UNIVERSITY OF CAMBRIDGE
Faculty of Economics

JANEWAY INSTITUTE CAMBRIDGE

CAMBRIDGE WORKING PAPERS IN ECONOMICS
JANEWAY INSTITUTE WORKING PAPERS

Experimental Evidence on the Relation between Network Centrality and Individual Choice

Syngjoo Choi
Seoul National University

Sanjeev Goyal
University of Cambridge

Fulin Guo
University of Cambridge

Frédéric Moisan
Emlyon Business School

Abstract

Social interactions shape individual behavior and public policy increasingly uses networks to improve effectiveness. It is therefore important to understand if the theoretical predictions on the relation between networks and individual choice are empirically valid. This paper tests a key result in the theory of games on networks: an individual's action is proportional to their (Bonacich) centrality. Our experiment shows that individual efforts increase in centrality but at a rate of increase that is lower than the theoretical prediction. These departures from equilibrium are accompanied by significant departures in individual earnings from theoretical predictions. We propose a model of network based imitation decision rule to explain these deviations.

Reference Details

2401 Cambridge Working Papers in Economics
2401 Janeway Institute Working Paper Series

Published 16 January 2024
Revised 7 February 2024

JEL Code C92, D83, D85, Z13

Websites www.econ.cam.ac.uk/cwpe
www.janeway.econ.cam.ac.uk/working-papers

Experimental evidence on the relation between network centrality and individual choice *

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

January 16, 2024

Abstract

Social interactions shape individual behaviour and public policy increasingly uses networks to improve effectiveness. It is therefore important to understand if the theoretical predictions on the relation between networks and individual choice are empirically valid. This paper tests a key result in the theory of games on networks: an individual's action is proportional to their (Bonacich) centrality. Our experiment shows that individual efforts increase in centrality but at a rate of increase that is lower than the theoretical prediction. Moreover, efforts are higher than predicted in some cases and lower than predicted in other cases. These departures from equilibrium have large effects on individual earnings. We propose a model of network based imitation decision rule to explain these deviations.

JEL: C92, D83, D85, Z13.

*The paper was supported by the Keynes Fund (University of Cambridge), the Center for Behavioral Institutional Design (NYUAD), and the Creative-Pioneering Researchers Program (Seoul National University). We thank Antonio Cabrales, Dan Friedman, Edoardo Gallo, Moritz Janas, Karl Schlag and Simon Weidenholzer for helpful comments.

[†]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

[§]Faculty of Economics, University of Cambridge. Email: fg400@cam.ac.uk

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

1 Introduction

A literature spanning different disciplines argues that our behaviour is affected by that of our peers[1] The behaviour of our peers is in turn affected by their peers, and so forth. An enquiry into individual behaviour pushes us toward an enquiry into the influence of the social network on individual behaviour.

The economic theory of networks shows that an individual's action is shaped by both the structure of the network and the nature of spillovers across individuals' actions that are 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]). This theoretical insight is increasingly used to design policy interventions in education, crime, finance, development, macroeconomics, international trade, and industrial organization (see e.g., Banerjee, Chandrasekhar, Duflo, and Jackson [2013], Galeotti, Golub, and Goyal [2020], Jackson, Rogers, and Zenou [2017]). 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 different classes of economic situations within a common design.

In a wide range of circumstances – a prominent example is public goods – an increase in others' efforts lowers an individual's incentive to exert effort: this is the case of *strategic substitutes*. In others – examples include coordination problems, pupil/scientists exerting efforts – an increase in others' efforts raises an individual's returns from their action: this is the case of *strategic complements* (Bulow, Geanakoplos, and Klemperer [1985]). Figure 1 illustrates the rich implications of the theory for two well known networks (core-periphery networks and Erdos-Renyi networks) and for games of strategic substitutes and strategic complements. The networks have 25 nodes. We chose the core-periphery network because it is a widely-studied and empirically important network that has only two distinct centrality values. The Erdos-Renyi network is chosen as it is a baseline example for complex networks in which each of the nodes has a distinct centrality.

[1]Prominent contributions include Duesenberry [1949], Emerson [1976],Freeman [1979],Granovetter [1985], Coleman [1994],Ohtsuki et al. [2006] and Christakis and Fowler [2009]. For an overview of the literature see Goyal [2023].

Our *first* finding summarizes the relation between subjects' efforts and equilibrium predictions. We find that, across the four treatments, subjects' choices increase in their centrality but the rate of increase is not as steep as predicted by equilibrium. Moreover, the direction of deviation from equilibrium differs 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.

Our *second* finding addresses the question of whether departures from equilibrium are motivated by efficiency seeking. We find that in three out of four treatments earnings are lower and in one treatment earnings are greater than predicted by theory. The lower welfare attained in three treatments suggests that efficiency seeking motives cannot account for the departures from equilibrium.

Our *third* finding pertains to the role of complexity: we find that subjects' actions in the Erdos-Renyi network are less responsive to centrality than in the core-periphery network.

We then examine the decision rules that can explain these departures from theoretical predictions.

We start by noting that the myopic best response dynamics converge to equilibrium; so, in our experiment, subjects are not choosing the myopic best response. We next show that efficiency seeking preferences and level-k reasoning (Charness and Rabin [2002] and Stahl and Wilson [1995]) cannot account for our two experimental findings. This leads us to explore other behavioural rules.

Imitation-based rules are appealing in our experimental setting because one, strategic reasoning and computing best responses is complicated and two, we provide information about individuals' choices and payoffs to everyone and this information can be used by subjects to make inferences about good courses of action because nodes in similar network positions have similar incentives. We propose a new model that combines DeGroot style models of learning with imitation based models to incorporate network heterogeneity (DeGroot [1974], Golub and Jackson [2010], Conlisk [1980], Vega-Redondo [1997] and Schlag [1998b]). Our *fourth* finding is that this network based imitation model can replicate the observed behaviour of subjects across the 4 treatments.

Our paper is a contribution to the experimental studies of games on networks (Cassar [2007], Hoelzemann and Li [2021], (Choi et al. [2017],Gale and Kariv [2009], (Charness et al. [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]). Our findings on the lower than equilibrium response to centrality and the different level effects on actions across different types of games and networks is novel.

An influential body of experimental research shows that individuals tend to imitate the choices of more successful others when they have the necessary information (e.g., Apesteguia, Huck, and Oechssler [2007], Apesteguia, Huck, Oechssler, and Weidenholzer [2010], Friedman, Huck, Oprea, and Weidenholzer [2015], Huck, Normann, and Oechssler [1999]). The seminal models of imitation in Conlisk [1980], Vega-Redondo [1997], Schlag [1998a], and Schlag [1999] consider imitation rules when individuals are similar and can observe all choices and payoff outcomes. We extend this model to a network setting where individuals' imitation behaviour depends on both payoffs and network positions. Our finding that a network-based imitation explains the departures from equilibrium predictions is novel.

The rest of the paper is organized as follows. In Section 2, we describe the model of continuous action games on networks and formulate our hypotheses, 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 individual behavior rules. Supplementary materials are presented in the Appendix.

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. 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

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

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 $\beta \sum_{j \in N-i(g)} s_j$. 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*

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

An individual's equilibrium action is proportional to their Bonacich centrality.

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 $\mathbf{I}$ is the $n \times n$ identity matrix and $\mathbf{1}$ 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 widely studied networks – core-periphery and Erdos-Renyi – and we consider both games of strategic substitutes and games of strategic complements. In all the networks there are 25 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 brings out the role of complements vs substitutes: core individuals choose the highest effort under strategic complements and the lowest effort under strategic substitutes. As a result, they achieve a higher payoff than the periphery in the strategic complements game and they obtain a lower payoff than the periphery nodes in the case of strategic substitutes.

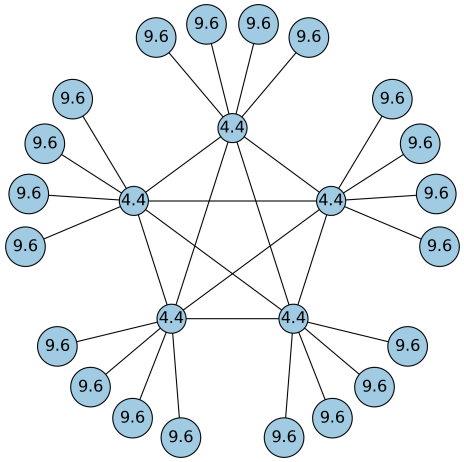
Figures 1 (a) and (b) presents core-periphery networks with 5 core nodes and 20 periphery nodes. Links take on binary values 1 and 0. In the case of complements, the spillover parameter $\beta = 0.1$, and for substitutes the parameter $\beta = -0.1$. For simplicity, we assume that the standalone parameter b takes on value 10 across all nodes and all treatments. 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 are more than 4 times the payoffs of the least central nodes. And in Figure 2 (b) for strategic complements we see that the payoffs of the highest centrality nodes are more than eight times the payoffs of the least central nodes.

The Erdos-Renyi graph is the natural baseline for complex networks (Newman [2018]). Figures 1 (c) and (d) and 2 (c) and (d) show that the 25 nodes in the Erdos-Renyi network are each unique in terms of their centrality and that the range of efforts and payoffs is comparable to that in the core-periphery network.[2]

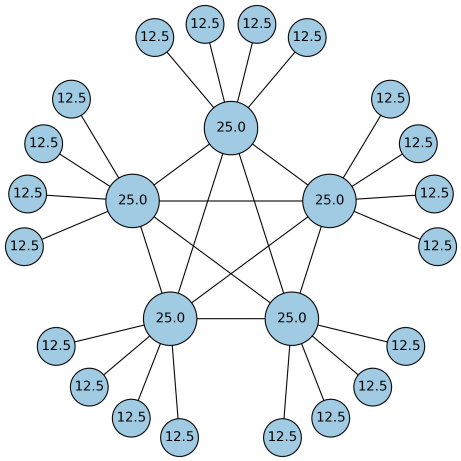
Due to the computational complexity of the decision problem and the uncertainty about what others will do, it is unlikely players will choose equilibrium actions right away: to facilitate learning our experiment involves repeated plays of the one-shot game. In each treatment, a group takes part in a session that consists of 40 periods. The group with

[2]In the core-periphery and the Erdos-Renyi network, centrality and degree are perfectly correlated. 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 respond to centrality. These networks are discussed in section D of the Appendix.

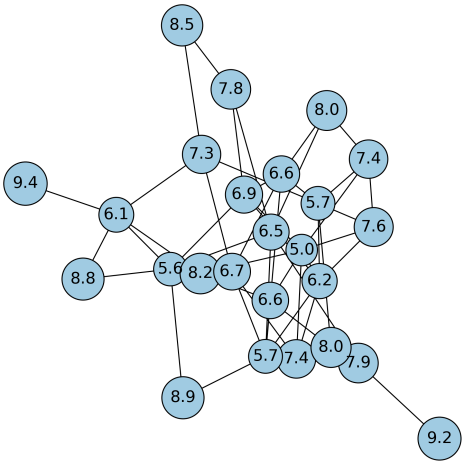
Figure 1: Games on Networks: Theoretical Prediction



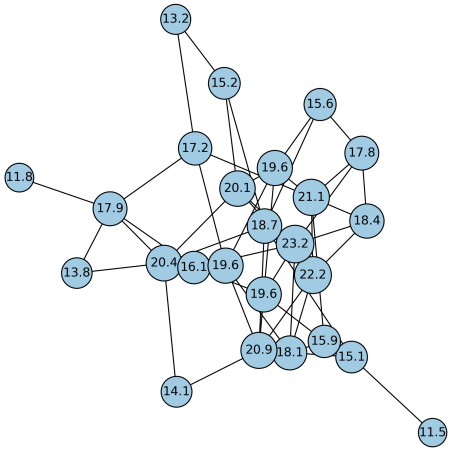
(a) CP substitutes



(b) CP complements



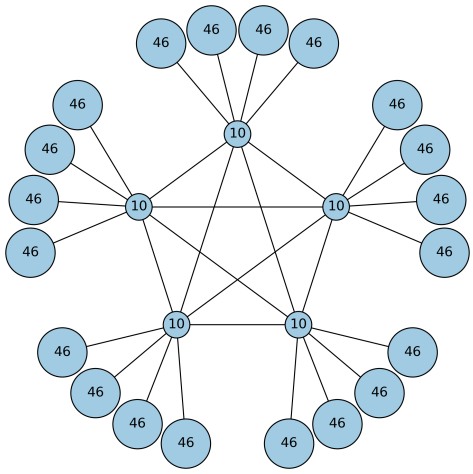
(c) ER substitutes



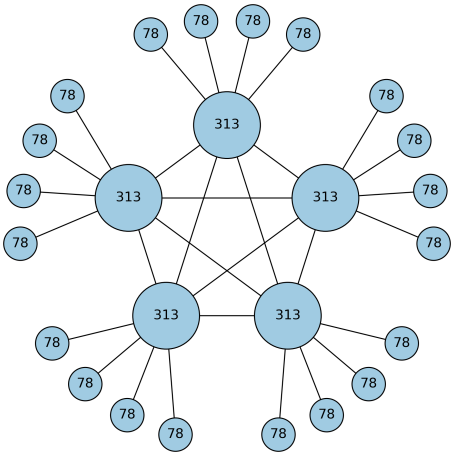
(d) ER complements

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 which could cause large payoff inequity across them. This mitigates

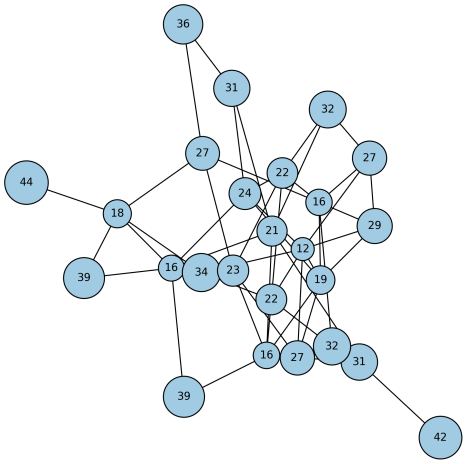
Figure 2: Games on Networks: Equilibrium Payoffs



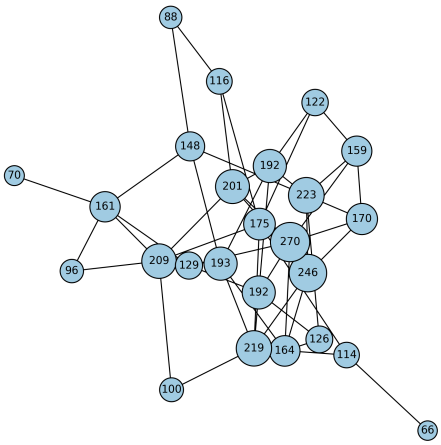
(a) CP substitutes



(b) CP complements



(c) ER substitutes



(d) ER complements

the role potential influence of social preferences such as inequality aversion in shaping behaviour. In every period, subjects choose an action lying in the interval $[0, 40]$ using a

sliding scale.[3]

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 detailed information as a baseline case as it should help ensure learning and convergence to equilibrium. Section A presents the screen interface and feedback protocol 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 800 points = £1 for tree network strategic complements, 2000 points for tree network strategic substitutes, 700pts=£1 for core-periphery network and Erdos-Renyi network under strategic complements, and 150pts=£1 for 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 group there were $8,000$ observations on individual choices in all.

4 Hypotheses

Theorem 1 provides a sharp prediction on behaviour. 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 $t-1$. We simulate this process. 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

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

best response action falls outside the range of $[0, 40]$, the action is truncated to 0 or 40 accordingly. Figure 16 in the appendix plots the dynamics of the best response dynamics against the Nash equilibrium: we see that convergence is very fast and similar 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 1: Subject choices are consistent with Nash equilibrium, i.e., their action is equal to their Bonacich centrality multiplied by the standalone value b.

(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: Every subject chooses a different action. In the substitutes game, actions range from 5 to 9.4. In the complements game, actions range from 11.5 to 23.2.

In the complements (substitutes) game an increase in individual actions raises (lowers) the neighbours' payoffs. In other words, spillovers are positive (negative) in games of complements (substitutes). It follows from standard considerations that equilibrium efforts will be too low (high) in games of strategic complements (substitutes) relative to the socially optimal actions.[4] Building on the large literature on social preferences with efficiency seeking, a possible alternative conjecture is that subjects may be expected to choose higher (lower) than predicted actions in the case of complements (substitutes) (Charness and Rabin [2002], Gallo and Yan [2021]).

Hypothesis 2: In games of substitutes and negative spillovers subjects' actions are lower than equilibrium predictions. In games of complements and positive spillovers subjects' actions are higher than equilibrium predictions.

When we compare core-periphery with Erdos-Renyi networks, a possible conjecture is that the greater richness of actions makes learning and computation of payoffs more difficult and that this has the capacity to weaken the relation between centrality and effort. Based on considerations of network complexity (Rubinstein [1998], Chatterjee and Sabourian [2020]), we propose:

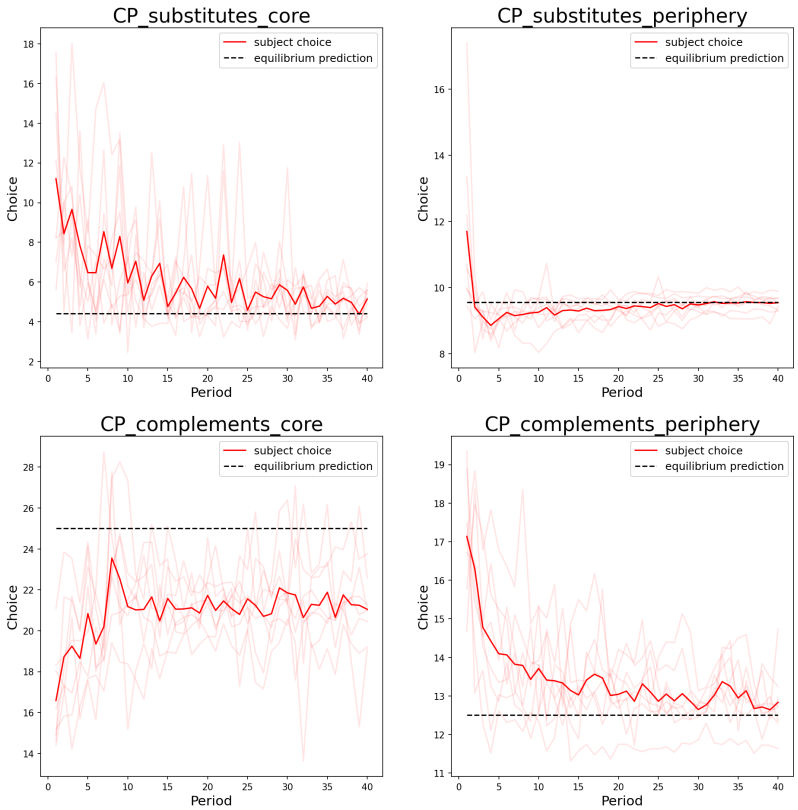
Hypothesis 3: Subject choices are more sensitive to centrality in the core-periphery network as compared to the Erdos-Renyi network.

[4] The social optimal efforts are given by $\mathbf{s}^* = [I - 2\beta\mathbf{G}]^{-1}\mathbf{b}$.

5 Equilibrium predictions vs subject behaviour

We start by very briefly summarizing the dynamics of choices in each treatment of the experiment. Figure 3 shows the evolution of choices for the core and the periphery in the core-periphery network.

Figure 3: Time series of choices in the core-periphery network

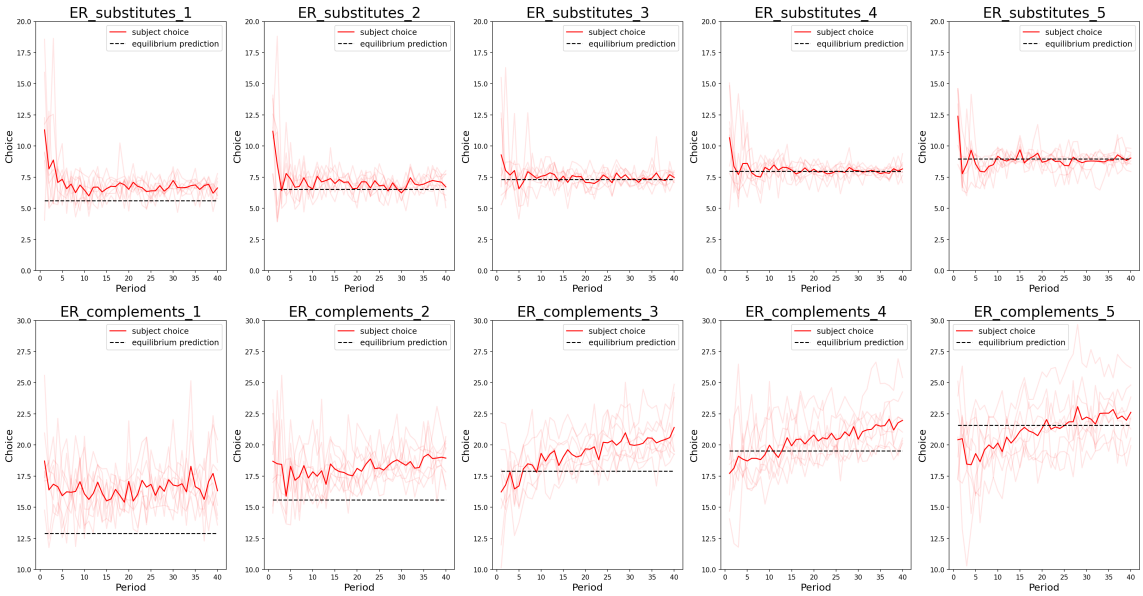


Notes: The black dashed line represents the equilibrium prediction of each position. The dark red curve shows the time series of average choice over all nodes in the same position and across all groups. The light red curve shows the time series of average choice over all nodes in the same position, for each session.

Figure 4 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. These figures suggest that the actions settle down as we get to the end of the experiment. We will focus on the actions in the last ten rounds in our analysis (also see section B.2 in the Appendix for further analysis of the convergence of actions.

Figure 4: Time series of choices in the Erdos-Renyi network



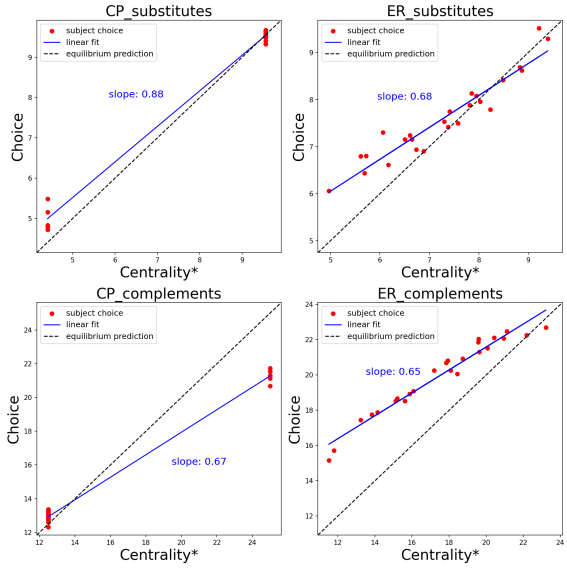
Notes: The black dashed line represents the average equilibrium prediction of the five nodes for each category. The dark red curve depicts the time series of the average choice for all nodes in the same category across all sessions. The light red curve shows the time series of the average choice for all nodes in the same category, for each session separately.

Figure 5 presents the relation between equilibrium prediction and subjects' choices (in the last ten rounds). The x-axis plots the Bonacich centrality of a subject 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.

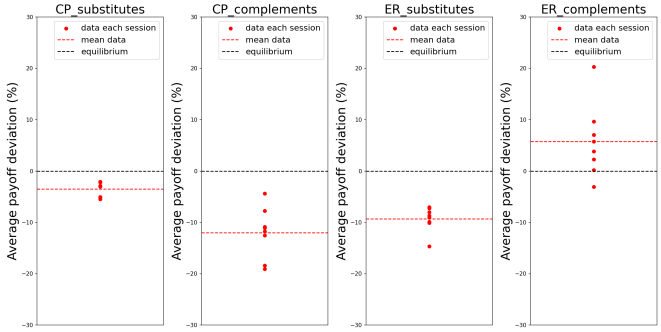
Our first observation on Figure 5 is that (on average) subjects' choices increase with centrality but that they do not increase as sharply as predicted by equilibrium.[5] In other words, the slope between choices and centrality is flatter than 1 in all treatments. This is

[5]This pattern is robust to different ways of organizing the data including panel regressions and regressions with averaged data per node or group. See Tables 1, 3, 4 in section B in the Appendix.

Figure 5: Theoretical Predictions and Subjects' Behaviour



(a) Subjects' actions



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average action chosen by subjects in the last 10 periods of a given network position, averaged across the eight sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the action level. The 45-degree black dashed line represents the values where the action level equals the equilibrium prediction. The blue line is a linear OLS fit of the subject actions on theoretical prediction, reported in Table 1. A red dot represents the percentage deviation of mean subject payoff (from mean equilibrium payoff) in the last ten periods for a given session. The red dashed line represents the average outcome across the eight sessions.

shown by the blue line which represents linear fit of subject choice on equilibrium prediction.

This finding are confirmed by the regression analysis presented in Table 1. In these regressions, 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.

Table 1: 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 $p < 0.001$. $centrality^* = centrality \cdot b$

We next examine the level of choices: whether they are systematically higher or lower than the equilibrium prediction. Figure 5(a) summarizes the experimental data. Consider the core-periphery network: under strategic substitutes, choices of core agents are higher and choices of periphery agents are equal to equilibrium predictions; under strategic complements, core agents choices are lower and periphery agents actions are (roughly) equal to equilibrium predictions. In the Erdos-Renyi network, choices of all agents are larger than the equilibrium under both strategic complements and strategic substitutes. We summarize these observations as follows:

Finding 1: In all treatments, agents' choices increase with centrality but the effect of centrality on subjects' choices is smaller than predicted by the equilibrium.

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

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

Figure 6: Payoff vs. centrality

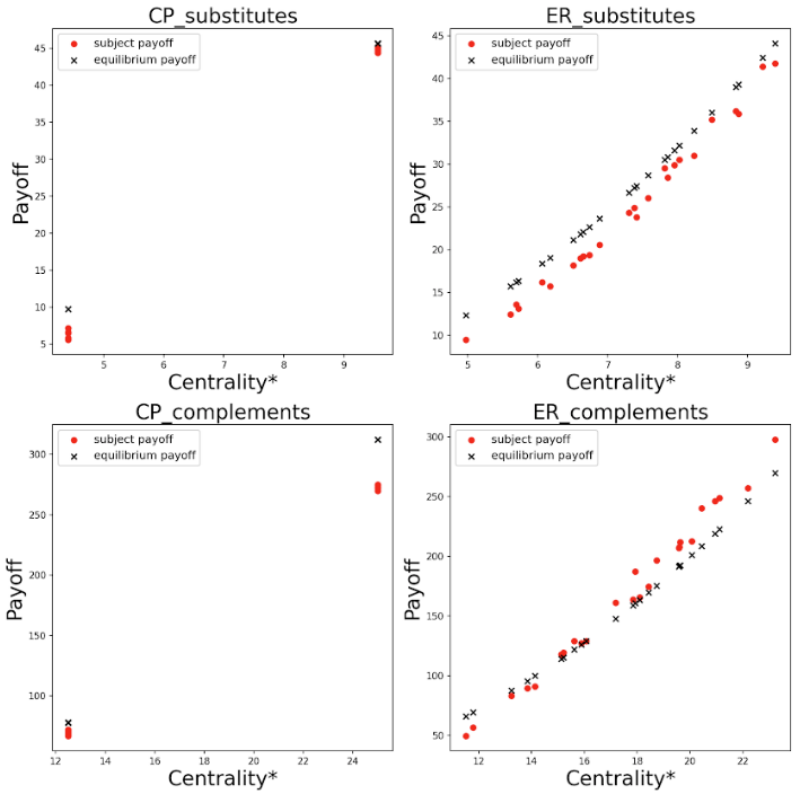


Figure 5(b) shows that the subjects behaviour has large effects on their payoffs: (average) payoffs are lower than the predicted payoffs in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments (two-sided Wilcoxon signed-rank (WSR) test, $p < 0.01$). The (average) 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 6 summarizes how our treatments affect subjects with different centrality. Consider 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.

We summarize these observations on payoffs in our second finding:

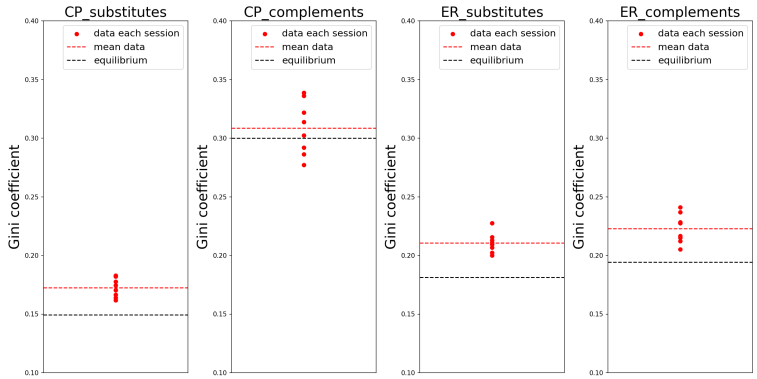
Finding 2: Subjects' actions are inconsistent with efficiency seeking behaviour in three out of four treatments.

We turn next to the impact of complexity on individual action: Figure 5(a) tells us that in the game with strategic substitutes the slope coefficient is higher for core-periphery network than for Erdos-Renyi network; for the game with strategic complements the slope coefficient is similar across the two networks. To summarize:

Finding 3: Subjects' actions in the Erdos-Renyi network are less responsive to centrality than in the core-periphery network.

A potential explanation for the flatter relationships between actions and centrality could be that subjects care about equity: lower dispersion of effort will help in attaining lower inequality in payoffs. However, in our experiment the Gini-coefficient of earnings is higher than the theoretically predicted levels in three out of the four treatments as shown in Figure 7.[6]

Figure 7: Gini coefficient



This leads us to a more systematic exploration of decision rules that can help us in understanding the deviations from theoretical predictions.

[6]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.

6 Explaining the departures from equilibrium predictions

We study behavioral rules that can account for these departures from equilibrium. Our point of departure is the best response dynamics: recall from the simulations reported in Figure 16 that the best response dynamics converge to the unique Nash equilibrium. We supplement these best response dynamics with noise, where the time-varying noise level is calculated according to the root mean squared error (RMSE) of subject choices compared to best responses in each round.[7] These simulations indicate that noisy best responses yield average action levels that are (almost) identical to those in Nash equilibrium in the last ten rounds, thus they do not provide a good match with the experimental data: in particular, they do not lead to the flat relationships between choices and centrality observed in the experimental data. To understand our results we therefore need to go beyond best response dynamics. We next examine models of imitation.[8]

When computing payoffs from different actions is challenging it may be attractive to *imitate* the choices of more successful others (Conlisk [1980], Vega-Redondo [1997], Alós-Ferrer and Weidenholzer [2008], Schlag [1998b]).

6.1 A simple model of imitation

We consider a simple imitating-the-best model in discrete time. Denote the individual choice at node $i \in \{1, 2, ..., 25\}$ and in period $t \in \{1, 2, ..., 40\}$ by s_{it} and denote the payoff node i obtained in period t by π_{it}. In each period $t \geq 2$, we assume an individual in network position i imitates the best choice from $t-1$ among those in i's reference group, R_i. The reference group is based on how "similar" two nodes are, which can be determined by, e.g., degree and centrality. More precisely, the imitation choice is defined as $s_{i,t} \in \{s_{j,t-1} | j \in argmax_{h \in R_i} \ \pi_{h,t-1}\}$.

The above imitation rule along with an initial condition $\boldsymbol{s}_0$ defines a dynamical system $\boldsymbol{s}_{t+1} = f(\boldsymbol{s}_t)$. An action profile $\boldsymbol{s}^*$ is a steady state if it satisfies $\boldsymbol{s}^* = f(\boldsymbol{s}^*)$. It is clear that

[7] It is worth noting that the average patterns of the simulated noisy best response outcomes are robust to the noise level.

[8] We also considered two other models. One, the level-k reasoning model (Nagel [1995], Stahl and Wilson [1995], Crawford et al. [2013]). Section C.4 of the Appendix shows that this model is unable to generate key patterns of the data. Two, we consider a behavioral rule where an agent plays a best response to their neighbours but believes that every neighbour plays the same action, and this action corresponds to the average action in the population; this is inspired by the notion of cursed equilibrium, Eyster and Rabin [2005]. Section C.4 of the Appendix shows that this model cannot account for the patterns in our data.

all individuals choosing the same action ($\boldsymbol{s}_i = \overline{s}$) is a steady state, i.e., there is a continuum of steady states.

To make progress, we therefore consider local stability of steady states. Suppose that an individual deviates from the steady state to a small amount, whether the action profile of the network will return back to the steady state or not. If it will, we refer that steady state to a locally stable steady state.

We define the reference group of node i with centrality c_i by $R_i = \{j | c_j = c_i\})$, then a necessary condition for local stability is: for any i and j with the same centrality,

$$\begin{aligned} \frac{\partial \pi_i(\boldsymbol{s}^*)}{\partial s_i^*} &= \frac{\partial \pi_j(\boldsymbol{s}^*)}{\partial s_i^*} \\ \Longrightarrow b - s_{ij}^* + \beta \sum_{h \in N_i(g)} s_h^* &= g_{ij} s_{ij}^* \end{aligned} \tag{3}$$

where $s_{ij}^* = s_i^* = s_j^*$ is the choice of i and j in the steady state.

To see why (3) holds. Suppose, without loss of generality, that $\frac{\partial \pi_i(\boldsymbol{s}^*)}{\partial s_i^*} > \frac{\partial \pi_j(\boldsymbol{s}^*)}{\partial s_i^*}$, then a small positive deviation of s_i will make the payoff of i larger than that of j, which will cause j to imitate the new choice of i, and so $\boldsymbol{s}^*$ will not be stable.

We next apply this notion of local stability to the core-periphery network. Suppose the choices of the core and the periphery in a locally stable steady state are s_c^* and s_p^*, respectively. Then for a periphery node, it must satisfy:

$$\frac{\partial \pi_p(\boldsymbol{s}^*)}{\partial s_p^*} = 0 \tag{4}$$

To see why equation (4) must hold, consider a small deviation of s_p^*; it is easy to see that will lower the payoff of the periphery node that deviated. Then, other periphery nodes will not imitate it and periphery node that deviated will return to the steady state next period. Next suppose equation (4) does not hold: for example, suppose it is positive, then a positive deviation will increase the payoff of the periphery node that deviated, which will make other periphery nodes imitate it and drive the system away from the original steady state.

Next, let us consider core nodes c and c': the (necessary) condition for the core is

$$\frac{\partial \pi_c(\boldsymbol{s}^*)}{\partial s_c^*} = \frac{\partial \pi_{c'}(\boldsymbol{s}^*)}{\partial s_c^*}$$
$$\implies b - s_c^* + 4\beta s_c^* + 4\beta s_p^* = \beta s_c^* \tag{5}$$

To see why it must hold, note that if the L.H.S of (5) is greater (smaller) than the R.H.S, then a positive (negative) deviant core node will earn a higher payoff than the other core nodes. This means that other core nodes will imitate it in the next period, implying that the steady state is not locally stable.

For concreteness, we now calculate the locally stable steady state in the core-periphery network with our parameter values: $b = 10$ and $\beta = 0.1$ (strategic complements) and $b = 10$ and $\beta = -0.1$ (strategic substitutes). For these parameters, there is a unique value that satisfies the local stability conditions:

- complements: $s_c^* = 21.2$ and $s_p^* = 12.1$
- substitutes: $s_c^* = 4.76$ and $s_p^* = 9.52$.

We observe that the unique locally stable steady state has certain relationship with the Nash equilibrium. Consider the strategic complements case, recall that the Nash equilibrium is 25 and 12.5 for the core and periphery, respectively; we note that in the complements case, the locally stable steady states lie below the Nash equilibrium. For strategic substitutes, the Nash equilibrium are 4.41 and 9.56 for the core and periphery, respectively. Under locally stable steady state, the core has a higher choice than the Nash choice while the periphery node has a (slightly) lower choice than the Nash. Finally, we observe that the imitation dynamics yield action levels that respond less than proportion to centrality. That is, the relationship between action and centrality is flatter than that predicted by the theory.

The above characterises the locally stable action profiles that are robust to small individual deviations. It is not clear whether they are globally stable. We conduct simulations of the dynamical process starting from random initial choices to examine whether imitation dynamics converge, and if so, what they converge to.

In the simulation, agents choose uniformly at random in the first period. Starting from the second period, their choices are made according to the aforementioned imitation rules. In order to prevent getting stuck in an unstable steady state, we introduce a small

amount of noise into individuals' choices. Formally, we suppose a noise following a normal distribution with standard deviation $\sigma = 0.1$. We conduct 100 simulations with each lasting 1,000 periods. Table 2 summarises the average and the range of outcomes in the simulation.

It can be observed that average choices are essentially equal to the locally stable choice and all the choices consistently cluster around that locally stable steady state within a narrow range. For example, in the case of strategic complements, the locally stable choice of the core is 21.1, and the mean choice of simulation in the last 100 periods (out of 1000-period simulation) is also 21.2, with all choices in those periods falling between 19.4 and 23.3.

Table 2: Imitating the best outcome for the core-periphery network

	locally stable choice	mean simulation	range
substitutes core	4.76	4.77	(4.00, 5.68)
substitutes periphery	9.52	9.53	(9.00, 10.02)
complements core	21.2	21.2	(19.4, 23.3)
complements periphery	12.1	12.1	(11.6, 12.7)

So far we have considered the case where for each node i, there are other nodes that have the same centrality. More generally, a node may have a unique centrality value (as in the Erdos-Renyi network). In that case, we consider the situation in which a node may want to imitate those whose centrality is close to themselves. We now propose a a general model of reference groups.

6.2 Network based imitation model

We extend the existing model by proposing a smooth model of imitation that assigns lower probability to imitating agents with lower payoffs and those who are further away in network characteristics. Building on the imitation literature and models of learning (see DeGroot [1974]), we suppose that the choice of node i at time t, denoted as $s_{i,t}^{IM}$, is a convex combination of the choices of all nodes at the previous time period $(t-1)$:

$$s_{i,t}^{IM} = \sum_{j \in N} w_{i,j,t} s_{j,t-1} + \epsilon_{i,t} \tag{6}$$

where $s_{j,t-1}$ represents the choice of node j at time $t-1$ and $\epsilon_{i,t}$ captures noise in choice

(it has a normal distribution with mean 0). The number $w_{i,j,t} \in [0,1]$ reflects the weight that node i assigns to node j in period t, and is calculated as follows:

$$\begin{aligned} w_{i,j,t} &= \frac{e^{z_{i,j,t}}}{\sum_{k \in N} e^{z_{i,k,t}}} \\ z_{i,j,t} &= -\delta|\tilde{x}_i - \tilde{x}_j| + \lambda \tilde{\pi}_{j,t-1} \end{aligned} \tag{7}$$

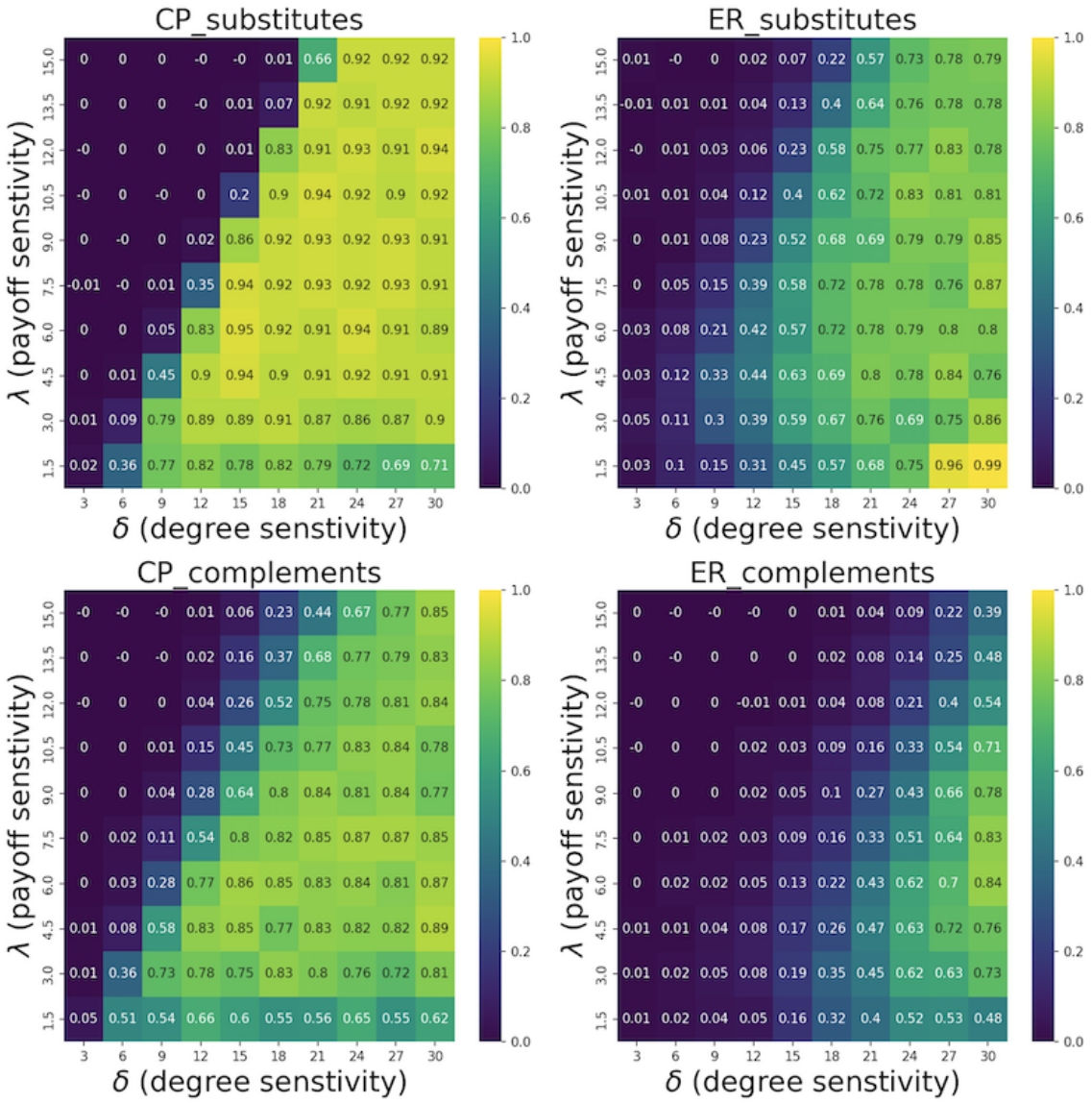
where $\tilde{x}_i$ represents the (normalized) network property of node i (e.g., degree, centrality) and $\tilde{\pi}$ represents the (normalised) payoff.[9] The weight node i puts on node j at time t therefore depends on the payoff of node j at time $t-1$ and the network difference between them. The parameter λ captures the sensitivity of the weight to payoff, while δ captures the sensitivity to network difference.

When the imitation dynamics is more responsive to network property as compared to payoff (low value of λ as compared to δ) the model predicts a close relation between actions and centrality. On the other hand, if imitation dynamics is more responsive to payoffs as compared to network property (a high value of λ compared to δ), the model predicts a coefficient close to 0, since all individuals put most of the weight on the individual with the highest payoffs.

To understand under what circumstances the network-based imitation model can generate the positive but flat relationship between actions and centrality, we conduct the simulation of the model with a wide range of parameters. In Figure 8, the network property being considered for nodes is the degree, and the noise level is 1. We conduct 100 simulations for each pair of (δ, λ). When the imitation dynamics is responsive to network property compared to payoff (e.g., the lower triangular part of the heat map figure), the simulated model predicts the positive but flat relationship as in the data across networks and strategic contents. On the other hand, when the imitation dynamics is dominated by payoff differences (i.e., with high value of λ and relatively low value of δ), the model predicts the completely flat relationship with the estimated slope coefficient close to 0. These patterns are robust to different levels of noises and to different network properties (as shown in section B.4 in the Appendix).

[9] The normalisation procedure is as follows: $\tilde{x}_i = \frac{x_i - min(\mathbf{x})}{max(\mathbf{x}) - min(\mathbf{x})}$ and $\tilde{\pi}_{j,t-1} = \frac{\pi_{j,t-1} - min(\overline{\pi})}{max(\overline{\pi}) - min(\overline{\pi})}$, where $\mathbf{x}$ represents the network characteristic vector and $\overline{\pi}$ represents the equilibrium payoff vector. $max(\cdot)$ and $min(\cdot)$ represents the maximal and minimal element of a vector, respectively.

Figure 8: Slope for different parameter values ($\sigma = 1$)



6.3 Estimating the network-based imitation model

We estimate the parameters by minimizing the mean absolute error (MAE) between the predicted and actual choices (over all treatments, groups, individuals, and all but the first

period) and use residuals to estimate the levels of choice noises. We estimate common parameters for all the treatments.

$$\sigma_{treat,t} = \sum_{i,grp} (a_{i,t,treat,grp} - s^{IM}_{i,t,treat,grp}) \tag{8}$$

The results are as follows: $\delta = 13.673$ and $\lambda = 5.108$ for degree-based imitation (and they are $\delta = 19.608$ and $\lambda = 4.653$ for centrality-based imitation). Consistent with intuition, the parameters for the imitation model are all positive, suggesting that people will put more weights on those with similar network features and high payoffs.

The predicted imitation choice for each individual in each period ($t \geq 2$), $s^{IM}_{i,t}$, can then be calculated based on the formula (7) and the estimated parameters (λ, δ) and using an estimated variance of choice noise for each period of the data.

We next present simulations of the model and compare them with the experimental data. In the simulation, we assume that there is noise in individual choices, so that the actual choice of node i in period $t \geq 2$ is $s_{i,t} = \hat{s}_{i,t} + \epsilon_{i,t}$, where $\hat{s}_{i,t}$ is the expected choice predicted by the model given the *simulated* outcomes in period $t-1$, and we assume that the noise $\epsilon_{i,t}$ follows a normal distribution. The noises might be interpreted as errors or trembling in decision making, or intentional exploration of choices in the game. We estimated the variance of this noise for each period from the data. We assume that the initial actions are drawn uniformly at random in the action space $[0, 40]$.[10]

Figure 9 presents the scatter plot of actual choices (in red dots) versus simulated choices (in blue dots) over centrality. We can see that imitation dynamics generate a flatter relationship between choice and centrality than Nash equilibrium, consistent with the experimental data. Table 6 in the Appendix B reports estimated slope coefficients from the regressions of actual choices as well as simulated choices. We also note that the direction of deviation from Nash equilibrium is consistent with the experiment: the core nodes' choices in the core-periphery treatment are below the equilibrium and choices are above Nash equilibrium in the Erdos-Renyi network.

There are two effects at work in the network-based imitation model. The first pertains to a 'negative cross effect on payoffs'. The idea is as follows: when an agent lowers action from an equilibrium action her payoff falls but it may be that the cross effects on payoffs of other agents are even more negative. In this case the individual who is deviating becomes an

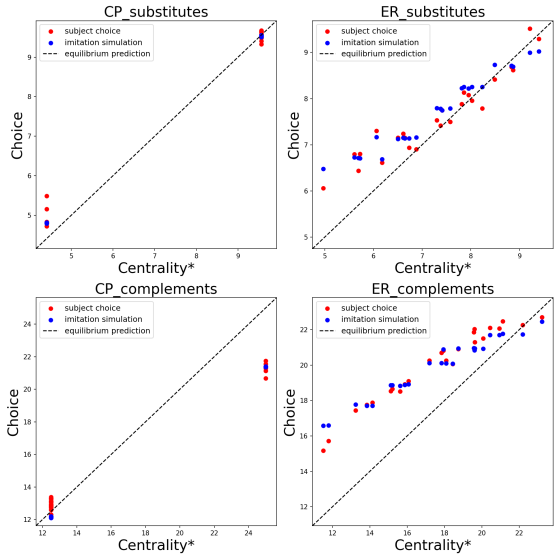
[10]The outcomes in the last ten rounds of the imitation simulation are robust to the distribution of the initial actions.

object of imitation and this creates a cascade of deviations leading away from equilibrium (Vega-Redondo [1997]).

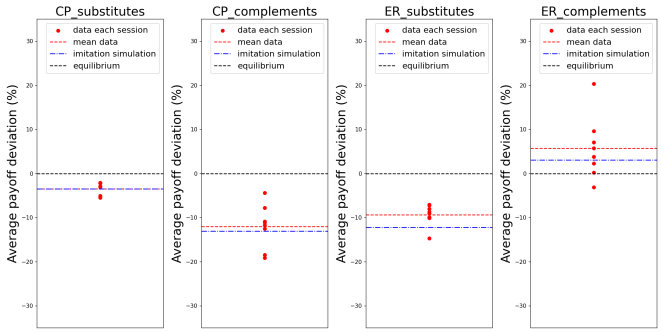
The second effect is an "imperfect network differentiation effect": individuals tend to imitate the choices of others with different (albeit similar) network positions. Intuitively, imperfect differentiation among various network positions can lead to different nodes making similar choices, thereby creating a flat relationship between choices and theoretical predictions. Therefore the second effect can explain the flat relationship. But it does not have much to say on the specific direction of deviation from equilibrium.

As centrality measure of core and periphery nodes is very distinct in the core-periphery model, the first effect dominates in that network. On the other hand, in the Erdos-Renyi network the 25 nodes each have distinct centrality and every node sees other nodes who have slightly higher or lower centrality than itself. In this setting, the second effect dominates. Higher centrality nodes have higher equilibrium payoffs (under both strategic complements and strategic substitutes). As subjects cannot perfectly distinguish different positions, they tend to imitate those with higher centrality – this pushes activity to levels in excess of the equilibrium prediction. Moreover, the smaller differences in network property (degree, centrality) in ER network also limit the network sensitivity for a fixed value of delta (which therefore creates more sensitivity to higher payoff).

Figure 9: Fitting the experimental data to the imitation model



(a) Subjects' actions vs. imitation model



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. A red dot represents the average action made by subjects in the last 10 periods of a given network position across eight sessions. A blue dot represents the average simulation action made in the last 10 periods of a given network position across 1,000 simulations. The 45-degree black dashed line represents the values where the action level equals the equilibrium prediction. (b) A red dot represents the percentage deviation of mean subject payoff (from mean equilibrium payoff) in the last ten periods for a given session. The red dashed line represents the average outcome across the eight sessions. The blue dashed line represents the average outcome across 1,000 simulations.

7 Robustness

The baseline experiment suggests that one, individual efforts are less sensitive to centrality than predicted by the theory and two, actions are higher than equilibrium in some situations and lower than equilibrium in others. These deviations from equilibrium have large effects on individual earnings. We propose a new model of network based imitation based choice to explain these deviations. To assess the generality of our findings, we also considered alternative networks and experimental designs. This section reports on these investigations.

7.1 Extrapolations

We explore whether the key findings of the experiment can be generalized beyond the settings of the experimental design, through the help of the network-based imitation model. We do so by increasing group size up to 100 and considering an alternative network structure, scale-free networks, that is widely studied in the literature (see e.g., Barabási and Albert [1999]). In this extrapolation exercise, we adjust the model parameter across variations so that the range of Nash equilibrium actions is comparable and the estimated noise levels are re-used. Specifically, the standalone parameter is fixed to be 10 across the group sizes, while the spillover effect is ± 0.1, ± 0.07, and ± 0.05 for group size $n = 25$, 49, and 100, respectively.

Figures 25 - 27 (in the appendix) present the results of simulations across different group sizes in the three different network structures. This extrapolation exercise suggests that the positive but flat relationship between actions and centrality continues to hold beyond the settings of the experiment.

7.2 Additional experimental treatments

We conduct three other experiments to examine key aspects of our experimental design. Following Gallo and Yan [2021], the *first* additional experiment studied the question of whether subjects follow centrality or degree. The baseline experiment involves subjects being relocated in the network after every round. This eliminates repeated game effects and ensures symmetry across subjects but at the cost of greater complexity in the learning problem. Recall that this complexity was also a key consideration underlying the use of the imitation based decision rule. In our *second* additional experiment we fix the location of subjects in the network. As imitation rests on knowledge of others' actions and payoffs,

there is a possibility that restricting information on others' payoffs could discourage imitation and this may facilitate actions closer to Nash equilibrium. In our *third* additional experiment, subjects were shown the actions of everyone but only their own payoffs. This allows us to study how subjects learn when they cannot compare their payoffs with the payoffs of other subjects.

7.2.1 Is behaviour driven by degrees or centrality?

In both core-periphery and Erdos-Renyi networks degrees are monotonic with respect to centrality. In a recent paper, Gallo and Yan [2021] suggest that subjects' behaviour may be driven by direct network measure such as degree (rather than their centrality). To investigate whether individuals base their actions on centrality or degree, we considered an additional experimental treatment featuring a network with non-monotonic relationship between degree and centrality. This experiment is reported in section D in the Appendix.

We created networks and proposed parameters such that an increase in centrality does not translate into a increase in degree. In particular, under strategic substitutes, the equilibrium action decreases in centrality but does *not* monotonically decrease with degrees. Likewise, under strategic complements, equilibrium action increases with centrality but not with degree. We investigate whether subjects' choices correlate with their Bonacich centrality or if they correlate with their degree in the network. Figure 31 (in the appendix) shows a positive relationship between subject choice and centrality as the theory suggests. We also note that the slope is less than 1 in all cases, as in the baseline experiments. We also find that actions increase in centrality and that they are non-monotonic in degree. We interpret this as evidence in support of the theory – centrality drives behaviour.

7.2.2 Does fixed location in networks lead to better match with theory?

We considered a design with core-periphery and Erdos-Renyi networks and with strategic substitutes and complements as in the baseline experiment. The only difference was that agents were assigned a location that remained unchanged throughout the 40 rounds of the experiment. The principal hypothesis is that fixing location simplifies learning and that this will facilitate faster convergence of actions and also a closer match with the Nash equilibrium prediction. The results of this experiment are reported in section D in the appendix.

Our first finding is that actions settled down significantly faster in all the four treatments as compared to the baseline treatments. This is in line with our hypothesis. Our second finding pertains to the match with the equilibrium prediction: we found that the match with theory was better for some treatments and less good for other treatments, as compared to the baseline experiments. This goes against our hypothesis. Our third finding is that the coefficient of centrality on actions is positive but strictly lower than 1 in three out of four treatments, except the Erdos-Renyi network under strategic complements. Our fourth finding is that the level of actions mirror those seen in the treatments in the baseline experiment.[11]

The outcomes in the fixed network position treatment are broadly consistent with the baseline outcomes, with the only exception being that the relationship between choice and centrality in the Erdos-Renyi network with strategic complements is not flatter than theoretical prediction.

7.2.3 Does limited information on others' payoffs lead to better match with theory?

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. When players do not observe others' payoffs they cannot imitate actions of others based on relative earnings. On the one hand this makes learning from others more difficult but on the other hand it may push subjects toward learning from their own experience and choosing best responses more often. Our hypothesis is that learning will be slow and so behaviour will remain noisy but on average subjects will be closer to the equilibrium as compared to the outcomes in the baseline experiment. The results of this experiment are reported in section D in the appendix.

Our first finding is that the rate of convergence is slower than the baseline treatment and this is in line with our hypothesis. However, the match of average behaviour with equilibrium prediction is better for some treatments and worse for others, as compared to the baseline experiment. In other words, the lack of information on others' payoffs does not lead to a higher likelihood of subjects choosing best responses (on average). Our third

[11] It is worth noting another difference with the baseline treatment: some subjects are persistent outliers in the sense that they choose very high or very low effort. We comment on this and discuss the outcomes from median individual choices in the appendix.

finding is that as in the baseline setting, the slope coefficient of centrality on actions is positive but strictly lower than 1 across all treatments. Finally, the impact of network complexity on individual actions mirrors that observed in the baseline case: the slope coefficients in the Erdos-Renyi network are weakly smaller than those in the core-periphery network.

References

C. Alós-Ferrer and S. Weidenholzer. Contagion and efficiency. *Journal of Economic Theory*, 143(1):251–274, 2008.

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.

J. Apesteguia, S. Huck, J. Oechssler, and S. Weidenholzer. Imitation and the evolution of walrasian behavior: Theoretically fragile but behaviorally robust. *Journal of Economic Theory*, 145(5):1603–1617, 2010.

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

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

A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *science*, 286 (5439):509–512, 1999.

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

J. I. Bulow, J. D. Geanakoplos, and P. D. Klemperer. Multimarket oligopoly: Strategic substitutes and complements. *Journal of Political economy*, 93(3):488–511, 1985.

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.

K. Chatterjee and H. Sabourian. Game theory and strategic complexity. *Complex Social and Behavioral Systems: Game Theory and Agent-Based Models*, pages 639–658, 2020.

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

N. A. Christakis and J. H. Fowler. *Connected: The surprising power of our social networks and how they shape our lives.* Little, Brown Spark, 2009.

J. S. Coleman. *Foundations of social theory.* Harvard university press, 1994.

J. Conlisk. Costly optimizers versus cheap imitators. *Journal of Economic Behavior & Organization*, 1(3):275–293, 1980.

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.

M. H. DeGroot. Reaching a consensus. *Journal of the American Statistical Association*, 69(345):118–121, 1974.

J. S. Duesenberry. *Income, Saving and the Theory of Consumer Behaviour.* Cambridge: Harvard University Press, 1949.

R. J. Emerson. Social exchange theory. *Annual Review of Sociology*, 2:335–362, 1976.

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

E. Eyster and M. Rabin. Cursed equilibrium. *Econometrica*, 73(5):1623–1672, 2005.

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

L. Freeman. Centrality in social networks: I. Conceptual clarification. *Social Networks*, 1: 215–239, 1979.

D. Friedman, S. Huck, R. Oprea, and S. Weidenholzer. From imitation to collusion: Long-run learning in a low-information environment. *Journal of Economic Theory*, 155:185–205, 2015.

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.

B. Golub and M. O. Jackson. Naive learning in social networks and the wisdom of crowds. *American Economic Journal: Microeconomics*, 2(1):112–149, 2010.

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

M. Granovetter. Economic action and social structure: The problem of embeddedness. *American journal of sociology*, 91(3):481–510, 1985.

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.

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.

H. Ohtsuki, C. Hauert, E. Lieberman, and M. A. Nowak. A simple rule for the evolution of cooperation on graphs and social networks. *Nature*, 441(7092):502–505, 2006.

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

A. Rubinstein. *Modeling bounded rationality*. MIT press, 1998.

K. Schlag. Why imitate, and if so, how? a bounded rational approach to multi-armed bandits. *Journal of Economic Theory*, 78:130–156, 1998a.

K. H. Schlag. Why imitate, and if so, how?: A boundedly rational approach to multi-armed bandits. *Journal of economic theory*, 78(1):130–156, 1998b.

K. H. Schlag. Which one should i imitate? *Journal of Mathematical Economics*, 31(4): 493–522, 1999.

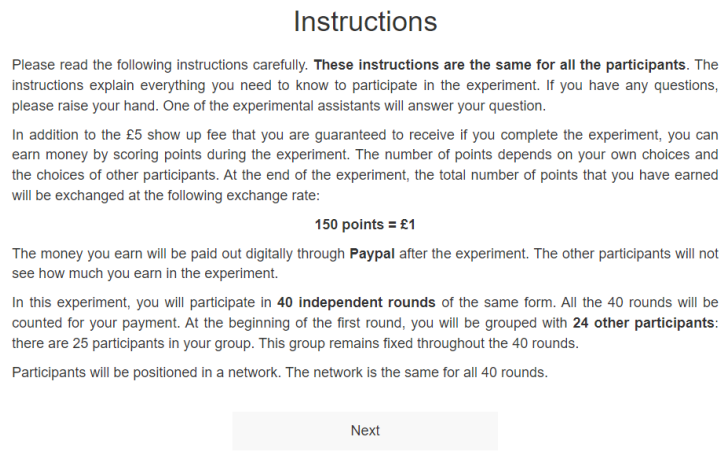
D. O. Stahl and P. W. Wilson. On players' models of other players: Theory and experimental evidence. *Games and Economic Behavior*, 10(1):218–254, 1995.

F. Vega-Redondo. The evolution of walrasian behavior. *Econometrica: Journal of the Econometric Society*, pages 375–384, 1997.

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

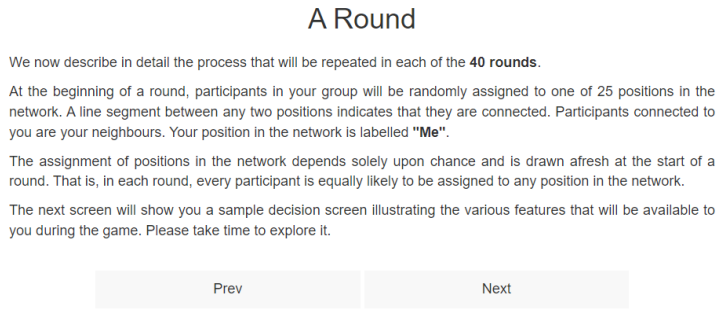
The money you earn will be paid out digitally through **Paypal** after the experiment. The other participants will not see how much you earn in the experiment.

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"**.

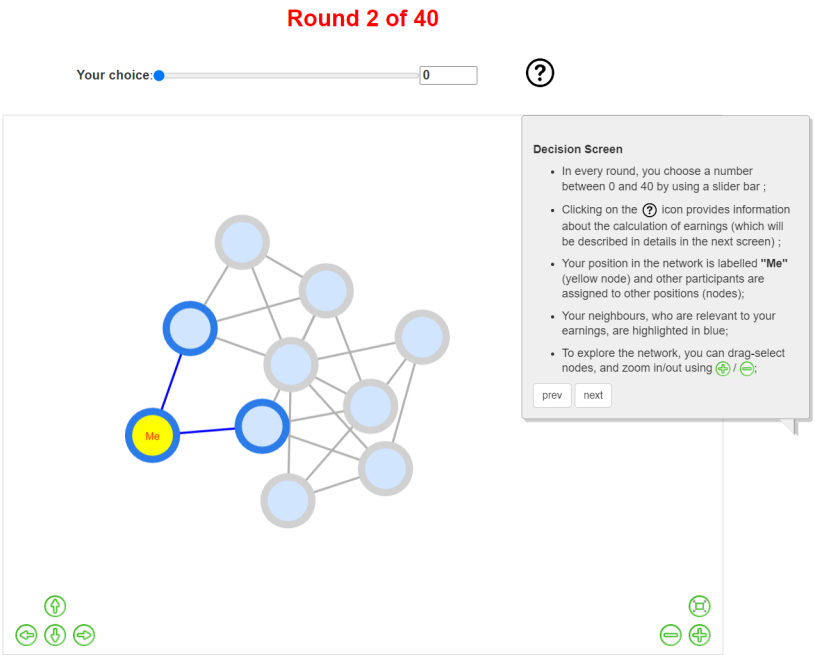
The assignment of positions in the network depends solely upon chance and is drawn afresh at the start of a round. That is, in each round, every participant is equally likely to be assigned to any position in the network.

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.

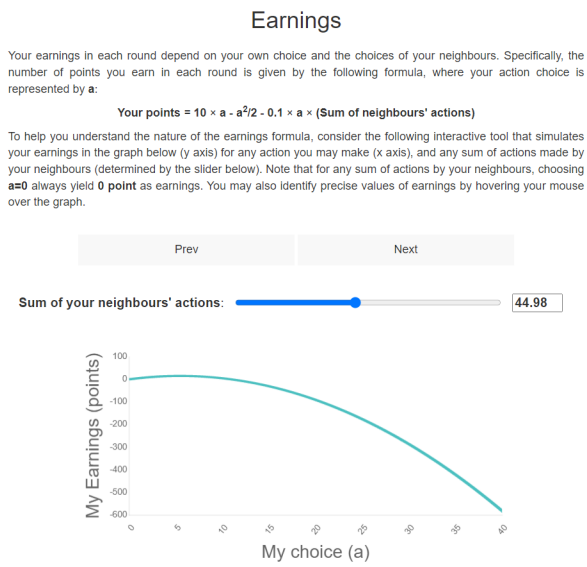
Prev Next

(b) Screen 2

Figure 10: Main instructions (ER substitutes treatment)



(a) Screen 3



(b) Screen 4

Figure 11: 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.

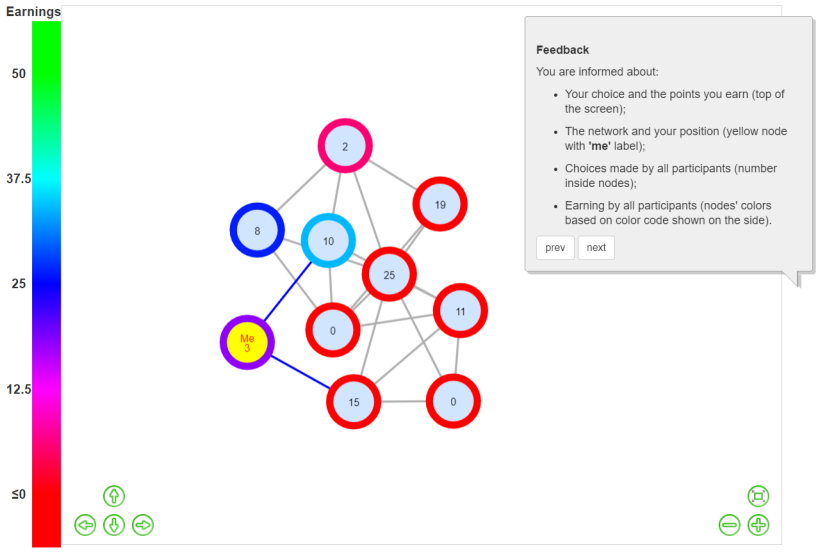
Prev | Next

(b) Screen 6

Round 2 of 40

Your choice: **a=3**

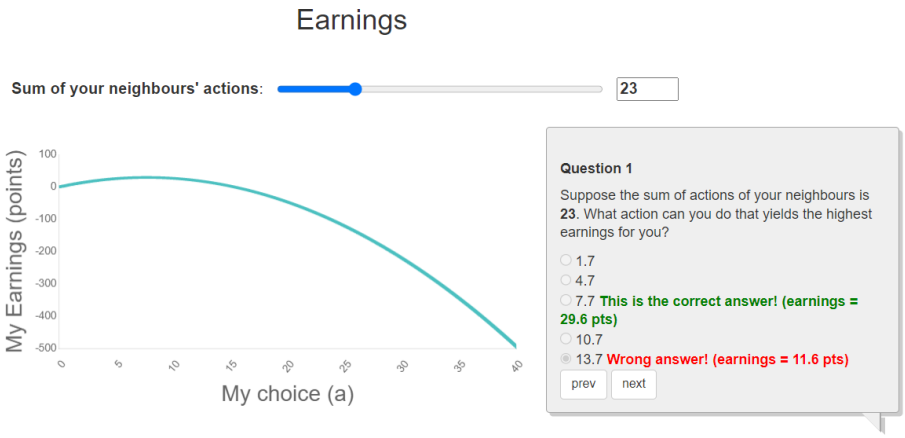
Your earnings: **18 points**



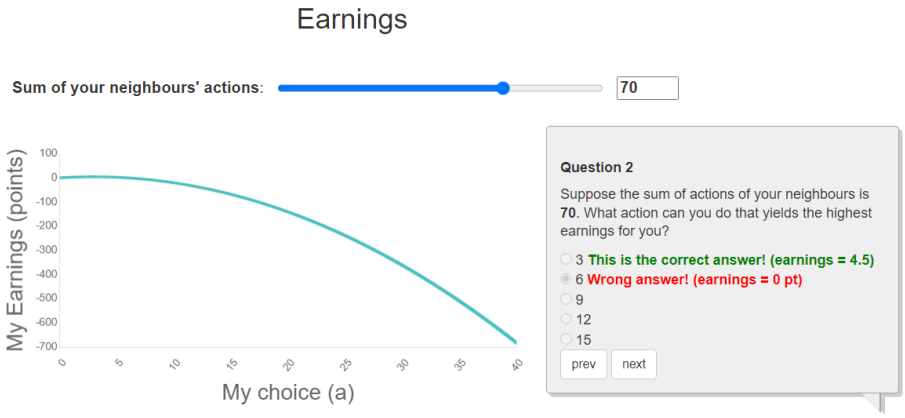
(c) Screen 7

Figure 12: Main instructions (ER substitutes treatment, Cont.)

A.2 Tutorial



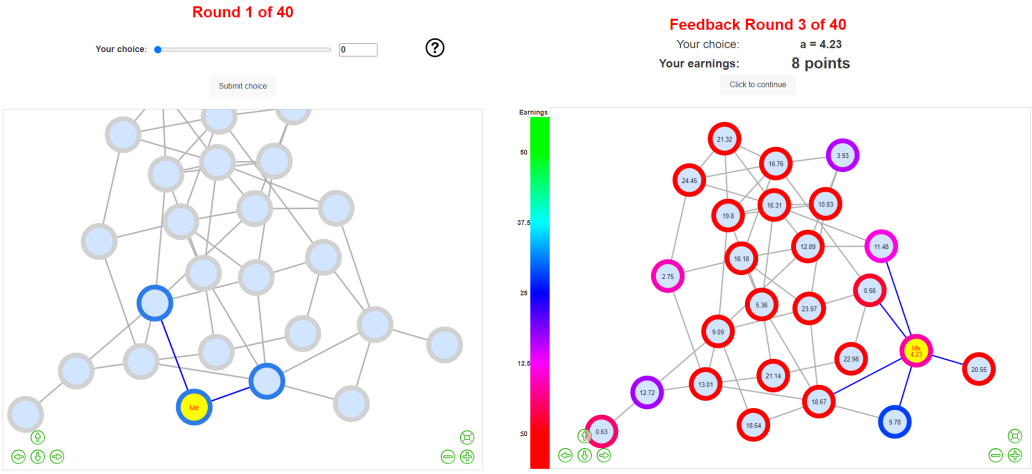
(a) Screen 1



(b) Screen 2

Figure 13: Comprehension questions (ER substitutes treatment)

A.3 Game interface



(a) Decision screen

(b) Feedback screen

Figure 14: Illustrations of game interface (ER substitutes treatment)

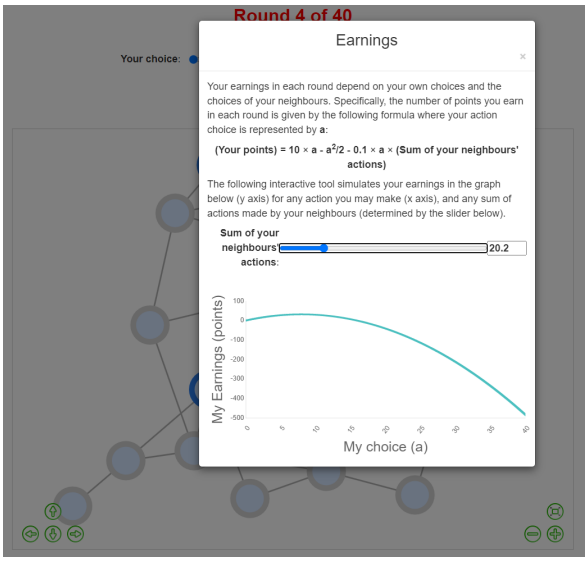


Figure 15: Help screen during the experiment

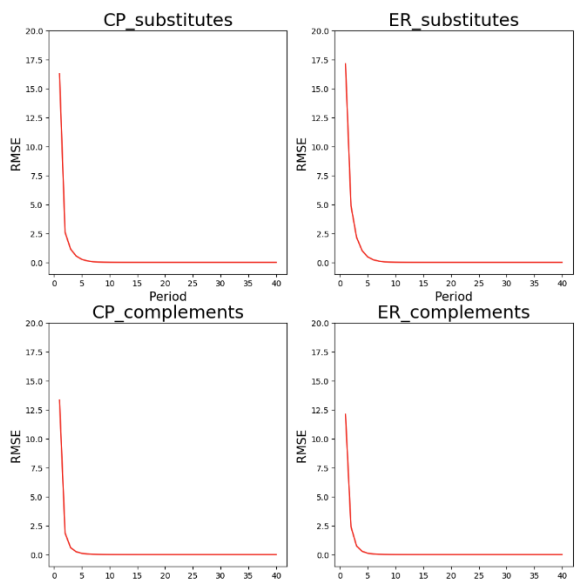
B Additional Experimental Findings, Behavioural Models and Results

B.1 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 $t-1$. We simulate this process. 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 16 in the appendix plots the dynamics of the best response dynamics against the Nash equilibrium based on 1000 simulations in each treatment (the value for each period represents the mean across the 1,000 simulations).

Figure 16: Best response dynamics



RMSE measures the distance between choices generated by best response dynamics $s_{i,t}^B$ and the theoretical prediction s_i^*: $\text{RMSE}_t = \sqrt{\frac{\sum_{i=1}^{N}(s_{i,t}^B - s_i^*)^2}{N}}$. RMSE is widely used as a measure of the discrepancy between predicted values and target values.

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

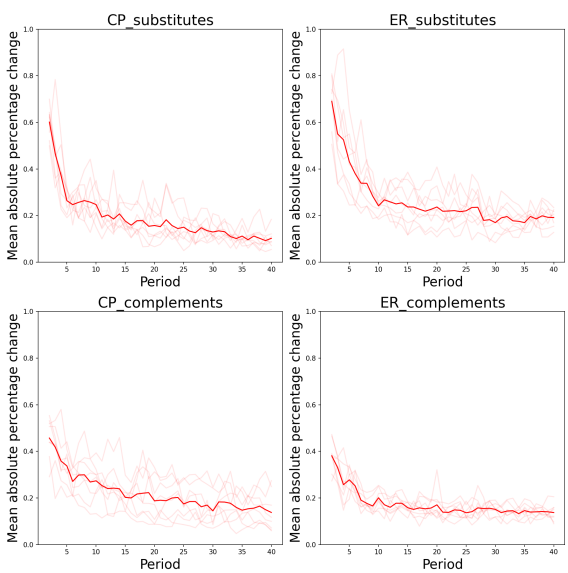
B.2 Convergence of actions

This section elaborates on our discussion on the dynamics of subjects' choices and provides a more formal analysis of convergence of actions. 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:

$$\begin{aligned} MAPC_{grp,t} &= \frac{\sum_{i=1}^{25} |s_{i,grp,t} - s_{i,grp,t-1}|}{\sum_{i=1}^{25} |s_{i,grp,t-1}|} \\ MAPC_t &= \frac{\sum_{grp=1}^{8} MAPC_{grp,t}}{8} \end{aligned} \tag{9}$$

The light red curves in Figure 17 plot the time series of $MPAC$ for each group (i.e., $MAPC_{grp,t}$), while the bold red curves plot the MAPC averaged across groups (i.e., $MAPC_t$).

Figure 17: Change of choices



In particular, the mean absolute percentage change (MAPC) are below 20% in the last ten periods for all the treatments. Our analysis will focus on these last ten periods.

B.3 Regression Tables

Table 3 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 3: 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 4 shows Random effect regressions of individual action level on centrality (or equilibrium choice) in the last 10 periods. Those results are consistent with Table 3.

Table 4: Panel Regression of Choice on Equilibrium

	CP sub	CP com	ER sub	ER com
centrality*	0.878***	0.675***	0.688***	0.631***
	(0.011)	(0.011)	(0.023)	(0.018)
constant	1.151***	4.479***	2.590***	8.927***
	(0.107)	(0.215)	(0.179)	(0.352)
N	2000	2000	2000	2000
R^2	0.7524	0.6429	0.3154	0.3809

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

In order to explain individual behavior in the experiment, we run random effects regressions predicting individual choices based on choices specified by specific individual decision

Table 5: Random Effects Regression of Individual Choice on Predictors

	CP sub	CP com	ER sub	ER com
Best Response	0.061	-0.006	0.254***	0.236***
	(0.035)	(0.031)	(0.027)	(0.017)
Imitation	0.603***	0.924***	0.476***	0.548***
	(0.039)	(0.042)	(0.035)	(0.023)
Constant	3.093***	1.609***	2.204***	4.405***
	(0.126)	(0.249)	(0.196)	(0.294)
N	7800	7800	7800	7800
R^2	0.237	0.457	0.111	0.303

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

models. Specifically, we consider a best response decision model according to which an individual is expected to choose an action at period t that is a best response to actions by neighbours at period $t-1$. We also consider the imitation model described in the paper. The results reported in Table 5 show that the imitation choice has a significantly positive coefficient in all the treatments and have a stronger explanatory power for the imitation model than the best response model.

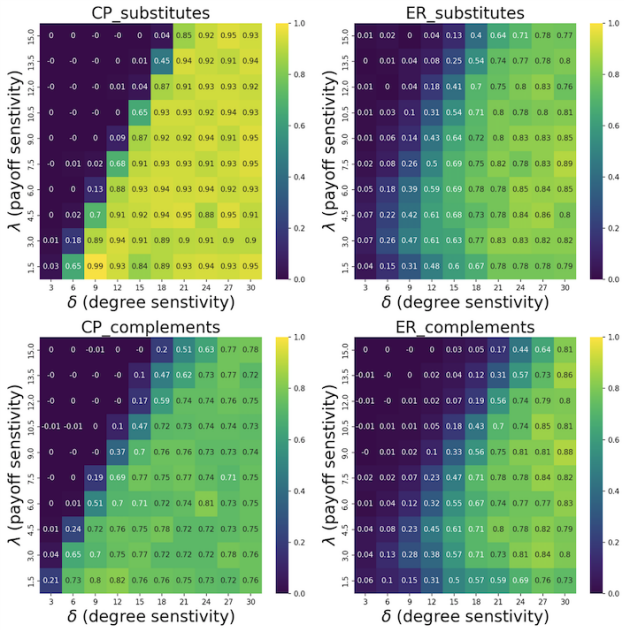
Finally, Table 6 compares the relationship between choice and centrality as measured in the experiment through the corresponding coefficient in the group-level regressions reported above (see Table 3), and the same coefficient measured through simulations based on the imitation model. Only the last 10 periods are considered for both the experimental data and the imitation simulation. This analysis shows a close match between simulations and subjects' behavior in the experiment.

Table 6: Slope of choice on equilibrium

Treatment	experimental data	imitation
CP substitutes	0.883***	0.932***
	(0.015)	(0.001)
CP complements	0.667***	0.746***
	(0.012)	(0.001)
ER substitutes	0.679***	0.664***
	(0.045)	(0.026)
ER complements	0.650***	0.501***
	(0.030)	(0.020)

Notes: *** represents $p < 0.001$

Figure 18: Slope for different parameter values (estimated noise)



B.4 Simulations of the imitation model

In Figure 18 where we take the level of (time-variant) noise estimated from the data, we report an estimated slope coefficient from the regression of simulated actions on centrality in each different pair of (δ, λ). In Figure 19– 20, the noise level is 3, and 5, respectively. 100 simulations are conducted for each pair of (δ, λ).

We next compare the dynamics of choice under best response and imitation rule: We simulate the dynamics of choices when individuals choose different behavioral models, and compare it with subjects' choices from the experiment. We consider the myopic best response model and the imitation model presented earlier at any period t given the choices of others at period $t-1$. For each model, we run 1,000 simulations (in period 1, we assume individuals make decisions uniformly at random). Figures 21 and 22 plot the corresponding time series for each treatments when averaging across individuals from the same category (based on similar centrality, as specified above).

Figure 19: Slope for different parameter values ($\sigma = 3$)

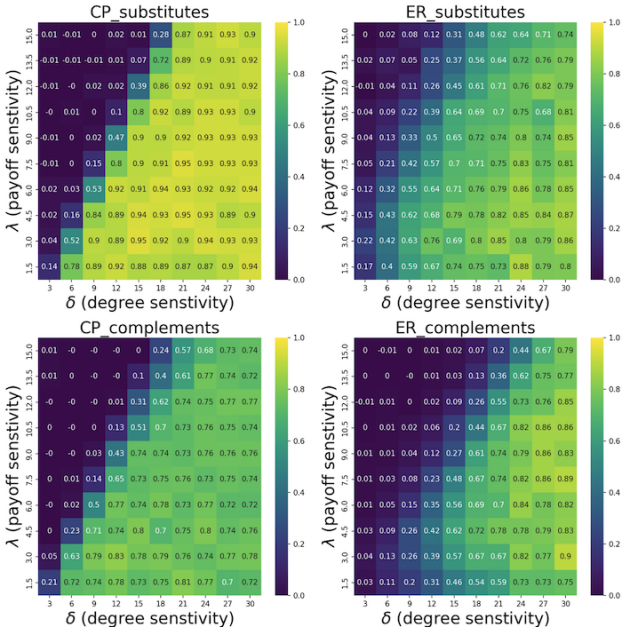


Figure 20: Slope for different parameter values ($\sigma = 5$)

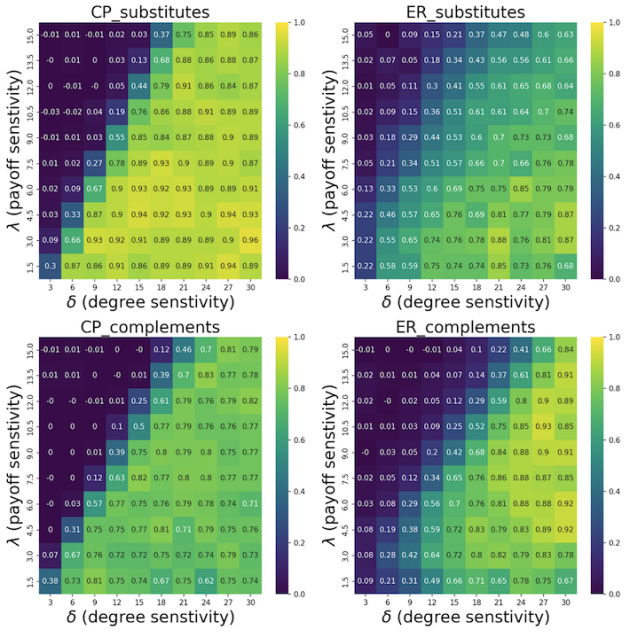
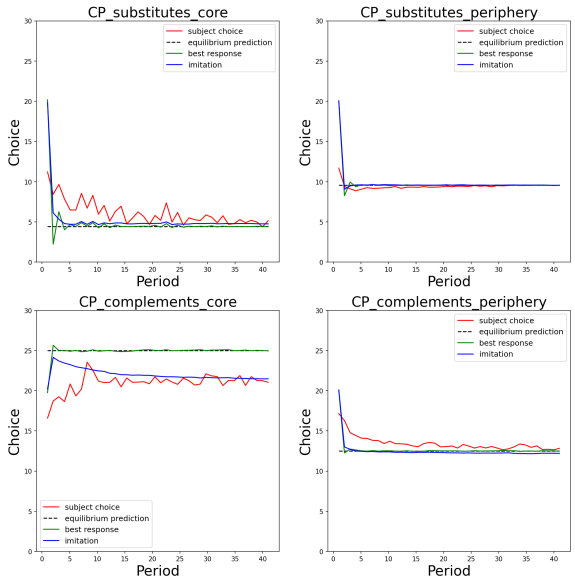


Figure 21: Time series of subject and simulated choices in the CP network



B.5 Alternative Behavioural Models

B.5.1 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 $m \in [0, 40]$ where m 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:

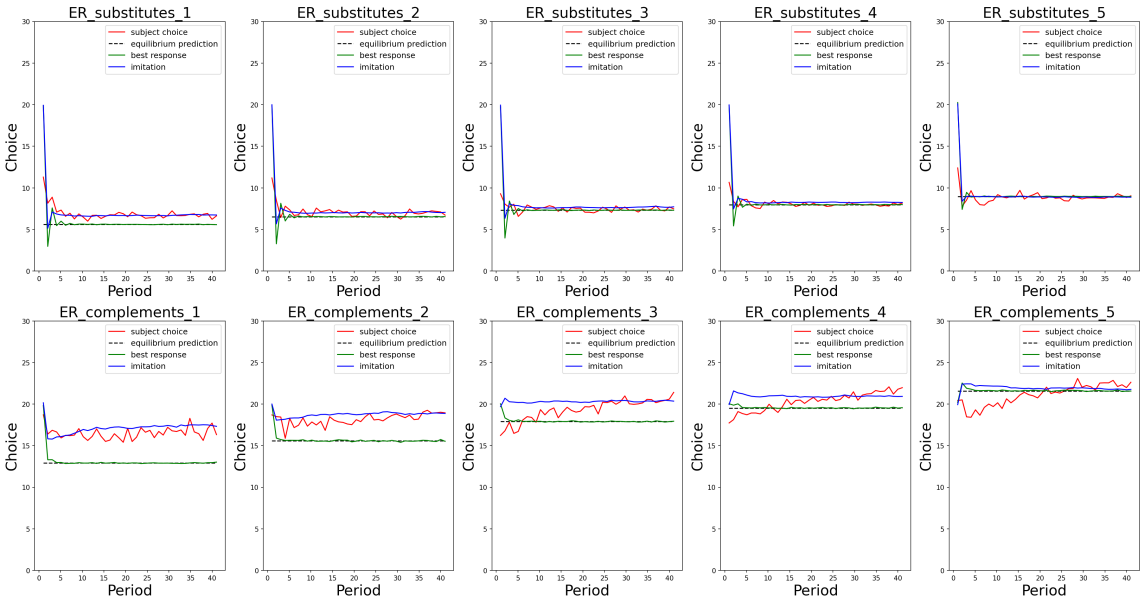
level k: $\hat{\mathbf{s}}^{l_k} = \mathbf{b} + \beta G \mathbf{s}^{l_{k-1}}$ and $\mathbf{s}_i^{l_k} = \max(\min(\hat{\mathbf{s}}_i^{l_k}, 40), 0)$ for each $i \in N$

In the level-k model, each individual makes a best response to the level-(k-1) action profile, represented by $\mathbf{b} + \beta G \mathbf{s}^{l_{k-1}}$. Because the behaviours of level-k individuals depend critically on the behaviour of level-0 agent m, we vary the value of m in the simulation exercise below.

In relation to our treatments, if an individual's action falls below 0, we truncate it to 0; if it exceeds 40, we cap it at 40. This adjustment is because the permissible range of choices in our experiment lies between 0 and 40.

Figure 23 shows the slope coefficient of choice on Nash for each value of k and the

Figure 22: Time series of subject and simulated choices in the ER network



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.

B.5.2 Best response to the average

Instead of making best response to the choices of the exact neighbours, individuals make best response by anticipating that each of the neighbour plays the average choice level of the population, represented by $\mathbf{s} = \mathbf{b} + \beta G\bar{\mathbf{s}}$. We can write the equilibrium vector for this model as $\mathbf{s}^*_{BA} = \mathbf{b} + \beta G\Pi\mathbf{s}^*_{BA}$, where Π is a 25×25 matrix with each element equal to $\frac{1}{25}$ for calculating the average action.

The blue dots in Figure 24 show the choice of best response to the average for each centrality value. It shows that this model does not consistently generate flat relationship between choice and centrality.

Figure 23: Slope for different k and level-0 action

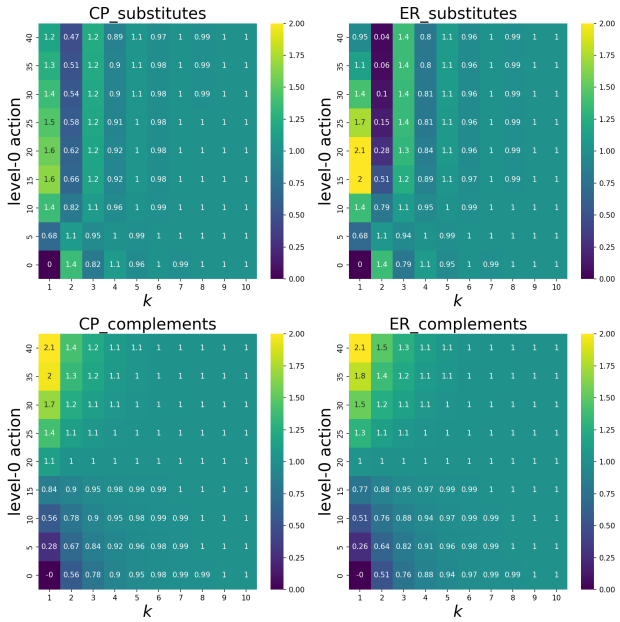
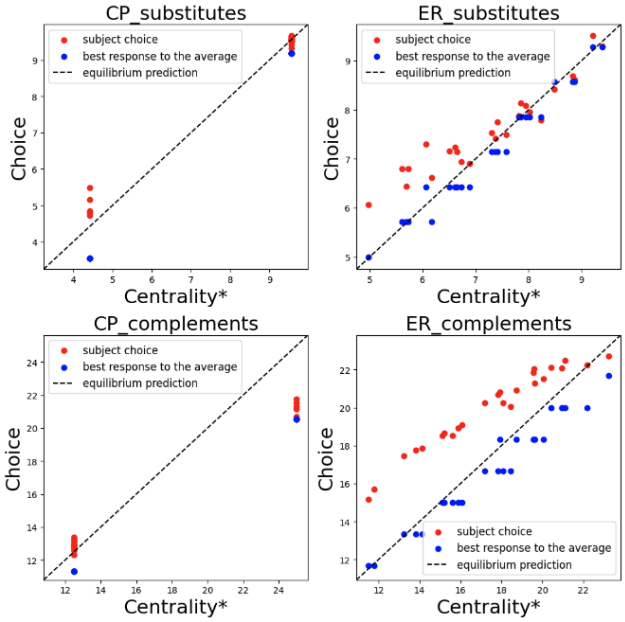


Figure 24: Choice vs. centrality for best response to the average



C Extrapolation

In this section we present our results when we extrapolate behaviour beyond the experimental setting by increasing group size up to 100 and considering an alternative network structure, scale-free networks, that is widely studied in the literature (e.g., Barabási and Albert [1999]). The standalone benefits are kept fixed at 10 (as in the baseline experiments). When we increase the group size of core-periphery networks, we hold constant the ratio of the number of core neighbours to that of periphery neighbours from the core player's perspective. For Erdos-Renyi networks, the linking probability is $p = \frac{1}{6}$, 0.12, and 0.08 for $n = 25$, 49, and 100, respectively. These linking probabilities are chosen to ensure that there is no isolated node in the Erdos-Renyi network. Regarding scale-free networks, we generate them according to the Barabási–Albert preferential attachment model (Barabási and Albert [1999]) where the number of edges to attach from a new node to existing nodes is set to one for all group sizes.

Figures 25 - 27 present the results of simulations across different group sizes in the three different network structures including scale-free network. The network for a given setting is fixed across the 1,000 simulations.

Figure 25: Imitation choices (core-periphery network)

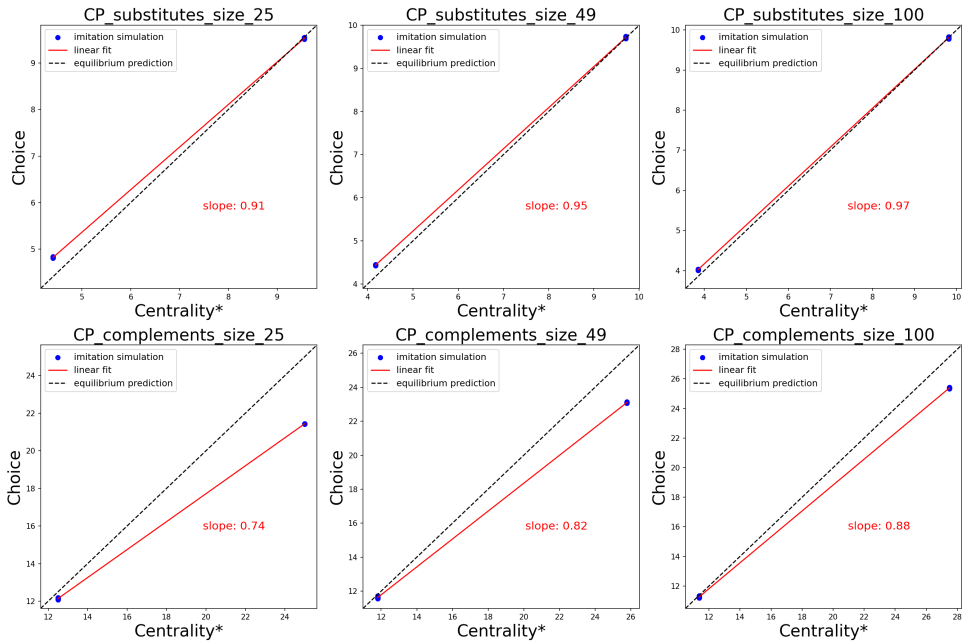


Figure 26: Imitation choices (Erdos-Renyi network)

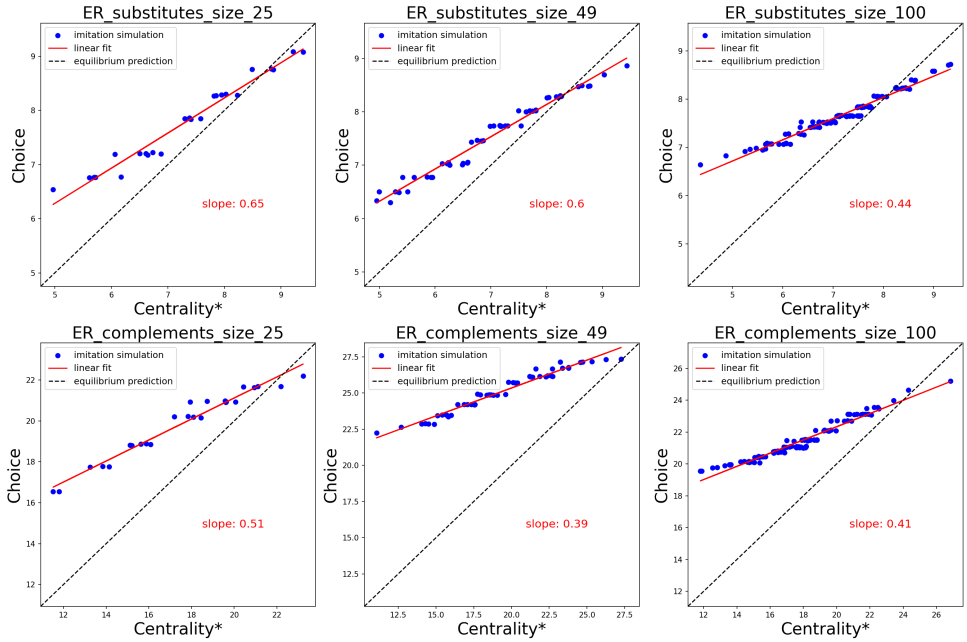
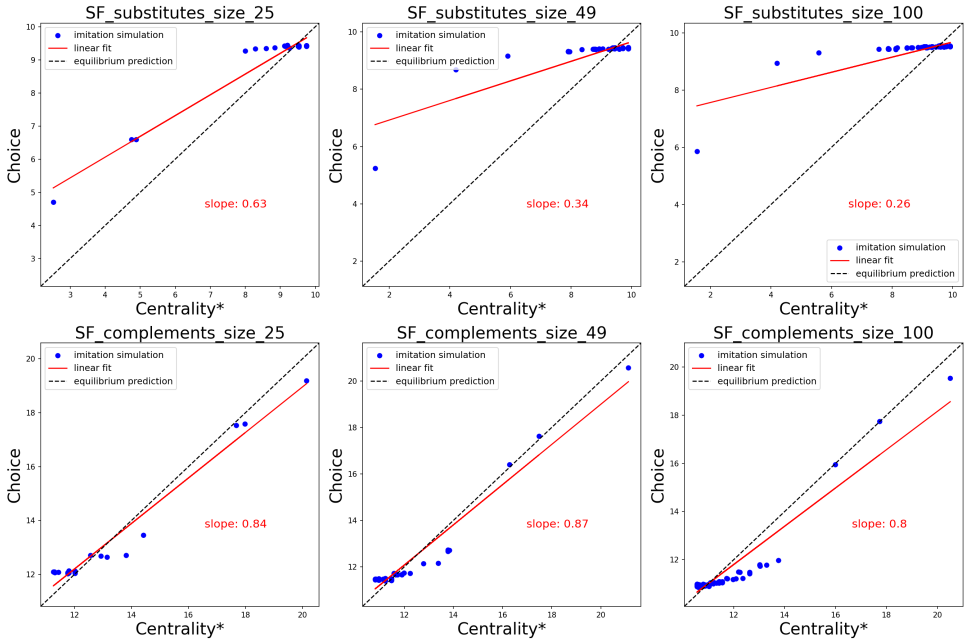


Figure 27: Imitation choices (scale free network)



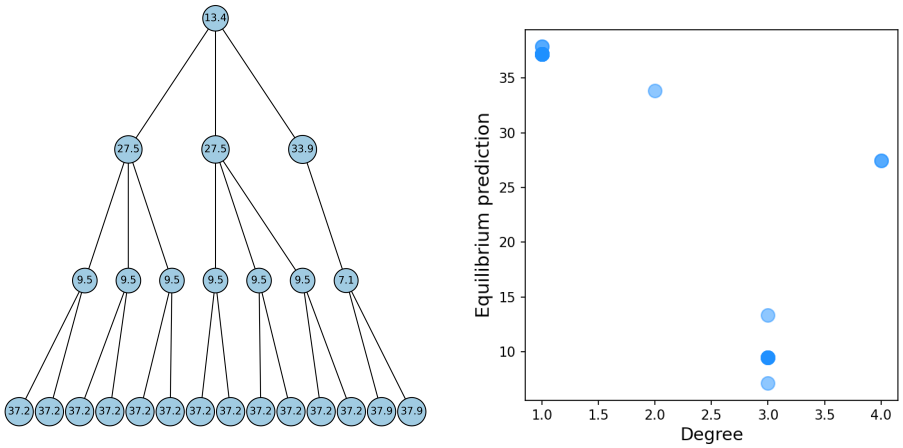
D Additional treatments

D.1 Tree network

In both the core-periphery and Erdos-Renyi networks, the equilibrium effort (centrality) level shows a roughly monotonic relationship with degrees. That is, in the complements (substitutes) scenario, high-degree nodes tend to have a larger (lower) equilibrium effort level than low-degree nodes. To explore whether individuals consider indirect network-based influences when making their decisions, we create two tree networks depicted in Figures 28 and 29, which show that there exists non-monotonicity between centralities and degrees. Under strategic substitutes, the equilibrium action does *not* monotonically decrease with degrees: degree-3 agents have lower equilibrium effort levels than degree-4 agents. Conversely, under strategic complements, centrality and hence equilibrium action does *not* monotonically increase with degrees: degree-3 agents have higher equilibrium effort levels than degree-4 agents. 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

Figure 28: Equilibrium in a tree network under strategic substitutes



(a) Network

(b) Equilibrium prediction vs. degree

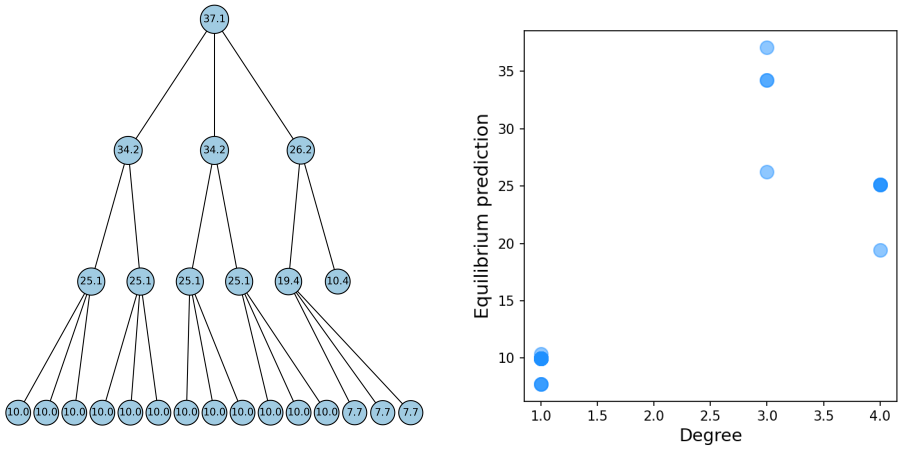
complements to $b = 0.15$ and $\beta = 0.39$. These parameters are designed to generate non-monotonicity in the relationship between centrality and degree.

Figure 30 presents the time series of choices for different positions in the tree network. The 25 network positions are grouped into five categories based on the increasing order of their equilibrium choice. For instance, the leftmost figure on the top displays the five nodes with the five lowest equilibrium prediction under strategic substitutes in the tree network. The black dashed line represents the average equilibrium prediction of the five nodes for each category. The dark red curve depicts the time series of the average choice for all nodes in the same category across all sessions. The light red curve shows the time series of the average choice for all nodes in the same category, for each session separately.

Figure 31 shows the average subject choice in the last ten periods for each network position in the tree treatments. Similarly 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. Figure 32 show the fittings of the network-based imitation model in the tree treatments.

Degree vs. centrality We investigate whether subjects' choices in the experiment are predicted by their Bonacich centrality, as predicted by theory, or if they correlate with their degree in the network.

Figure 29: Equilibrium in a tree network under strategic complements



(a) Network

(b) Equilibrium prediction vs. degree

Figure 30: Time series of choices in the tree network

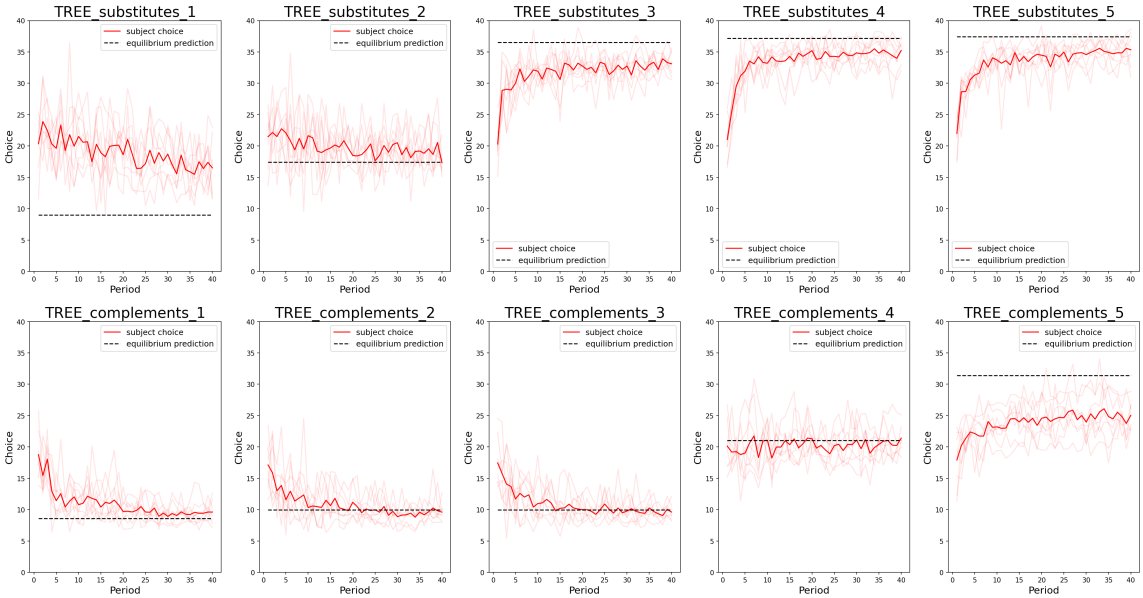
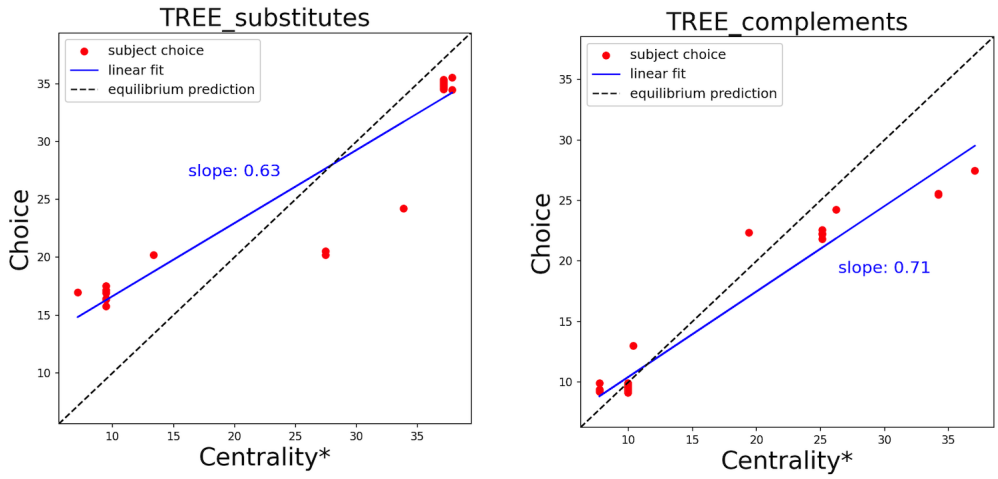
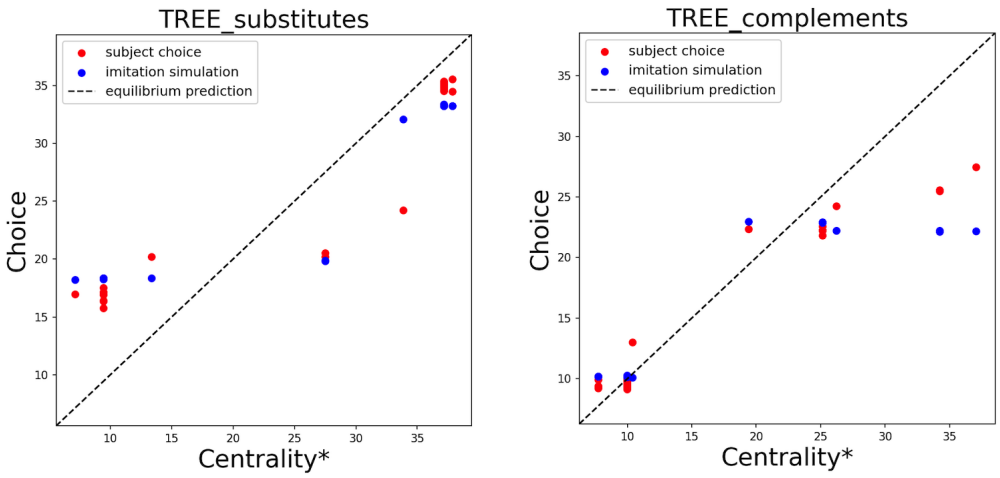


Figure 31: Choices vs. equilibrium prediction



(a) Tree substitutes (b) Tree complements

Figure 32: Imitation Simulation



(a) Tree substitutes (b) Tree complements

The CP and ER networks do not allow us to address this question as there exists a roughly monotonic relationship between centrality and degree.

Recall that in the tree network under strategic substitutes, there exists non-monotonicity between centrality and degree as the three degree-3 nodes have lower centralities than the unique degree-4 node. We conduct one-sided Wilcoxon Signed-Rank test against the three pairs for the last 10 periods. The result shows that two of the degree-3 positions indeed have significantly lower choices than the degree-4 position ($p < 0.05, N = 8$).

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

This analysis reveals a non monotonic relationship between subjects' choices and degree, suggesting that subjects' choices are more sensitive to centrality than degree, as predicted by theory.

D.2 Fixed network position

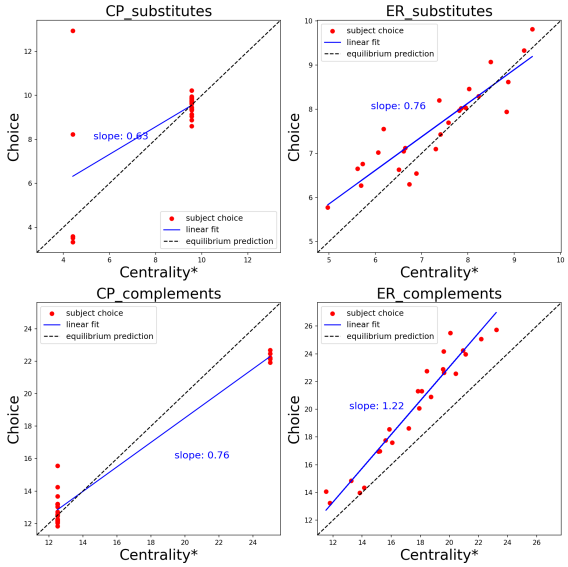
In the baseline setting, individuals' positions are randomly shuffled after each round, and the outcomes show that choices deviate from Nash equilibrium significantly. To examine whether reducing the complexity of learning may result in better convergence and alignment to Nash equilibrium, we consider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

Table 7 shows that subject choices are more stable in the last ten periods of the game compared to the baseline experiment in all the four treatments. Despite the improved convergence of actions, notable deviations from Nash equilibrium still appear in this fixed position treatment, as shown in Table 8 and Figure 33(a). The match with Nash equilibrium is only slightly better than in the baseline experiments for three out of four treatments and is worse in the core-periphery network with strategic substitutes.[12]

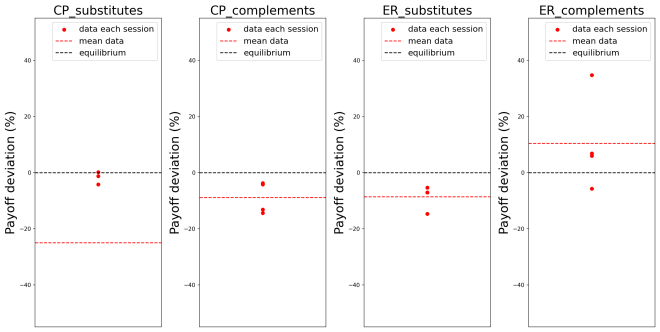
Figure 33(a) presents the relation between predictions and subjects' actions in the fixed position setting. It shows that the slope coefficient of centrality on actions is positive but strictly lower than 1 in three treatments, except in the Erdos-Renyi network with strategic

[12] 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).

Figure 33: Theoretical Predictions and Subjects' Behaviour in the Fixed Position Setting



(a) Subjects' actions



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average action chosen by subjects in the last 10 periods of a given network position, averaged across the four sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the action level. The 45-degree black dashed line represents the values where the action level equals the equilibrium prediction. The blue line is a linear OLS fit of the subject actions on theoretical prediction. (b) A red dot represents the percentage deviation of mean subject payoff (from mean equilibrium payoff) in the last ten periods for a given session. The red dashed line represents the average outcome across the four sessions. Due to space limitations, the figure does not show the result of one (outlier) group in the core-periphery network with strategic substitutes, which has a payoff deviation of -94.7%.

complements whose coefficient is larger than 1.[13] 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 average payoff individuals obtained as shown in Figure 33(b) is similar to the baseline setting: (average) payoffs are lower than the predicted payoffs in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments. The (average) payoff is larger than the predicted payoff in the Erdos-Renyi network with strategic complements.

To conclude, the outcomes in the fixed network position treatment are broadly consistent with the baseline outcomes, with the main exception being that the relationship between choice and centrality in the Erdos-Renyi network with strategic complements is not flatter than theoretical prediction. To explain this, note that in the imitation model we developed, one important drive of flat relationship is the learning from people in similar but different network positions. When positions are fixed, individuals may put more emphasis on learning from one's own past experiences instead of mimicking others. Intuitively, this may result in larger difference in action among individuals and thus sharper relationship between choice and centrality as compared to the baseline experiment. We leave the development of the learning model based on own experience to future work.

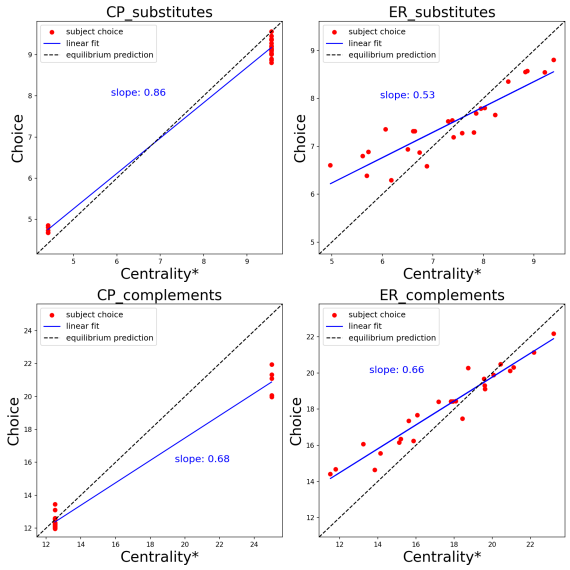
D.3 Limited information on payoffs

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. When players do not observe others' payoffs this limits their ability to imitate actions of others based on relative performance. We aim to examine whether this change will induce players to conduct best response and thus lead to better match with Nash equilibrium.

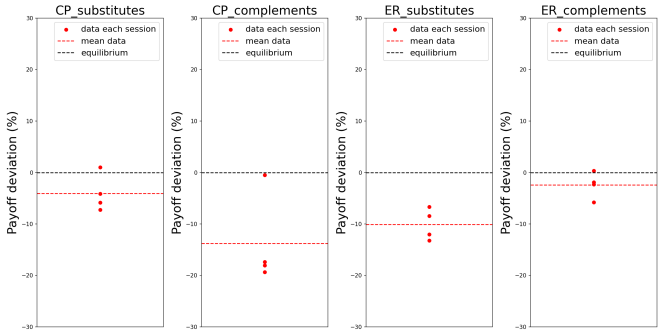
Table 7 shows that the rate of convergence is slower than the baseline treatment and this is in line with our hypothesis. However, as shown in Table 8, the match of average

[13] The slope coefficient using median data for each network position is approximately one in the core-periphery substitutes and Erdos-Renyi complements cases, and is smaller than one in the other two treatments. These differences are caused by outlier behaviors of some individuals on specific network locations.

Figure 34: Theoretical Predictions and Subjects' Behaviour



(a) Subjects' actions



(b) Payoffs

Notes: (a) $Centrality^* = Centrality \cdot b$, which is equal to Nash equilibrium. Each red dot represents the average action chosen by subjects in the last 10 periods of a given network position, averaged across the eight sessions. The x-axis represents the Bonacich centrality * b and the y-axis represents the action level. The 45-degree black dashed line represents the values where the action level equals the equilibrium prediction. The blue line is a linear OLS fit of the subject actions on theoretical prediction. (b) A red dot represents the percentage deviation of mean subject payoff (from mean equilibrium payoff) in the last ten periods for a given session. The red dashed line represents the average outcome across the eight sessions.

Table 7: Change of choices

	baseline	fixed position	limited information
CP substitutes	0.11	0.06	0.18
CP complements	0.16	0.08	0.18
ER substitutes	0.19	0.09	0.24
ER complements	0.14	0.07	0.17

Notes: The table presents the mean absolute percentage change (MAPC) of choice in the last ten rounds for each treatment. Specifically, for each group grp and each period $t \geq 2$, $MAPC_{grp,t} = \frac{\sum_{i=1}^{25} |s_{i,grp,t} - s_{i,grp,t-1}|}{\sum_{i=1}^{25} |s_{i,grp,t-1}|}$ and the reported $MAPC$ is averaged across groups and last ten periods.

Table 8: Deviation from Nash

	baseline	fixed position	limited information
CP substitutes	0.10	0.20	0.16
CP complements	0.13	0.11	0.13
ER substitutes	0.16	0.13	0.18
ER complements	0.19	0.18	0.13

Notes: The table presents the mean absolute percentage deviation (MAPD) of choice to Nash equilibrium in the last ten rounds for each treatment.

behaviour with equilibrium prediction is better for some treatments and worse for others, as compared to the baseline experiment. The relationship between predictions and subjects' actions, as shown in Figure 34(a), is similar to that in the baseline setting in three out of four treatments and is flatter in the Erdos-Renyi substitutes case. As in the baseline setting, the slope coefficient of centrality on actions is positive but strictly lower than 1 across all treatments.

We next examine whether actions are higher or lower than the prediction, the pattern in the core-periphery complements case aligns with that of the baseline treatment, while the action levels in the other cases are (slightly) smaller than those in the baseline setting. 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 actions.

The impact of network complexity on individual action mirror those observed in the baseline case: the slope coefficients in the Erdos-Renyi network are weakly smaller than those in the core-periphery network. Turning to average payoffs, Figure 34(b) shows that

the results replicate those of the baseline in three out of the four treatments. The average payoffs are lower than predicted in the core-periphery substitutes, core-periphery complements, and Erdos-Renyi substitutes treatments. However, 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).

To conclude, the results in the limited payoff information setting are largely consistent with those in the baseline setting. The large deviation in the limited information setting indicates that individuals do not conduct best response and may still imitate others despite the lack of payoff information. Indeed, the imitation of others without payoff information could explain the slightly smaller average action levels observed in the limited information setting for the Erdos-Renyi network as players can no longer imitate those highly-paid players who typically have high equilibrium action level.