, the distribution for the ER network roughly first-order stochastically dominates that of the CP network.

Figure 32: Distribution of individual sensitivity to best response choices

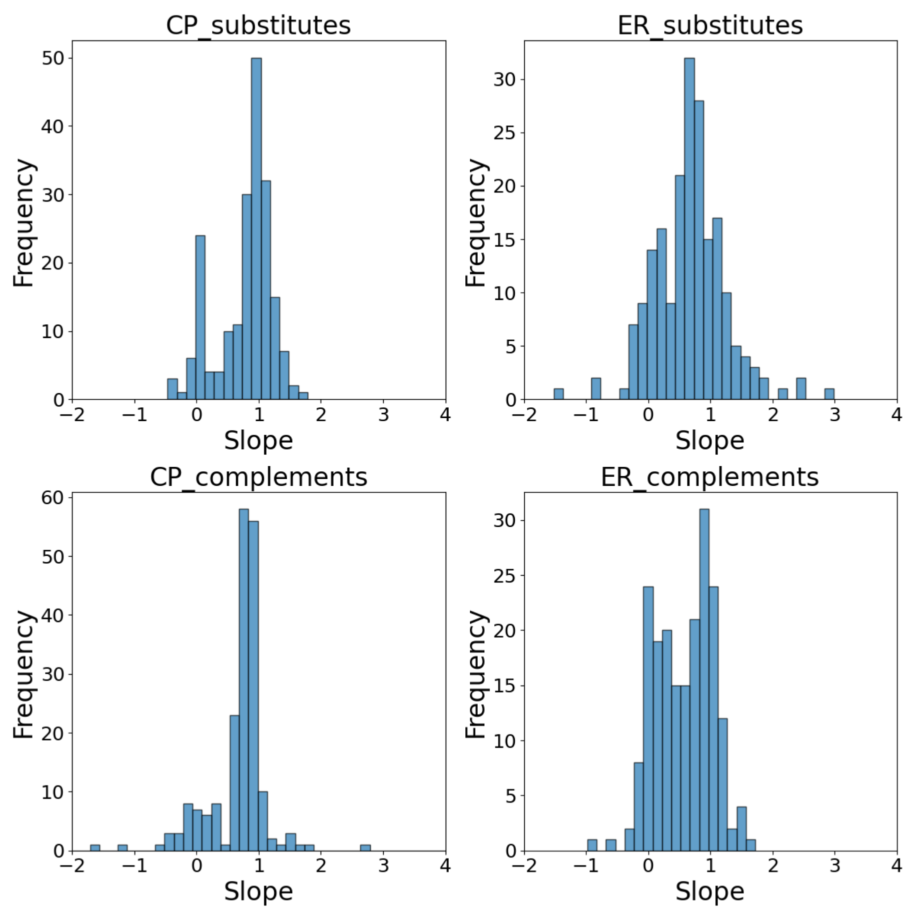


Figure 33: CDF of individual sensitivity to best response choices

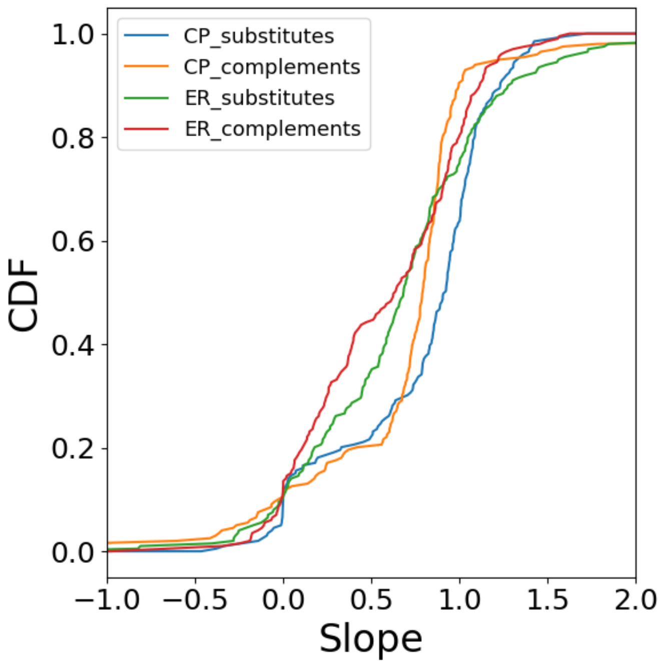


Table 5: Distribution of individual sensitivity to best response choices

Treatment	lower quartile	median	upper quartile
CP substitutes	0.56	0.92	1.06
CP complements	0.62	0.79	0.89
ER substitutes	0.28	0.68	1.00
ER complements	0.18	0.63	0.94

Figure 34: Distribution of individual MAPE from best responses choices

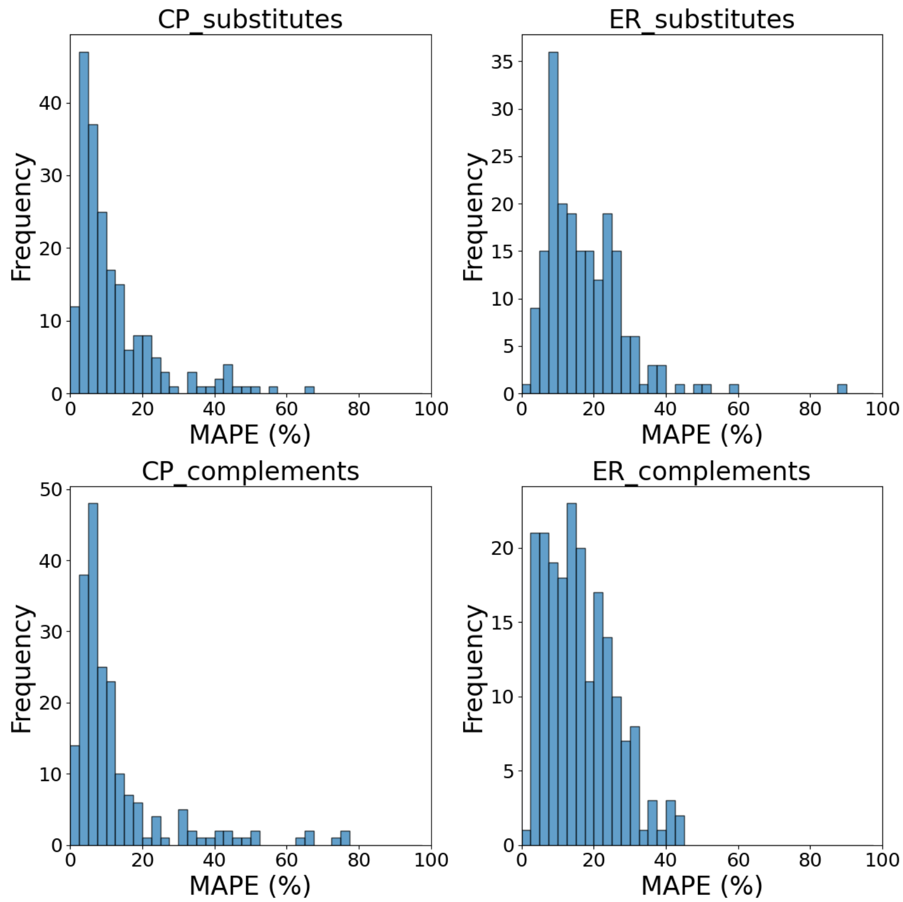


Figure 35: CDF of individual MAPE from best responses choices

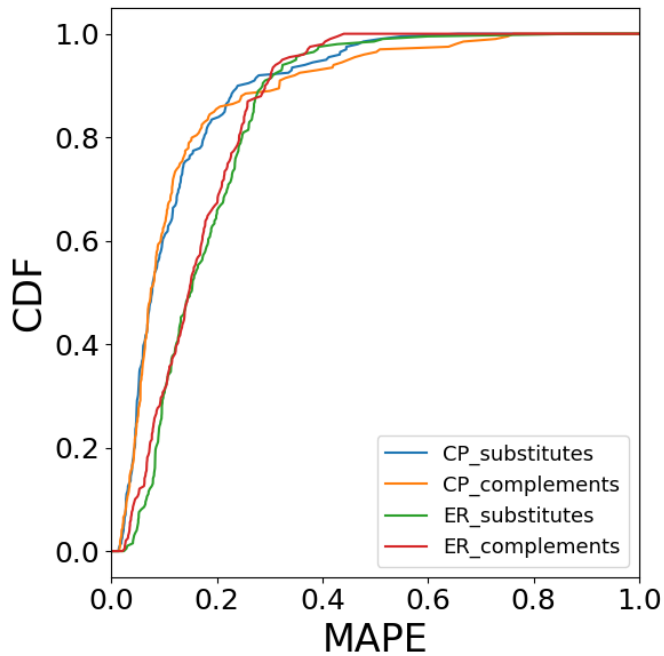


Table 6: Distribution of individual MAPE from best responses choices

Treatment	lower quartile	median	upper quartile
CP substitutes	4.7%	7.7%	13.8%
CP complements	4.9%	7.5%	13.1%
ER substitutes	9.4%	15.1%	23.4%
ER complements	8.1%	14.7%	22.1%

C.4 Non-monotonicity between centrality and degrees

This section investigates the question whether subject choices align with the ranking of centrality when the rankings of centrality and degree are reversed.

In the Erdős-Rényi network, centrality generally decreases (increases) with degree under strategic substitutes (complements). However, there is one exception in the case of substitutes and two exceptions in the case of complements where the rankings between centrality and degree are reversed.

In the case of ER substitutes, one degree-5 node has a centrality value of 6.06, which is smaller than the centrality of a degree-6 node (6.17). However, the actual mean choice over the last 10 periods of the degree-5 node is 7.30, larger than the mean choice of the degree-6 node, which is 6.61. In the case of ER complements, one degree-5 node has a centrality value of 17.93, which is smaller than the centrality values of two degree-4 nodes (18.09 and 18.44, respectively). Regarding actual data, the degree-5 node's mean choice over the last 10 periods is the largest among the three (20.82 vs. 20.25 and 20.06). These results suggest that in the ER network, the ranking of subject choices tends to align with degree rather than with centrality in the (rare) cases where the rankings of centrality and degree are reversed.

In the tree networks, we find that the ranking of subject choices in the last ten periods aligns with centrality instead of degrees in the 9 non-monotonic pairs of nodes where the rankings of centrality and degree are reversed. Moreover, we conducted a one-sided Wilcoxon Signed-Rank test on the non-monotonic pairs. In the case of strategic substitutes, where the three degree-3 nodes have lower equilibrium effort levels than the degree-4 node, the results show that all three rankings align with the predictions of centralities, and two out of the three are statistically significant ($p < 0.05, N = 8$).

Similarly, in the tree network under strategic complements, the three distinct centrality values from degree-3 nodes are higher than the two centralities of degree-4 nodes. We conduct one-sided Wilcoxon Signed-Rank test against the six pairs. The results show that all the three degree-3 node positions indeed have significantly higher choices than the two degree-4 node positions ($p < 0.05, N = 8$).

C.5 Additional figures and tables

Table 7 shows session-level OLS regressions of choice on centrality for each treatment. In these regressions, each observation represents the average outcome for a specific session over the last 10 periods and across the nodes with a given centrality: each session yields 2 observations in the CP network (core and periphery players), and 25 observations in the ER network (every node has different centrality in this network).

Table 8 shows the node-level OLS regressions of choice on centrality. Each observation represents the average outcome for a specific node over the last 10 periods and across all sessions. There are 25 observations (corresponding to the 25 network nodes) for each treatment. The coefficient of centrality is positive but strictly lower than 1 for all treatments. Those results are consistent with Table 7.

Table 7: Session-level OLS regression of choice on equilibrium

	CP sub	CP com	ER sub	ER com
centrality*	0.883***	0.667***	0.679***	0.650***
	(0.028)	(0.054)	(0.032)	(0.039)
constant	1.106***	4.595***	2.658***	8.593***
	(0.211)	(1.068)	(0.238)	(0.697)
N	16	16	200	200
R^2	0.986	0.916	0.690	0.581

Notes: *** represents $p < 0.001$. $centrality^* = centrality \cdot b$

Table 8: Node-level OLS regression of choice on equilibrium

	CP sub	CP com	ER sub	ER com
centrality*	0.883***	0.667***	0.679***	0.650***
	(0.015)	(0.012)	(0.045)	(0.030)
constant	1.106***	4.595***	2.658***	8.593***
	(0.129)	(0.190)	(0.335)	(0.527)
N	25	25	25	25
R^2	0.994	0.993	0.907	0.954

Notes: *** represents $p < 0.001$. $centrality^* = centrality \cdot b$

Figure 36 plots the deviation of mean choice from the Nash equilibrium in the four treatments, which show that the average choice is below equilibrium in CP complements and above equilibrium in the other three treatments. Figure 37 presents the mean absolute percentage deviation (MAPD) from Nash equilibrium in the four treatments, which show that the MAPD ranges from 10% to 20% in the four treatments, with ER network exhibiting a higher deviation than the CP network.

Figure 36: Mean action

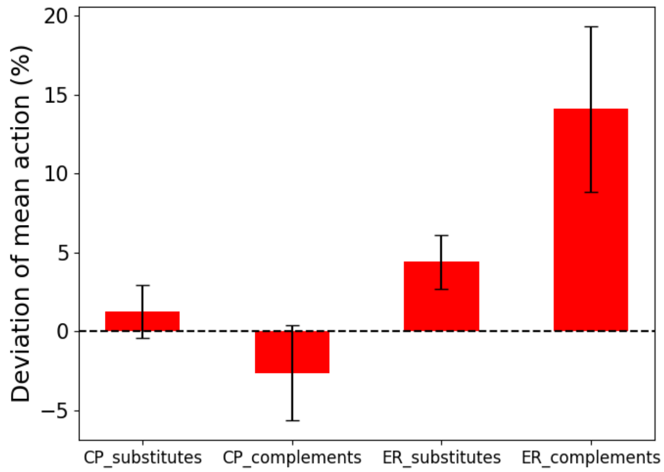
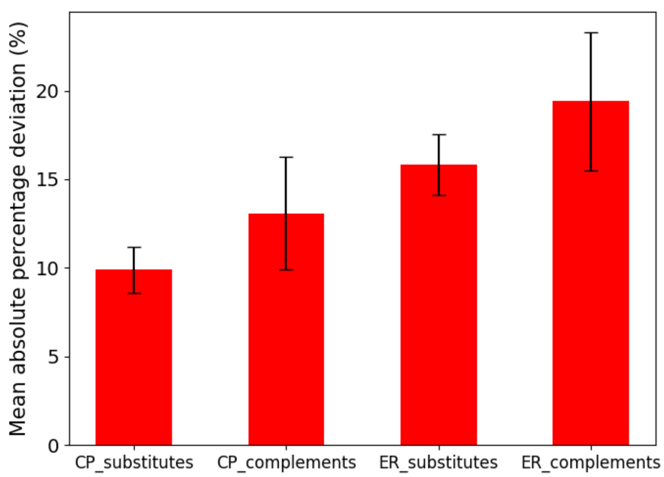


Figure 37: MAPD



Tables 9 and 10 present the random effects panel regression of subject choice on centrality and degree for the core-periphery and Erdos–Renyi networks. In the core-periphery network, since there are only two distinct network positions, degree and centrality are perfectly correlated, resulting in exactly the same R^2. The perfect correlation between centrality and degree means that we cannot identify which of the two measures, centrality or degree, determines subject choice.

In the Erdős–Rényi network with strategic substitutes, when both degree and centrality are included in the regressions, choice significantly decreases with degree while the coefficient on centrality is not significant. This suggests that centrality does not impact choice holding degree constant. In the case of complements, the coefficients of both degree and centrality are significantly positive. In both the substitutes and complements cases, the overall R^2 is similar whether we include degree, centrality, or both in the linear model to explain subject choice.

Table 9: Panel regression of choice on centrality* and degree in the core-periphery network

	CP sub	CP sub	CP com	CP com
centrality*	0.878***		0.675***	
	(0.029)		(0.047)	
degree		-0.645***		1.205***
		(0.021)		(0.084)
constant*	1.151***	10.184***	4.479***	11.711***
	(0.233)	(0.098)	(0.631)	(0.212)
N	2000	2000	2000	2000
R^2	0.712	0.712	0.562	0.562

Notes: *** represents $p < 0.01$. $centrality^* = centrality \cdot b$. Parenthesis reports standard errors clustered over sessions.

Table 10: Panel regression of choice on centrality* and degree in the Erdos-Renyi network

	ER sub	ER sub	ER sub	ER com	ER com	ER com
centrality*	0.688***		-0.260	0.631***		0.445***
	(0.042)		(0.172)	(0.085)		(0.098)
degree		-0.513***	-0.699***		1.200***	0.361***
		(0.033)	(0.143)		(0.161)	(0.093)
constant*	2.590***	9.648***	12.289***	8.927***	15.164***	10.733***
	(0.321)	(0.140)	(1.822)	(1.187)	(0.414)	(1.261)
N	2000	2000	2000	2000	2000	2000
R^2	0.234	0.248	0.250	0.286	0.285	0.287

Notes: *** represents $p < 0.01$. $centrality^* = centrality \cdot b$. Parenthesis reports standard errors clustered over sessions.

Table 11 shows the panel regression of choice of each node on its centrality and degree. The results show that in both tree substitutes and tree complements, the coefficient of

Table 11: Panel regression of choice on centrality* and degree in the tree network

	Tree sub	Tree sub	Tree sub	Tree com	Tree com	Tree com
centrality*	0.637***		0.351***	0.707***		0.496***
	(0.036)		(0.044)	(0.035)		(0.056)
degree		-7.336***	-4.051***		4.994***	1.879***
		(0.329)	(0.223)		(0.192)	(0.251)
constant*	10.177***	41.777***	25.816***	3.343***	5.205***	3.162***
	(0.924)	(0.796)	(1.488)	(0.427)	(0.292)	(0.410)
N	2000	2000	2000	2000	2000	2000
R^2	0.622	0.617	0.683	0.704	0.630	0.730

Notes: *** represents $p < 0.001$. $centrality^* = centrality \cdot b$. Parenthesis reports standard errors clustered over sessions.

centrality is significantly positive, and the coefficient of degree is significantly negative (positive) in the case of strategic substitutes (complements). This suggests that both degrees and centralities impact subject choices.

D Additional results of the behavioral attenuation model

Figure 38 shows the slope of BE on NE for different value of $\lambda \in [0.5, 1]$ when there is no imitation tendency ($\alpha = 0$). We observe that the same level of individual behavioral attenuation has the greatest effect on network-level flatness between choice and centrality in the case of CP complements and the smallest effect in CP substitutes.

To examine the impacts of imitation tendency α on the action patterns across treatments, Figure 39 plots the slope of BE choice on Nash for different values of $\alpha \in [0, 1]$ under behavioral attenuation with $\lambda = 0.8$, while Figure 40 plots the average percentage deviation of choices under the same conditions. We observe that a larger imitation parameter α increases the slope, with this effect being stronger in strategic complements than in strategic substitutes. Additionally, when there is no imitation tendency ($\alpha = 0$), there is a negative deviation in average action in the core-periphery strategic complements and positive deviation in core-periphery substitutes, which is consistent with the level effect findings (see Finding 2).

Figure 38: Slope of BE on NE for different λ under $\alpha = 0$

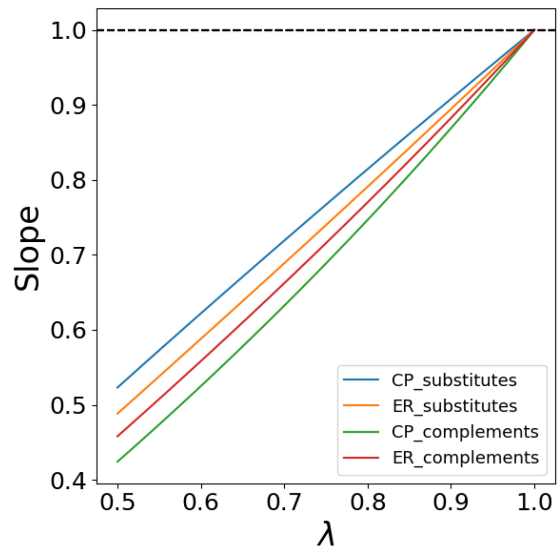


Figure 39: Slope of BE on NE for different α under $\lambda = 0.8$

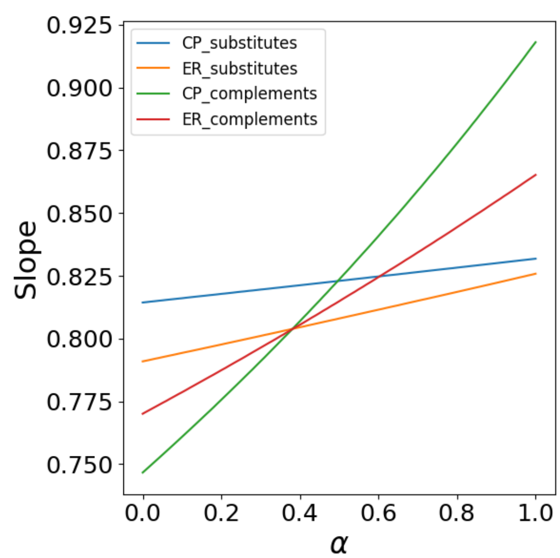


Figure 40: Average deviation of BE for different α (under $\lambda = 0.8$)

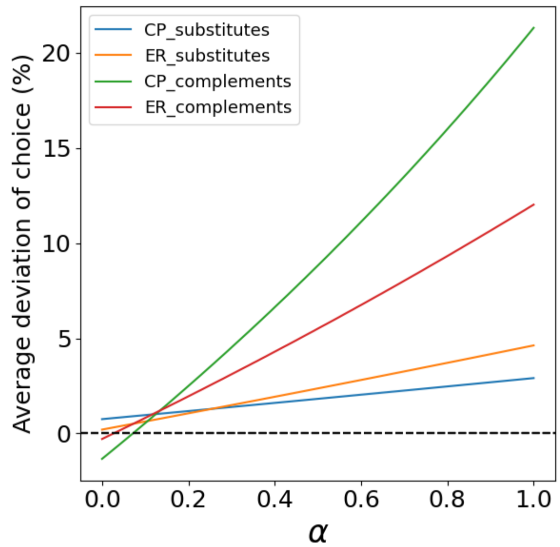
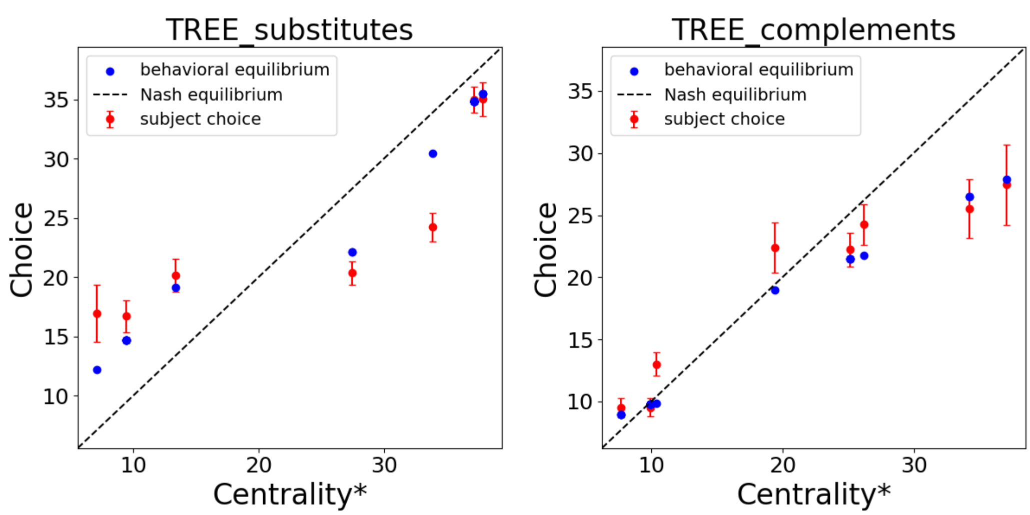


Figure 41: Behavioral equilibrium with estimated parameters in the tree networks



(a) Tree substitutes (b) Tree complements

Table 12: Estimated parameters for the behavioral model including the tree networks

	Core-periphery	Erdos-Renyi	Tree
λ	0.82***	0.63***	0.87***
	(0.04)	(0.07)	(0.01)
α	0.00	0.66***	0.28***
	(0.00)	(0.17)	(0.00)
N	4000	4000	4000
Obj.	2.43	3.38	6.53

Notes: *** represents $p < 0.01$ for the null hypothesis that $\lambda = 1$ and $\alpha = 0$, respectively. Parentheses show bootstrap standard errors based on 100 bootstrap samples at the session level.

E Additional treatments

E.1 Fixed network position

In the baseline setting, individuals' positions are randomly shuffled after each period, and the outcomes show that choices deviate from Nash equilibrium significantly. To examine whether reducing the complexity of learning may result in better alignment to Nash equilibrium, we consider a setting in which each player's network position remains fixed throughout the 40 periods of the game.

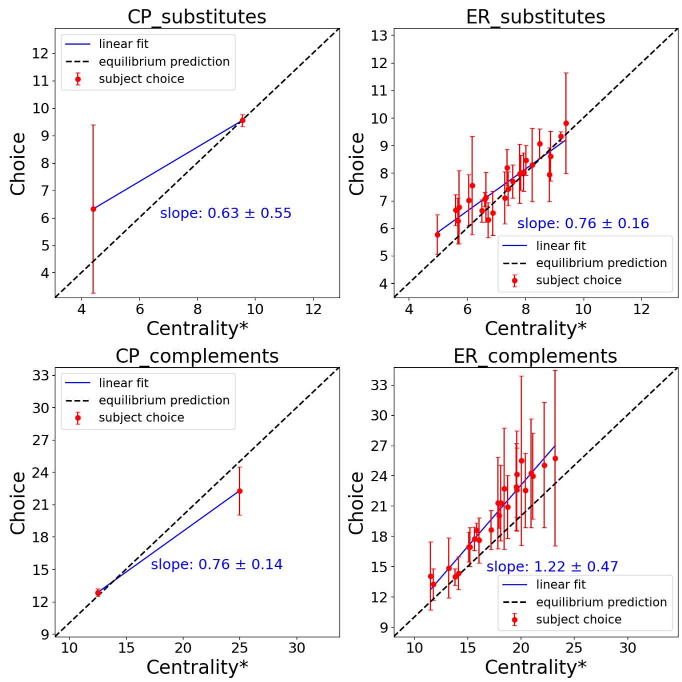
Figure 42(a) presents the relation between predictions and subjects' actions in the fixed position setting. It shows that the slope coefficient of choices on centrality is positive but lower than 1 in three treatments, except in the Erdos-Renyi network with strategic complements whose coefficient is larger than 1. The sensitivity of choice on centrality is larger compared to the baseline in three out of four treatments, with this effect being statistically significant in the ER complements ($p < 0.05$).[7]

Regarding whether actions are higher or lower than the prediction, it is observed that the patterns mirror those seen in the baseline setting. Finally, regarding the impact of complexity on individual action, in contrast to the baseline setting, the slope coefficients in the Erdos-Renyi network are (weakly) larger than those in the core-periphery network.

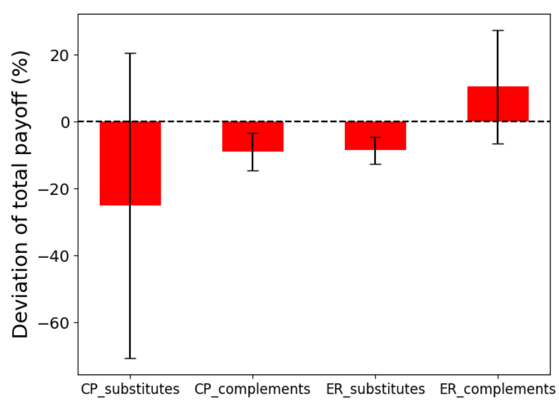
The total payoff individuals obtained as shown in Figure 42(b) is similar to the baseline

[7]The especially large deviation in the core-periphery network with strategic substitutes can be attributed to outlier individual behaviors — some individuals located in the core position constantly chose extreme action levels (e.g., very high levels). Indeed, the slope coefficient is not significantly different from one in CP substitutes and ER complements, while significantly below one in CP complements and ER substitutes ($p < 0.05$).

Figure 42: Theoretical predictions and subjects' behavior in the fixed position setting



(a) Choices



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average choice of subjects in the last 10 periods of a given network centrality, averaged across the eight sessions. The 95% confidence interval bars are calculated using clustered standard errors over sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the choice. The 45-degree black dashed line represents the values where the choice equals the equilibrium prediction. The blue line is the random effect panel regression fit of the subject choices on theoretical prediction, reported in Table 1. The text reports the slope coefficient and 95% confidence interval (CI). (b) This bar plot shows the percentage deviation of the total payoff across subjects from the total equilibrium payoff in the last ten periods. Error bars represent 95% CIs around the mean, calculated using clustered standard errors over sessions.

setting: total payoffs are lower than the predicted payoffs in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments. The total payoff is larger than the predicted payoff in the Erdos-Renyi network with strategic complements.

To conclude, the results from the fixed position setting is generally similar compared to the baseline, except in the case of ER complements where the sensitivity of choice to centrality is significantly increased. Note that in the fixed position setting, subjects no longer need to determine how optimal choices vary with different network positions; instead, they only need to make decisions for a single network position. This reduces the complexity of decision-making and may thus lower the tendency of regressing toward some intermediate value, as reflected in Table 13, which shows that the behavioral attenuation parameter λ is larger than that in the baseline, especially in the ER network (0.83 vs. 0.63).

Table 13: Estimated parameters of the behavioral model for the fixed position setting

	Core-periphery	Erdos-Renyi
λ	0.88***	0.83***
	(0.07)	(0.05)
α	0.00	0.83***
	(0.00)	(0.25)
N	2000	2000
Obj.	2.64	3.76

Notes: *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$ for the null hypothesis that the parameter is equal to one. Parentheses show bootstrap standard errors based on 100 bootstrap samples.

E.2 Limited information on payoffs

We also consider the scenario where each player can observe the choices of all individuals but do not observe others' payoffs. They do observe their own payoffs. This is in contrast to the baseline setting, where individuals have access to information about both the choices and payoffs of all players. This section presents our findings in this treatment.

The relationship between predictions and subjects' choices, as shown in Figure 44(a), is similar to that in the baseline setting in three out of four treatments and is flatter in the Erdos-Renyi substitutes case (not statistically significant). As in the baseline setting, the slope coefficient of choices on centrality is positive but strictly lower than 1 across all

Figure 43: Behavioral equilibrium with estimated parameters in the fixed position setting

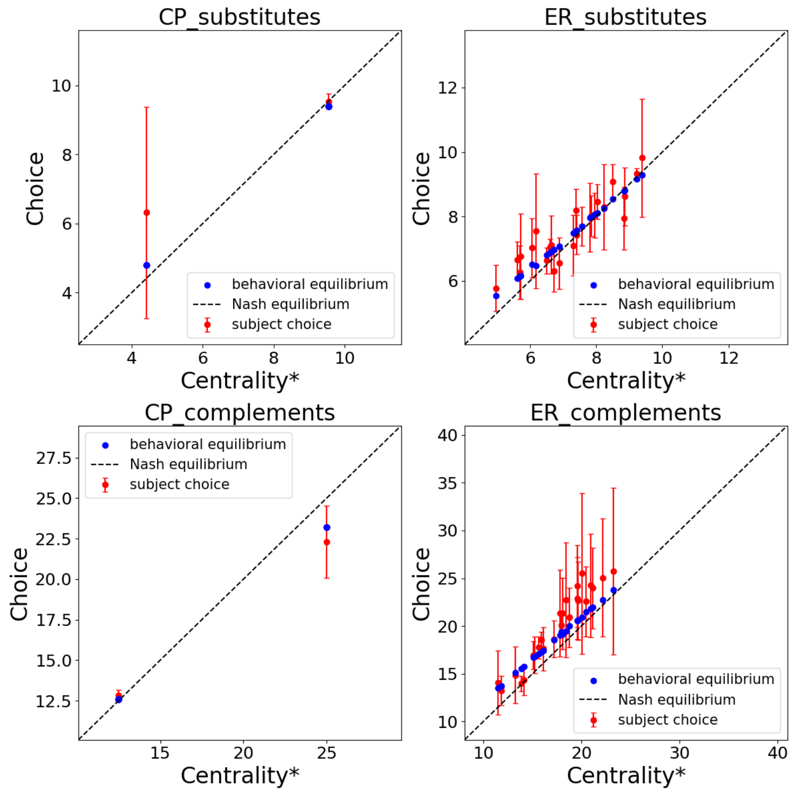


Table 14: Mean percentage deviation of choice

	baseline	fixed - baseline	limited info - baseline
CP substitutes	1.2%	+3.1%	-4.1%
	(0.01)	(0.03)	(0.03)
CP complements	-2.6%	+0.9%	-3.6%
	(0.02)	(0.03)	(0.03)
ER substitutes	4.4%	-0.2%	-2.1%
	(0.01)	(0.01)	(0.03)
ER complements	14.1%	+0.2%	-10.6%***
	(0.03)	(0.09)	(0.03)

Notes: The table presents the mean percentage deviation of choice from equilibrium prediction in the last ten periods for the baseline setting, and the two additional experimental settings compared to the baseline. Parenthesis reports standard error clustered over sessions. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$.

Table 15: Slope coefficient of choice on centrality*

	baseline	fixed - baseline	limited info - baseline
CP substitutes	0.88	-0.25	-0.01
	(0.03)	(0.28)	(0.12)
CP complements	0.67	+0.08	+0.01
	(0.05)	(0.09)	(0.12)
ER substitutes	0.69	+0.07	-0.14
	(0.04)	(0.09)	(0.10)
ER complements	0.63	+0.59**	+0.01
	(0.09)	(0.26)	(0.09)

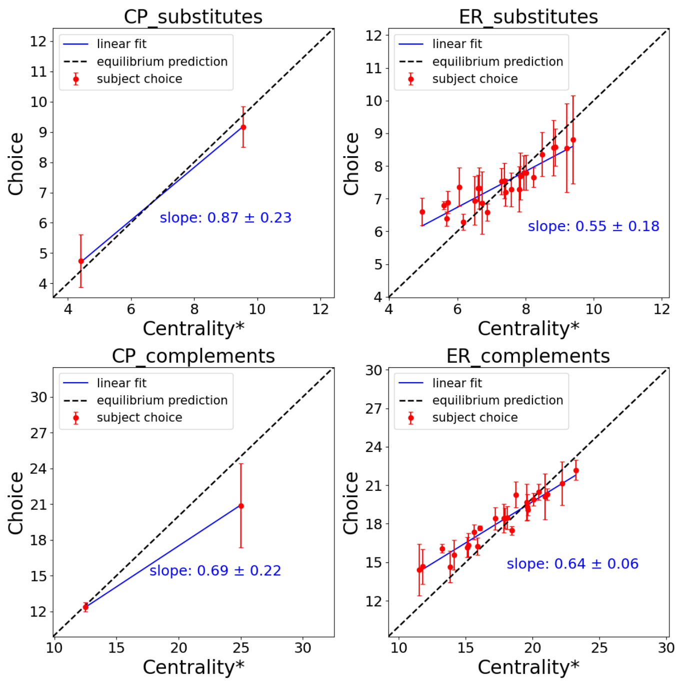
Notes: The table presents the slope coefficient of subject choice on centrality. Parenthesis reports standard error clustered over sessions. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$.

Table 16: Mean percentage deviation of payoff

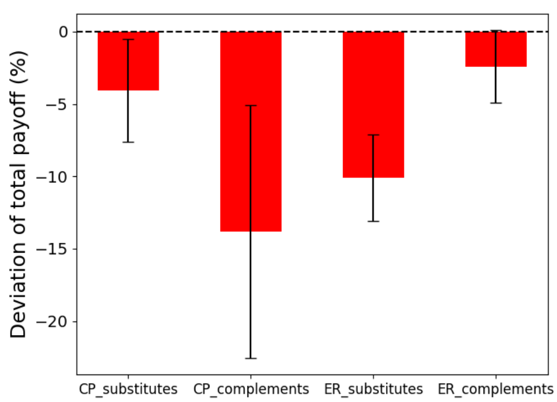
	baseline	fixed - baseline	limited info - baseline
CP substitutes	-3.5%	-21.5%	-0.6%
	(0.01)	(0.21)	(0.02)
CP complements	-12%	+3.1%	-1.8%
	(0.02)	(0.03)	(0.04)
ER substitutes	-9.4%	+0.8%	-0.8%
	(0.01)	(0.02)	(0.02)
ER complements	5.7%	+4.7%	-8.1%***
	(0.03)	(0.08)	(0.03)

Notes: The table presents the mean percentage deviation of payoff from equilibrium prediction in the last ten periods in the baseline setting, and in the two additional experimental settings compared to the baseline. Parenthesis reports standard error clustered over sessions. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$.

Figure 44: Theoretical predictions and subjects' behavior in the limited information setting



(a) Choices



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average choice of subjects in the last 10 periods of a given network centrality, averaged across the eight sessions. The 95% confidence interval bars are calculated using clustered standard errors over sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the choice. The 45-degree black dashed line represents the values where the choice equals the equilibrium prediction. The blue line is the random effect panel regression fit of the subject choices on theoretical prediction, reported in Table 1. The text reports the slope coefficient and 95% confidence interval (CI). (b) This bar plot shows the percentage deviation of the total payoff across subjects from the total equilibrium payoff in the last ten periods. Error bars represent 95% CIs around the mean, calculated using clustered standard errors over sessions.

treatments. These figures also reveal that limiting information on others' payoffs does not induce closer fit with best response and with Nash predictions on average. The impact of network complexity on individual action mirrors those observed in the baseline case: the slope coefficients in the Erdos-Renyi network are smaller than those in the core-periphery network.

We next examine the level effects. Table 16 shows that the average choice levels are smaller than those in the baseline in all four treatments. Recall that, in the baseline setting the action levels are consistently larger than equilibrium in the Erdos-Renyi network; by contrast, in the limited information setting, low centrality nodes choose above equilibrium while high centrality nodes choose below equilibrium. This pattern has implications for the average payoffs: Figure 44(b) shows that in contrast to the baseline case, the payoffs in the Erdos-Renyi network with strategic complements does not exceed the predicted payoff (since choices do not consistently exceed the equilibrium choices as in the baseline setting). Table 17 shows that the imitation parameter is much lower in the ER network when payoff information is limited (0.23 vs. 0.66). This suggests that limiting information about others' payoffs prevented subjects from placing greater weight on those highly-paid high choices of others in the complex ER network, thereby reducing consistent positive deviations of actions from equilibrium in the ER complements.

Table 17: Estimated parameters of the behavioral model for the limited information setting

	Core-periphery	Erdos-Renyi
λ	0.79***	0.75***
	(0.08)	(0.03)
α	0.00	0.23***
	(0.00)	(0.07)
N	2000	2000
Obj.	3.08	3.28

Notes: *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$ for the null hypothesis that the parameter is equal to one. Parentheses show bootstrap standard errors based on 100 bootstrap samples.

Figure 45: Behavioral equilibrium with estimated parameters in the limited information setting