

EFFICIENCY AND EQUILIBRIUM IN NETWORK GAMES: AN EXPERIMENT

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Abstract—The tension between efficiency and equilibrium is a central feature of economic systems. We examine this tradeoff in a network game with a unique Nash equilibrium in which agents can achieve a higher payoff by following a “collaborative norm.” Subjects establish and maintain a collaborative norm in the circle, but the norm weakens with the introduction of one hub connected to everyone in the wheel. In complex and asymmetric networks of 15 and 21 nodes, the norm disappears and subjects’ play converges to Nash. We provide evidence that subjects base their decisions on their degree, rather than the overall network structure.

I. Introduction

THE tension between efficiency and equilibrium is a central feature of social and economic systems. In some contexts, efficiency can be achieved and sustained through the establishment of a norm: a prominent example is the provision of a public good where we have abundant empirical (Ostrom, 1990) and experimental (Ledyard, 1995) evidence that individuals manage to coordinate away from the zero contribution equilibrium. Norms are intertwined with a society’s culture and social structure as their sustenance depends on a set of common beliefs and expectations, which are often maintained through social relations.¹ Social structure can also be a key determinant of an equilibrium: recent theoretical research has shown that the position of an individual in a social network is a determinant of equilibrium behavior in many economic contexts.²

Despite the importance of social structure for equilibrium behavior and the establishment of norms, we have scarce evidence of how conducive different social structures are to the establishment and sustenance of a norm in contexts where position in the social structure determines equilibrium play. A primary reason for this gap is the largely unresolved challenge of unambiguously identifying the causal link from position in the social structure to behavior. Experiments are a natural tool to pin down the causal link, but most of the experimental

research on networks in economics focuses on networks that are small in size and/or have a stylized structure, which limits the testing of the rich relation between network position and behavior predicted by the theory.

This paper addresses this gap by investigating experimentally a game of strategic complements played on sizable networks with a nontrivial structure. We have chosen this specific game for three reasons. First, it has a unique Nash equilibrium in which agents’ play is determined by their position in the network: they exert efforts that are proportional to their Bonacich centrality, a metric that captures the number of connections of an agent, her neighbors, her neighbors’ neighbors, and so on. Second, in all the networks we examine, it is possible for agents to achieve payoffs higher than Nash play if everyone coordinates on exerting higher efforts, which we dub a “collaborative norm.” Third, this type of game captures a broad range of phenomena involving collaboration among members of a group with complementary skills, such as teamwork in organizations, criminal activity, and coauthorships in academia.

The experiment consists of playing 40 rounds of the game on a given network structure. In a round each subject is randomly assigned to a different node of the network and picks a level of effort, which can be any integer in the $[0, 100]$ range. There are four treatments that differ in the network to which the subjects are exogenously assigned. Figure 1 illustrates the four networks: a circle network $\mathbf{g}^{\circ}$ and a wheel network $\mathbf{g}^{\otimes}$ with nine nodes each, a 15-node network $\mathbf{g}^{15}$, and a 21-node network $\mathbf{g}^{21}$. We conduct the experiment using *UbiquityLab*: a platform we built to conduct interactive experiments online with a large number of participants.

Our first finding is that in simple networks, subjects are able to establish and maintain a collaborative norm where they exert efforts higher than equilibrium play. In the simple and symmetric $\mathbf{g}^{\circ}$ network, subjects converge to average efforts that are in between the effort predicted by Nash play and the most efficient collaborative norm for the group. As a minimal degree of asymmetry is introduced in the $\mathbf{g}^{\otimes}$ network, the collaborative norm survives but it is weakened: efforts are closer to Nash play than to the most efficient collaborative norm. Finally, in the more asymmetric and complex³ $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks, subjects are unable to sustain any kind of collaborative norm.

The second result is that subjects converge to the Nash equilibrium in all positions of the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks with one exception. In spite of the presence of highly profitable collaborative norms, it is likely that the asymmetry and complexity of the networks make it challenging for subjects to

Received for publication May 26, 2020. Revision accepted for publication August 10, 2021. Editor: Shachar Kariv.

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We thank Marco Felici and Joyce Ong for outstanding research assistance. We are grateful to Stefano Caria, Syngjoo Choi, Vessela Daskalova, Sanjeev Goyal, Margaret Meyer, and Luca Stanca for helpful comments and suggestions. Thanks to seminar participants at the University of Oxford, Cambridge-INET, University of Cambridge, Università degli Studi di Milano-Bicocca, Seoul National University, UC Irvine, University of Essex, and the Psychometrics Center (Cambridge); and to conference participants at the Social Networks and Matching Processes Workshop (CSAE, Oxford), the Learning in Social Networks Workshop (IESE, Barcelona), the Keynes Fund Research Day (Cambridge), and the ESI Autumn Workshop (Max Planck, Jena). Generous research support by the Keynes Fund for Applied Economics in Cambridge, the Balliol Interdisciplinary Institute, and the Oxford-Man Institute of Quantitative Finance is thankfully acknowledged.

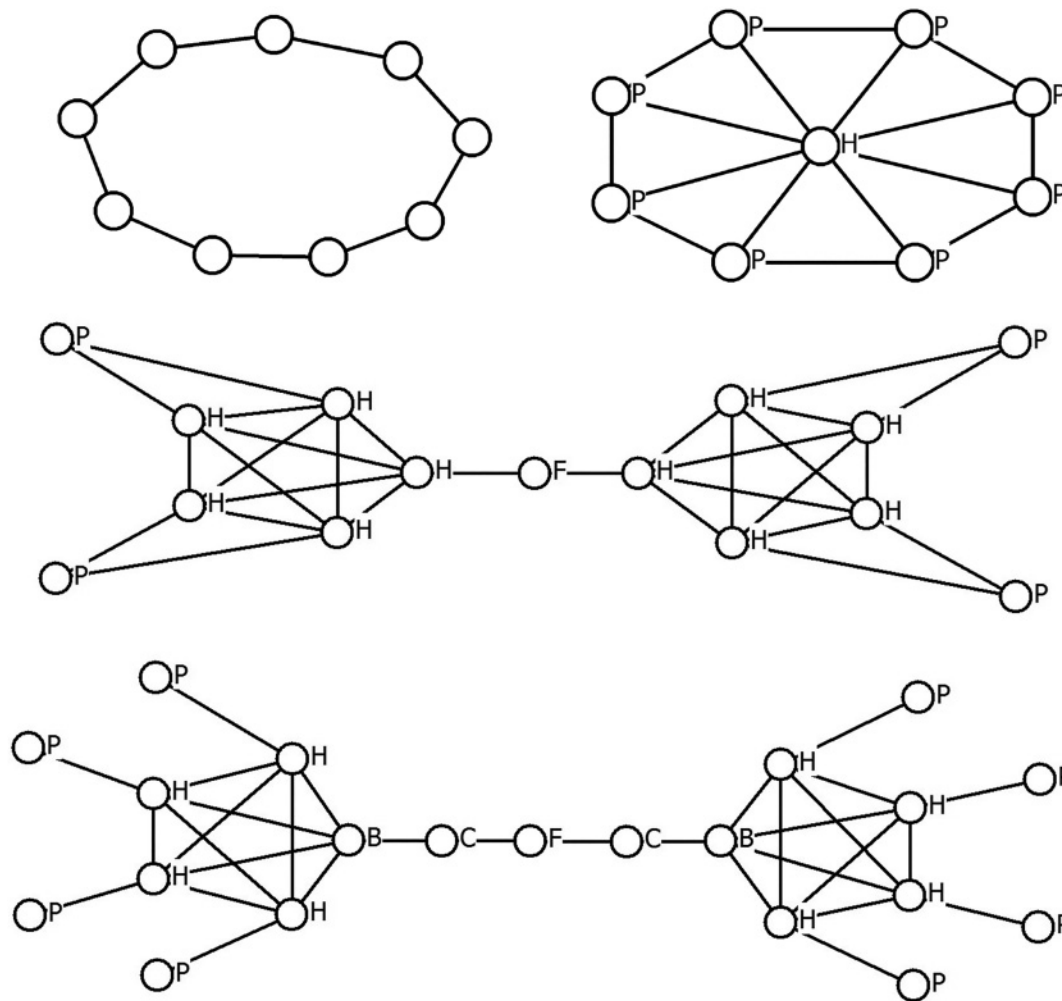
A supplemental appendix is available online at https://doi.org/10.1162/rest_a_01105.

¹See Young (2015) for a comprehensive review of research on social norms in economics.

²See Goyal (2007) and Jackson (2008) for comprehensive reviews.

³Throughout this paper, we use the terms “complex” and “complexity” in a nontechnical fashion to convey the intuitive fact that the structure of networks $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ has more asymmetries than networks $\mathbf{g}^{\circ}$ and $\mathbf{g}^{\otimes}$.

FIGURE 1.—NETWORKS USED IN THE EXPERIMENT



Top left: Circle network g^C with 9 nodes. Top right: Wheel network g^W with 9 nodes. Middle: 15-node network g^{15} with 2 completely connected clusters joined by a single node. Bottom: 21-node network g^{21} with 2 completely connected clusters joined by a chain of 3 nodes.

achieve coordination. It is somewhat remarkable that subjects are able to learn to play the equilibrium given the size of the strategy space and the number of different positions in the network structure. For instance, the g^{21} network has five types of positions and the Nash equilibrium predictions range from 33 to 78. In spite of this complexity, subjects' average efforts on almost all node types in the g^{15} and g^{21} networks are statistically indistinguishable from the Nash predictions.

These findings show that the position in the network structure is highly predictive of subjects' decisions in networks of significant complexity. The full validation of the Nash predictions in these complex networks is somewhat surprising, given the intricate relation between Nash play and position with respect to the overall network structure. It is clear from the data that subjects do not start by playing Nash, so a natural question is how they are able to converge to Nash over time. We investigate the hypothesis that subjects simplify the task by focusing on the local features of the network structure. A natural metric to capture the position in the network using local information is the number of connections, or

degree, which is highly correlated to Bonacich centrality in most networks.

Our third finding is that subjects base their decisions on the degree: the larger the degree is of the node to which they are assigned, the more effort they exert. We specifically designed the g^{21} network to be able to separate play according to degree from Bonacich. Equilibrium play in network g^{21} is such that subjects in node type P (degree 1) exert the same effort as subjects in the central node F (degree 2), and a lower effort than subjects assigned to node type C (degree 2) that is a neighbor of F . In the data we observe that subjects' play in node types P and C is indistinguishable from Nash, but subjects in the central node F choose an effort that is higher than the effort in node type P and indistinguishable from the effort in node type C , as expected if they based their decision on degree. Moreover, in a panel regression analysis, if we restrict the attention to nodes P , C , and F , then only degree remains a significant predictor of subjects' choices. Thus, in this context, it suffices to have information about a simple network metric, the degree of an individual, to predict behavior, rather

than having to collect information about the whole network structure.

These results highlight the importance of going beyond small and stylized networks to investigate how network structure determines behavior. As we will see below, experimental research on networks in economics has so far failed to investigate behavior in a game with a rich strategy space played on large networks with a complex structure. This simplification comes at the cost of largely failing to test the behavioral validity of the relation between a rich network structure and behavior predicted by the theory. We find that in stylized networks with a few nodes and/or asymmetries, such as the circle and the wheel, subjects are able to process the network structure and coordinate on norms of behavior. However, in complex networks with many asymmetries, subjects find it more challenging to achieve the coordination necessary to establish and maintain a norm, and they mainly base their decisions on the local network structure to reduce the cognitive cost of the task of processing complex network information. It is crucial to investigate experimentally the generalizability of these findings to different contexts if we want to give novel input for theoretical work and enhance its behavioral validity.

The remaining part of this section surveys the related literature. Section II presents an overview of the theory. Section III gives the details of the experimental design and lists our hypotheses. Section IV analyzes the experimental data and tests the validity of the hypotheses. Section V concludes. An online appendix contains robustness checks and further analysis, details on the web platform we developed to conduct the experiment, and the screenshots of the instructions for the experiment and the postexperimental questionnaire.

A. Literature Review

The study of whether individuals converge to equilibrium play in various games has been a major theme of inquiry since the beginning of experimental economics. In many contexts, a force that counters convergence to equilibrium play is the emergence of norms that lead to more efficient outcomes. Despite the large body of work along these themes, only recently researchers have turned their attention to how the overall structure of social networks and the position of individuals in the network play a role in mediating the tension between equilibrium play and efficiency. Our paper is a contribution to this more recent literature and it ties the role of social structure to some familiar findings in the experimental literature.

First of all, this paper contributes to examining the impact of asymmetries among individuals on the establishment and sustenance of a social norm. In the extensive experimental literature on public good games, several researchers have investigated the effect of introducing heterogeneity among subjects on the positive contribution norms observed in the benchmark case with homogeneous subjects. Ledyard (1995) surveys several papers and finds that the introduction of heterogeneity in preferences or endowments decreases the level

of contributions. For instance, Rapoport and Suleiman (1993) find that groups where individuals have different endowments are less successful in providing the public good compared to groups where everyone has the same endowment. To our knowledge, our paper is the first one to investigate position in the network structure as a source of asymmetry among agents in the context of the establishment and sustenance of a social norm. Our results on the gradual breaking down of the norm as more complexity, or asymmetry, is added to the network are consistent with results in the literature, albeit in the context of a different game where the role of norms has received little attention before.

Our paper is the first comprehensive experimental investigation of the game of strategic complements on a network in Ballester et al. (2006). The lack of experimental work on this topic is surprising because the causal relation between network position and behavior in this game has been well-understood at a theoretical level since Ballester et al. (2006), which is one of the seminal papers in the network literature in economics. Moreover, this type of game captures a wide range of applications in which social networks matter for behavior, and that have been extensively studied in sociology and other disciplines. Charness et al. (2014) is the most closely related paper in this vein of work. They investigate network games of strategic complements and substitutes, both with complete and partial knowledge of the network, in which the action space is binary. The focus of their paper is a test of the comparative statics predictions in the paper by Galeotti et al. (2010), which introduces incomplete information in network games. Moreover, their choice of binary actions means that all outcomes are corner solutions, which makes it challenging to investigate the rich relation between equilibrium play and network position in the framework of Ballester et al. (2006).

More broadly, this paper contributes to a growing literature in experimental economics investigating games played on exogenously given networks. Selected contributions include bargaining (Charness et al., 2007; Gallo, 2020), trading (Gale & Kariv, 2009; Choi et al., 2017), public goods (Choi et al., 2011; Rosenkranz & Weitzel, 2012), and coordination (Cassar, 2007) games.⁴ A common characteristic of these papers is that they largely focus on small and stylized networks that do not allow an in-depth investigation of the intricate causal relation from network position to behavior.⁵ In contrast, there are three elements in our setup whose combination allows the exploration of this relation: the size of the networks, the presence of asymmetry across nodes, and the large strategy space. To our knowledge, the presence of all three of these elements is a distinctive feature of our paper. Charness et al. (2014) has three treatments with asymmetric networks of a similar size to ours, but the strategy space is

⁴See Choi et al. (2016) for a comprehensive review of the literature.

⁵Outside of economics there is an experimental literature that investigates games played on large networks (e.g., Gracia-Lázaro et al., 2012; Kearns et al., 2006, 2009), but the focus is on the effect of the overall network structure rather than the relation between position in the network and behavior.

binary. Choi et al. (2017) explore large networks, and subjects can choose from a large strategy space, but the networks are highly symmetric. Moreover, our findings show that the analysis of behavior on both stylized and complex networks leads to novel insights compared to an investigation limited to either type.

A recent literature has begun to examine how individuals process information about complex networks and how they use this information to take decisions. Social psychologists have used a survey-based methodology proposed by Krackhardt (1987) to map individuals' cognitive perception of their social environment, and they have identified a variety of cognitive biases (see, e.g., Kumbasar et al., 1994; Casciaro, 1998). In a controlled experimental setting, Dessi et al. (2016) show that individuals utilize heuristics to memorize and recall information about networks of 15 individuals, and this leads to systematic biases. Despite the evidence that individuals resort to heuristics to cope with the complexity of network information, there are still very few studies that investigate how this affects individuals' decisions by analyzing treatments that differ in the degree of network information provided to participants. Two exceptions are Charness et al. (2014), who show that incomplete information about the network structure makes it more difficult to coordinate on an efficient equilibrium, and Gallo and Yan (2015), who show that individuals use information about the whole network to form separate communities in the context of a prisoner's dilemma game with endogenous network formation. In our paper, we do not have treatments with different network information, but we provide evidence that individuals cope with the complexity of the network by basing their decisions on local network information rather than the overall network structure.

In summary, this paper makes four contributions. First, it sheds light on the relation between network structure and the establishment of a social norm that leads to a better aggregate outcome than equilibrium play: the norm emerges and survives in stylized and symmetric networks, but it disappears in more complex networks that generate asymmetries across subjects. Second, it presents the first experimental test of the seminal result in Ballester et al. (2006) for games of strategic complements on a network: the theory turns out to be highly predictive of subjects' choices in complex networks. Third, it increases our understanding of how individuals cope with the complexity of a social structure that matters in their decisions: here they mainly focus on the local rather than the global structure of the network, which explains the single deviation from the Nash predictions that we observe in one of the two treatments with a complex network. Finally, it shows the potential of the novel methodology of interactive online experiments.

II. Theory

The theory underlying this experiment is well-established since the seminal article by Ballester et al. (2006). In this section we provide a brief overview that serves the purposes

of introducing relevant notation, providing intuition for the key result, and briefly mentioning some recent developments.

Consider a set of $N = \{1, \dots, n\}$ agents who are the nodes of a network $\mathbf{g}$. The network is undirected and unweighted⁶ so for any $i, j \in N$ we have that either there is a link $g_{ij} = g_{ji} = 1$, or they are not connected, that is, $g_{ij} = g_{ji} = 0$. Each agent i selects an effort level e_i and obtains utility:

$$u_i(e_1, \dots, e_n) = \alpha e_i - \frac{\beta}{2} e_i^2 + \lambda \sum_{j=1}^n g_{ij} e_i e_j, \quad (1)$$

where $\alpha > 0$ and $\beta > 0$ capture the strength of the idiosyncratic benefits and costs to i from her own effort. Note that these are symmetric across agents and that utility is strictly concave in its own effort. The parameter λ determines the strength of the complementarity effect: the higher λ is, the more higher efforts by i 's neighbors lead to higher incentives for i to increase her effort. This is the key result from Ballester et al. (2006):

Theorem [Ballester et al. (2006)]. *Let $\frac{\lambda}{\beta} \equiv \lambda^* < 1/\mu_1(\mathbf{g})$, where $\mu_1(\mathbf{g})$ is the largest eigenvalue of the adjacency matrix of $\mathbf{g}$, then we have that*

$$\mathbf{e}(\mathbf{g}) = \frac{\alpha}{\beta} \left[\mathbf{I} - \left(\frac{\lambda}{\beta} \right) \mathbf{g} \right]^{-1} \mathbf{1},$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{1}$ is a vector of 1s.

This closed-form solution relates the effort each agent exerts at Nash to the overall network structure. Intuitively, an agent equilibrium's effort increases in how well-connected she is, how well-connected her neighbors are, how well-connected her neighbors' neighbors are, and so on. The complementarity effect determines how much weight the connectedness of neighbors, neighbors' neighbors, etc. has on an agent's equilibrium play. The Nash equilibrium is unique as long as the complementarity effect is below a threshold, because if the complementarity is too high, then the equilibrium play becomes infinite effort.

Bramoullé et al. (2014) extend the result in Ballester et al. (2006) and they show that this is a potential game. Using standard results from the potential game theory literature, it follows that the unique Nash equilibrium is the equilibrium outcome of a best-reply dynamic process of agents playing this game on a network. This suggests that if subjects are randomly matched to play a series of one-shot versions of the game in the lab, then over time if they best-respond to the other subjects' choices they will converge to the Nash equilibrium play.

The uniqueness of the solution and the richness of the dependence of an agent's effort on the network structure makes Ballester et al. (2006) an ideal setting to test the impact

⁶Ballester et al. (2006) consider weighted networks and a more general theoretical framework. Here we limit the exposition to a simplified model that suffices for our purposes and facilitates understanding.

of social network structure on behavior. It also provides an ideal setting to investigate whether Nash-based results that tie network structure to outcomes are behaviorally relevant, or whether the complexity of processing network information may lead to outcomes different from the Nash predictions.

III. Experiment: Design and Hypotheses

The experiment was conducted using UbiquityLab, a novel platform we developed to run online experiments that allows a large number of subjects in different geographical locations to play a game by interacting in real time. The platform is designed to operate independently, although in the experiment in this paper we utilize *Amazon Mechanical Turk (AMT)* as a source of subjects.

In total, 234 subjects participated in the experiment between October and November 2013. We ran a total of 11 meta-sessions, and the number of subjects per meta-session varied from 12 to 60, so there were up to 5 sessions in the same meta-session.⁷ Each session lasted an average of 31 min., and there were 6 sessions for each treatment. The participants were recruited using a 5 min. survey on *AMT*, and section IVA shows that they span a broad range of socioeconomic characteristics. The average earnings for a subject was approximately \$4.79, which is inclusive of a \$1 show-up fee.⁸

After clicking on a URL provided on *AMT*, subjects enter the platform and start reading the instructions. The subjects are obliged to stay a minimum amount of time on each instruction page, and they can go back to previous instruction pages at any time. The first part of the instructions describes the general setup and how to pick a level of effort.⁹ The second part of the instructions includes an in-depth description of how points are computed depending on their decisions and the decisions of their neighbors, as well as two illustrative examples. At the end of the instructions, participants take a quiz that tests their understanding, and they are told in advance that it is necessary to answer the quiz questions correctly to proceed to the experiment. The quiz has three questions that test subjects' understanding of how the points are computed. There is complete anonymity throughout the experiment.

Before the beginning of the experiment, each participant plays a trial on a five-node network that consists of three rounds. In each round of the trial, each participant is assigned

to the same node of the trial network, and the efforts of the neighbors are randomly chosen by the computer. The trial allows the participants to become acquainted with the interface of the experiment, and the time they have to make a decision (20 sec.). In the left part of the screen they see the network with a position highlighted in blue that denotes the node they have been assigned to, and the countdown timer. The top right part of the screen tells participants the one-letter ID of the node they have been assigned to and the IDs of the neighboring nodes in this round. Below there is a slider that allows them to pick their effort level for this round. Once everyone has selected an effort level, the results of the round are displayed in the bottom-right part of the screen.

Participants play 40 rounds of the game on the same network structure, which is always displayed throughout the experiment. In a round, each subject is randomly assigned to a different node of the network, and picks a level of effort that can be any integer in the $[0, 100]$ range.¹⁰ Random re-assignment is the standard methodology in the experimental literature to mitigate repeated game effects, and it allows a clean test of the theoretical predictions. Additionally, it damps down path dependency in the dynamics of play. A potential drawback is that it may be more challenging for participants to coordinate their play, although there is no evidence that this is the case from the extensive experimental literature on public good games (Andreoni & Croson, 2008).

Participants win points in each round depending on their own and their neighbors' choice of efforts, according to the formula in equation (1) with values of (α, β, λ) as below. At the end of a round, each participant is reminded of the network position she was assigned to, the effort level she chose, who were her neighbors, and the number of points she won. She also receives information about the effort choices of her neighbors, but she does not know which effort corresponds to which neighbor as this information is not relevant to compute her payoff. The reason not to give subjects information about everyone's choice of efforts and payoffs is to suppress imitation dynamics, which would be a confounding factor to testing the equilibrium predictions.

At the end of the experiment, the subjects fill in a questionnaire with standard socioeconomic questions, and they take a Holt and Laury (2002) incentivized test to elicit their risk preferences. At the end of the questionnaire, we randomly pick 8 out of 40 rounds and convert the sum of points won in those rounds to the final earnings on top of the fixed \$1 fee.

There are 4 treatments in the experiment that differ in the network to which subjects are exogenously assigned. Figure 1 illustrates the 4 networks used in the experiment: a circle

⁷The size of a meta-session has no impact on the subject's experience. A subject is assigned to a session (i.e., group) and only interacts with the other participants in the same session so the experience is unaffected by the eventual presence of other groups in the same meta-session.

⁸These earnings are above the average per hour earnings for a worker on *AMT* and the US minimum wage. We also estimate that they are comparable to average per hour earnings in lab experiments if one takes into account that online experiments eliminate many of the activities that require subjects' time, such as getting to and leaving the lab location, waiting for late participants, payment of earnings, etc. The online appendix contains further details on UbiquityLab and the experimental instructions.

⁹In the experiment we used the wording "level of activity" rather than "effort" to avoid priming.

¹⁰The choice of any integer in the $[0, 100]$ range to approximate a continuous action space is standard in the experimental literature [e.g., Rosenkranz and Weitzel (2012) adopt the same discretization to test a game of strategic substitutes on a network]. Leung (2020) presents an algorithm to compute the equilibrium set in the model of Ballester et al. (2006) with a discrete action space. In general, this is well approximated by the continuous action space equilibrium as long as the action space is not too coarse and the $\lambda^* < 1/\mu_1(\mathbf{g})$ condition in the theorem in section II holds. Both these conditions hold in the calibration of our experiment.

network $\mathbf{g}^\circ$ with 9 nodes, a wheel network $\mathbf{g}^\otimes$ with 9 nodes, a 15-node network $\mathbf{g}^{15}$ with 2 completely connected clusters joined by a single node, and a 21-node network $\mathbf{g}^{21}$ with 2 completely connected clusters joined by a chain of 3 nodes. In treatments $\mathbf{g}^\circ$, $\mathbf{g}^\otimes$, and $\mathbf{g}^{15}$ we chose parameter values of $\alpha = 20$, $\beta = 1$, and $\lambda = 0.1$. In treatment $\mathbf{g}^{21}$ we chose parameter values of $\alpha = 20$, $\beta = 1$, and $\lambda = 1/6$. The choice of different values of the parameters for $\mathbf{g}^{21}$ is inconsequential for our analysis because we investigate how subjects behave depending on their position within the $\mathbf{g}^{21}$ network, rather than making comparisons with subjects' behavior in the other networks.

The networks in figure 1 have labels that indicate different “types” of nodes.¹¹ Note that we are using a definition of “type” for expository purposes: it does not coincide with the predicted Nash equilibrium play as we want to allow for potential deviations from Nash play for network positions that are equivalent in terms of Nash play but differ in terms of structural features irrelevant to Nash play. An example is the focal node F and the peripheral nodes P in $\mathbf{g}^{15}$: the Nash equilibrium play is the same, but the nodes are classified as different types because, for example, the focal position of F may lead subjects to treat this node differently from the peripheral nodes.

These four networks differ along several dimensions. First, the degree of asymmetry in the network structure, which is quantitatively captured by the number of types. Second, the number of nodes increases from nine in $\mathbf{g}^\circ$ and $\mathbf{g}^\otimes$ to 21 in $\mathbf{g}^{21}$. Third, the number of links also varies across the networks. In this paper, we use the term “complexity” to capture the notion that there is an ordering of these networks in terms of their level of asymmetry and size. It is important to remember, however, that the umbrella term of complexity is used in a nontechnical fashion to encompass all these dimensions that differentiate the networks, which we cannot disentangle in our experimental design.

A methodological innovation in the design is that in networks $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ we introduce “mirror” positions so there are 9 subjects playing in $\mathbf{g}^{15}$ and 12 subjects playing in the $\mathbf{g}^{21}$ network.¹² In the visual interface, a subject can be assigned to any position, but when a subject is assigned to a node type P , H , or B in, say, the left cluster, then the subject's play counts also for the mirror node in the right cluster.¹³ Mirroring fulfills the dual purpose of facilitating learning on node types F and C that are rare in the networks, and reducing the

¹¹These are of course different from the labels that were displayed to subjects: in the experiment each node had a one-letter label inside the node, and these labels were fixed for all sessions in a treatment.

¹²Note that in $\mathbf{g}^{15}$ the H nodes that are neighbors of F are not mirror nodes.

¹³Mirroring did not entail any deception. In particular, subjects were never told the total number of participants in a group/session. Furthermore, the two nearest mirrored positions in both the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks are at a geodesic distance equal to 4. This means that the neighbors of any participant are always different participants. This is consistent with the instruction which, in an example about the game, states that “[t]he Turkers assigned to positions A, C and D are your neighbors” (page 15 in the online appendix).

TABLE 1.—EQUILIBRIUM NASH AND COLLABORATIVE NORM PREDICTIONS FOR ALL TREATMENTS

Network	Position(s)	Nash	Collaborative [†]	% Δ Welfare [‡]
$\mathbf{g}^\circ$	any	25	33	7%
$\mathbf{g}^\otimes$	H	44	100	61%
	P	31	66	
$\mathbf{g}^{15}$	H	38	100	108%
	F, P	28	60	
$\mathbf{g}^{21}$	H	77	100	61%
	B	78	100	
	C	38	87	
	F, P	33	100	

[†]Effort levels for the collaborative norm that leads to the highest welfare for the group. Note that we constrain types of nodes that have the same Nash equilibrium effort to make the same effort in the collaborative norm as well. [‡]% increase in welfare from Nash equilibrium for the group if everyone chooses effort levels according to the collaborative norm.

number of subjects required to explore play on large networks. Note that the implementation of mirroring in this experimental design has no impact on strategic incentives because in each position there are never two neighbors of a node that are played by the same participant.

The first and second columns of table 1 summarize the different networks and positions, respectively. The third column lists the Nash equilibrium effort levels rounded at the nearest integer. For instance, the equilibrium effort level $e_H^*(\mathbf{g}^\otimes)$ for the hub node H in the wheel network $\mathbf{g}^\otimes$ is 44 and the equilibrium effort level $e_P^*(\mathbf{g}^\otimes)$ for the peripheral node P is 31. However, Nash equilibrium play does not maximize the welfare of the group, defined as the sum of the utilities of all the subjects. In all 4 networks it is possible for subjects to increase their earnings by coordinating on a *collaborative norm*: choosing an effort higher than the Nash equilibrium effort to get a higher payoff as long as everyone else follows the norm as well. The fourth column lists the effort levels for the most efficient collaborative norm in terms of maximizing the group's welfare.¹⁴ The last column in table 1 shows that there are very large welfare gains for the group if everyone follows the collaborative norm. For instance, in $\mathbf{g}^\otimes$ the collaborative norm that achieves the highest group welfare leads to a 61% increase in group welfare compared to the case where everyone plays Nash.

The first question that we want to investigate is whether subjects are able to coordinate on a collaborative norm. In any collaborative norm the subjects exert higher effort than equilibrium play in each network position so a basic test of the presence of a collaborative norm is that the observed effort levels the subjects converge to in the experiment are higher than the Nash predictions. This hypothesis leads to 11 inequalities that we can test in the four networks.

¹⁴Note that coordination on the collaborative norm that achieves the highest welfare may require subjects to take losses when assigned to certain positions in the network, which would naturally make the norm more difficult to sustain. However, in all 4 networks there are collaborative norms such that subjects achieve higher payoffs than Nash in every network position.

H1: *Subjects converge to a collaborative norm with effort levels higher than Nash play. The specific hypotheses to test are as follows:*

- (i) $e_F(\mathbf{g}^\circ) > 25$
- (ii) $e_H(\mathbf{g}^\otimes) > 44$ and $e_P(\mathbf{g}^\otimes) > 31$
- (iii) $e_H(\mathbf{g}^{15}) > 38$, $e_P(\mathbf{g}^{15}) > 28$, and $e_F(\mathbf{g}^{15}) > 28$
- (iv) $e_B(\mathbf{g}^{21}) > 78$, $e_H(\mathbf{g}^{21}) > 77$, $e_C(\mathbf{g}^{21}) > 38$, $e_P(\mathbf{g}^{21}) > 33$, and $e_F(\mathbf{g}^{21}) > 33$

In case subjects are unable to coordinate on a collaborative norm, a potential fall back option is to play the Nash equilibrium level of effort for each network position. This generates 11 point predictions that we can test in the four networks.

H2: *Subjects converge to Nash play. The specific hypotheses to test are as follows:*

- (i) $e_F(\mathbf{g}^\circ) = 25$
- (ii) $e_H(\mathbf{g}^\otimes) = 44$ and $e_P(\mathbf{g}^\otimes) = 31$
- (iii) $e_H(\mathbf{g}^{15}) = 38$ and $e_P(\mathbf{g}^{15}) = e_F(\mathbf{g}^{15}) = 28$
- (iv) $e_B(\mathbf{g}^{21}) = 78$, $e_H(\mathbf{g}^{21}) = 77$, $e_C(\mathbf{g}^{21}) = 38$, and $e_P(\mathbf{g}^{21}) = e_F(\mathbf{g}^{21}) = 33$

However, the complexity of the network structure may make it challenging for subjects to converge to Nash equilibrium play, either through learning or by figuring out what the equilibrium is. An intuitive way to reduce this complexity is to focus solely on the local, rather than the global, structure of the network. The degree, or number of connections, of a node is a prominent and easily distinguishable local feature of the structural position of a node in the network. Despite being a rather simple metric, it is also highly correlated with Bonacich centrality, which determines Nash play. The fact that degree is a very intuitive metric and that it is highly correlated with Bonacich makes it a natural way to investigate the role of the local structure of the network.

A potential approach to investigate the role of degree would be to formulate an alternative boundedly rational decision rule based on degree to derive point predictions that are different from Nash. As we have discussed in section IA, however, a drawback of this route is that we have scarce behavioral evidence on how individuals use information about degree to inform their choices in contexts where the structure of the network matters. We have therefore decided to adopt a more general approach that sidesteps the choice of a specific behavioral rule based on degree. In particular, individuals following any decision rule based on degree would pick efforts that are (weakly) increasing in the degree of the node to which they are assigned. The application of this general decision rule gives an *ordinal* ranking of effort choices across nodes that we can compare to the ordinal ranking predicted by Nash play.

A drawback of the high correlation between degree and Bonacich centrality is that in most networks subjects whose play is determined by the local structure of the network will be indistinguishable from subjects playing Nash. However, this is not the case for $\mathbf{g}^{21}$ with the value of λ that we

TABLE 2.—SUMMARY STATISTICS AND PAIRWISE CORRELATIONS FOR SOME OF THE MAIN VARIABLES¹

	n	Mean	s.d.	1	2	3	4	5
1. Gender ¹	233	0.39	0.49	1.00				
2. Age	233	30.72	10.48	0.00	1.00			
3. Trust ²	233	0.52	0.50	−0.04	−0.05	1.00		
4. Education ³	233	3.35	1.27	−0.00	0.00	0.07	1.00	
5. HL ⁴	212	7.30	1.59	−0.02	−0.10	0.14*	0.06	1.00

¹Female = 1. ²General trust question with 0 = “Need to be very careful” and 1 = “Most people can be trusted”. ³See the caption of figure 2 for the coding. ⁴Holt and Laury (2002)’s risk attitude test: 20 participants are excluded because they made at least one inconsistent choice (i.e., multiple switching points) and 1 participant is excluded because he/she had no switching point. Note that one participant did not complete the questionnaire. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

have chosen. As table 3 shows, the equilibrium Nash prediction is $e_C^*(\mathbf{g}^{21}) > e_F^*(\mathbf{g}^{21}) = e_P^*(\mathbf{g}^{21})$. From figure 1 we can see that nodes F and C have degree 2 while node P has only one connection, so subjects whose play is determined by the local network structure would pick efforts $e_F(\mathbf{g}^{21}) = e_C(\mathbf{g}^{21}) > e_P(\mathbf{g}^{21})$, which is a different ranking from Nash play. This leads to a complete ranking of effort levels that we can test for in networks $\mathbf{g}^\otimes$, $\mathbf{g}^{15}$, and $\mathbf{g}^{21}$, and that, crucially, departs from the ranking for Nash play for 3 types of nodes in $\mathbf{g}^{21}$:

H3: *Subjects choose effort levels based on their local position in the network as captured by degree, rather than taking into account how their position relates to the overall network structure as captured by Bonacich centrality. The specific hypotheses to test are as follows:*

- (i) $e_H(\mathbf{g}^\otimes) > e_P(\mathbf{g}^\otimes)$.
- (ii) $e_H(\mathbf{g}^{15}) > e_F(\mathbf{g}^{15}) = e_P(\mathbf{g}^{15})$.
- (iii) $e_H(\mathbf{g}^{21}) = e_B(\mathbf{g}^{21}) > e_F(\mathbf{g}^{21}) = e_C(\mathbf{g}^{21}) > e_P(\mathbf{g}^{21})$.

IV. Experiment: Results

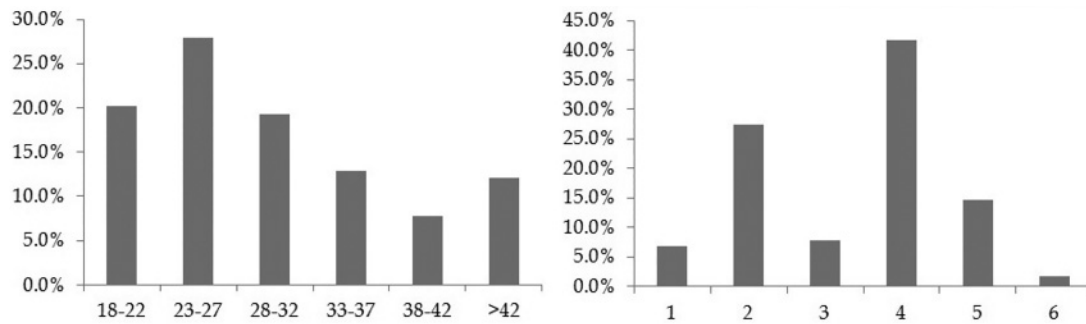
Section IVA describes basic data on the sample of subjects, and section IVB presents the results.

A. Sample Description

The experimental data contain the decisions of 234 subjects. Each subject participated in one session of one treatment so she played the game in one of the four network structures. We ran each treatment 6 times and there are 40 rounds in each game, so we have a total of 9,360 decisions or observations. The experimental data were matched with the data from the questionnaire that subjects had to fill in at the end of the experiment.

Table 2 summarizes some of the main sociodemographic characteristics of the participants and their pairwise correlations. All the participants are resident in the United States: 39% are female and the average age is 30.7 years old. We asked subjects the standard interpersonal trust question from the World Values Survey (WVS) and found that 52% believe that others can be trusted, which is higher than the average

FIGURE 2.—PERCENTAGES OF SUBJECTS OF DIFFERENT AGE GROUPS (LEFT) AND EDUCATION LEVELS (RIGHT) FOR 233 OUT OF 234 PARTICIPANTS



Classification of education levels: 1 = high school, 2 = some college, 3 = 2-year college, 4 = 4-year college, 5 = master, 6 = professional degree (e.g., MD) or PhD.

value from the WVS survey of the U.S. population. The level of trust is not correlated with gender or age.

Figure 2 illustrates in more detail one of the advantages of online experiments *vis-à-vis* lab studies: a heterogeneous subject pool that is more representative of the general population than the student populations that are typical of most laboratory studies. Figure 2a shows that subjects belong to different age groups ranging from a minimum of 18 to a maximum of 70 years old. Moreover, there is a significant heterogeneity in terms of the education level of the participants. Figure 2b shows that 76.8% of participants have some kind of college degree as the highest level of education attained, 6.9% only have a high school diploma, and 16.3% have a master, professional degree, or PhD.

After the questionnaire, subjects took the Holt and Laury (2002) risk attitude test. For each of 10 scenarios they had to pick between a safe and a risky lottery. In the early scenarios, the safe lottery gives a higher expected payment, while in the late scenarios it is the other way around. A risk-neutral participant would switch from the safe to the risky lottery at scenario 5. The participants are on average risk-averse because the mean switching point is 7.3. There are 4 (1.9%) participants who switch at scenario 4 and therefore are slightly risk-seeking, and 29 (13.7%) participants who are risk-neutral. There is a significant correlation between risk aversion and trust: participants who display a high level of trust tend to be more risk-averse. There is no significant correlation of risk aversion with gender, age, or education.

B. Results

In this section, we test the hypotheses formulated in section III using the experimental data. We start by investigating our hypotheses using nonparametric testing. In particular, we aggregate data at the session level and use the Wilcoxon signed-rank test (hereafter WSR) on matched samples. Data are matched between samples at the session level so there is no correlation in the data points within each sample because they belong to different sessions.¹⁵ Note that the choice of

¹⁵This correlation issue is relevant for the analysis in table 4, but not for the one in table 3. For consistency we use WSR for all nonparametric testing,

TABLE 3.—EFFORT LEVELS IN DIFFERENT NETWORK POSITIONS

Network	Position(s)	Nash	Effort last 10 rounds		
			Mean	s.d.	Median
g°	any	25	29.32**	7.63	30
$g^{\otimes}$	H	44	51.02*	22.88	50
	P	31	34.89**	10.98	33
g^{15}	H	38	39.15	12.63	40
	F	28	29.92	13.62	28.5
	P	28	27.88	11.45	25.5
g^{21}	H	77	78.95	24.01	88
	B	78	79.35	24.28	86
	C	38	40.79	16.00	40
	F	33	38.95**	19.86	34
	P	33	34.63	18.25	30

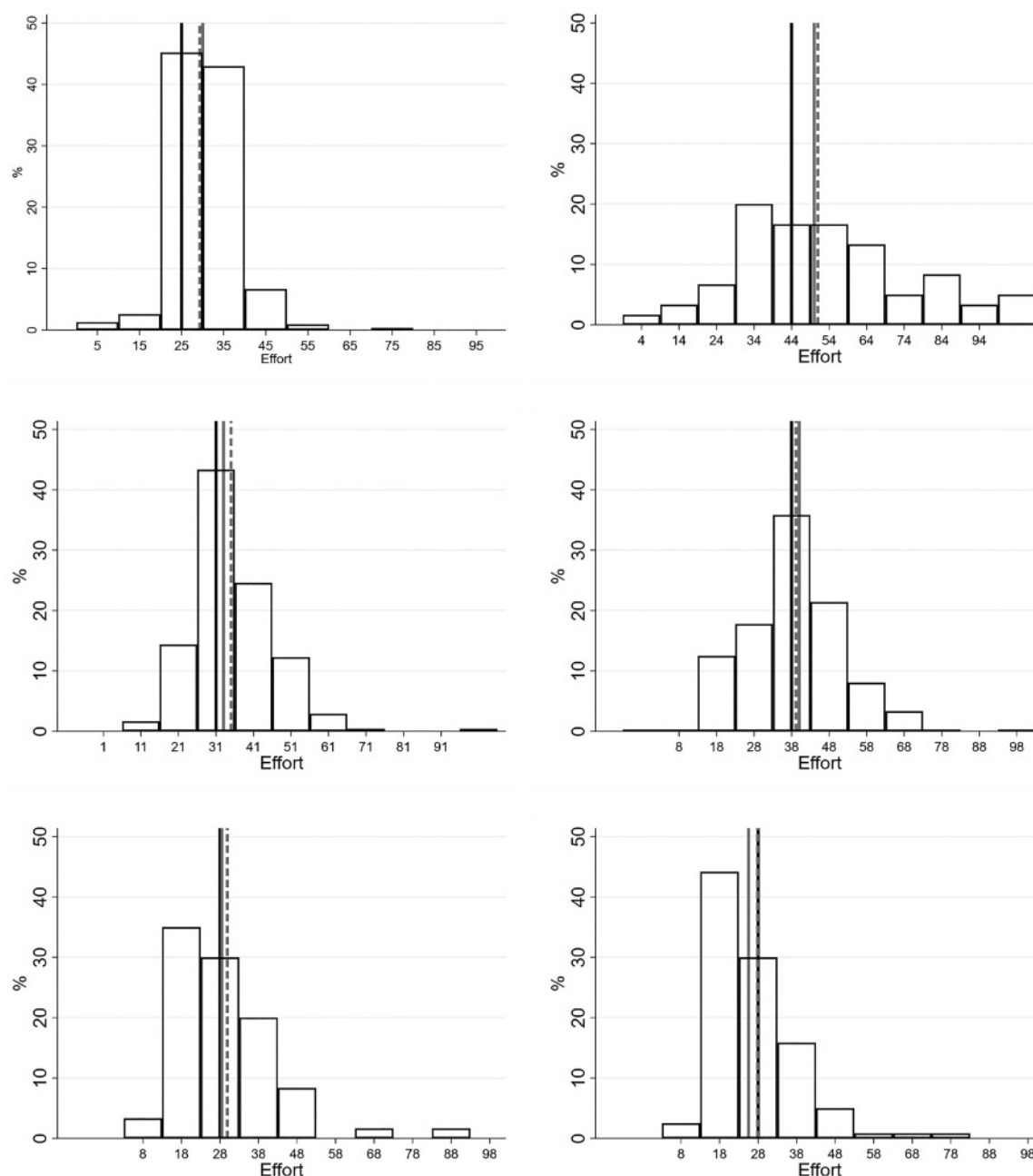
Summary statistics for effort levels in the different network positions for the last 10 rounds of play. Significance levels refer to a nonparametric test on matched data (Wilcoxon signed-rank). Data are aggregated and matched at the session level ($n = 6$ for each position); * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

a nonparametric test with a small ($n = 6$) sample per treatment after aggregation is very conservative, and therefore any statistically significant finding denotes a sizable treatment effect.¹⁶ Table 3 shows the average and median effort in the last 10 rounds for each type of node, and figures 3 and 4 show the distribution of efforts for each type of node in the last 10 rounds.

Our first finding is that subjects are able to coordinate on a collaborative norm in the simple g° and $g^{\otimes}$ networks. In the g° network, subjects' average effort level in the last 10 rounds is equal to 29.2, which is significantly higher (WSR, $p = 0.03$) than the Nash prediction $e^*(g^{\circ}) = 25$. As we saw in table 3, the collaborative norm that would lead to the highest welfare for the group requires an effort level equal to 33 so subjects converge to an average effort level that is in between Nash and the most efficient collaborative norm. The top left panel of figure 3 shows the distribution of effort levels in the last 10 rounds: the large majority of subjects choose efforts in between the Nash prediction and the most efficient

but the results would be unchanged if one were to use nonparametric testing on unmatched data (i.e., Mann-Whitney) to test significance in table 3.

¹⁶Indeed, the highest possible level of significance with an $n = 6$ sample using WSR is $p = 0.0313$.

FIGURE 3.—DISTRIBUTION OF EFFORTS CHOSEN IN THE LAST 10 ROUNDS BY TYPE OF POSITION IN NETWORKS g° , $g^{\otimes}$, AND g^{15} 

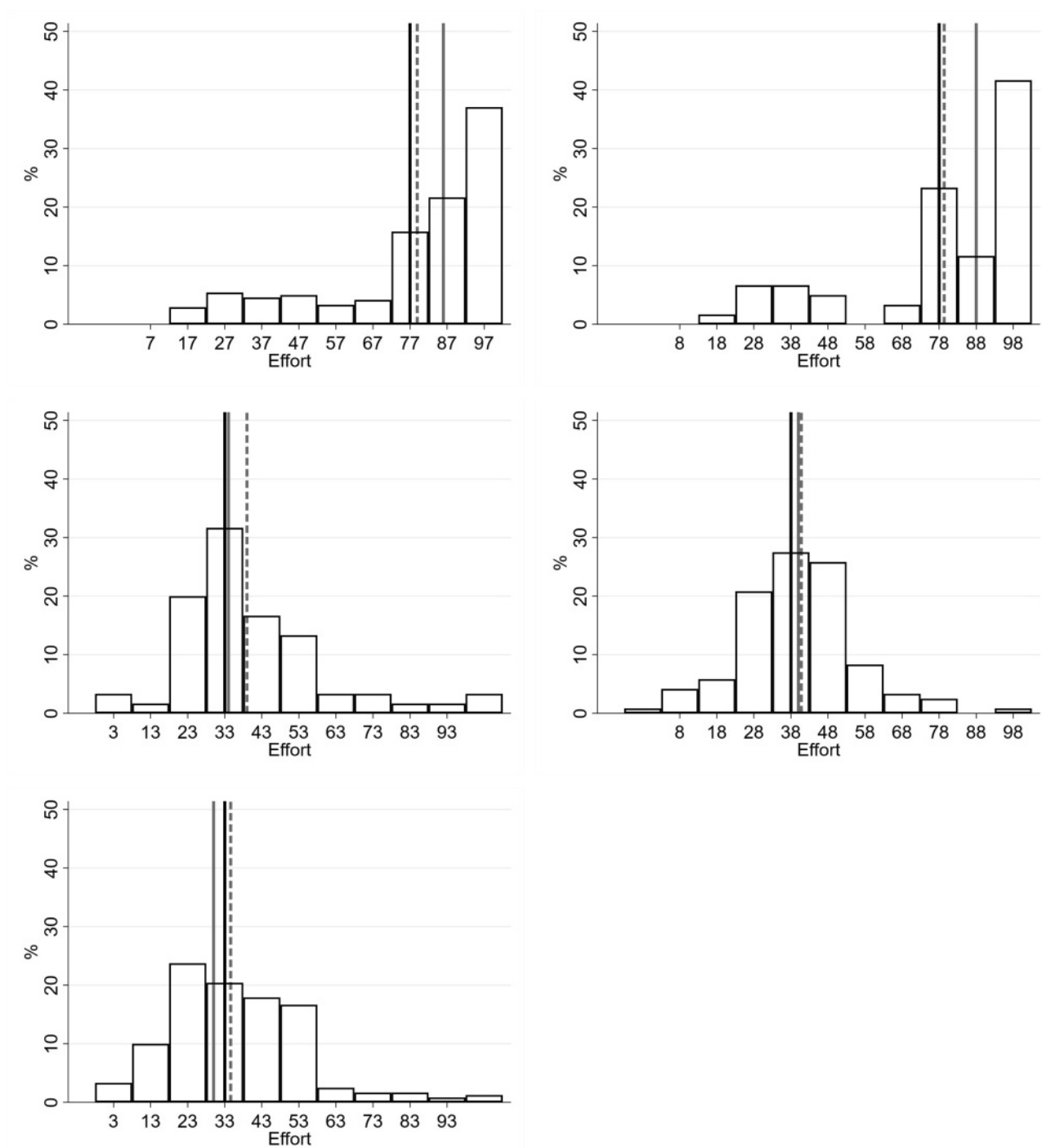
Top: g° (Left) and H type in $g^{\otimes}$ (Right). Middle: P type in $g^{\otimes}$ (Left) and H type in g^{15} . Bottom: F (Left) and P (Right) type in g^{15} . Vertical lines indicate predicted Nash play (black), mean (dashed gray), and median (gray) efforts.

collaborative norm. There is some loose analogy between this type of collaborative norm and the contribution norms observed in public good experiments with quadratic payoffs: Laury and Holt (2008) find levels of collaboration that are similar to what we find in the g° treatment.¹⁷

The collaborative norm is still present in the $g^{\otimes}$ network, but it is weaker. The average effort level in the last 10 rounds

in the H type node is 51, which is marginally higher (WSR, $p = 0.06$) than the Nash prediction $e_H^*(g^{\otimes}) = 44$. Similarly, the average effort level in the last 10 rounds in the P type node is 34.9, which is significantly higher (WSR, $p = 0.03$) compared to the Nash prediction $e_P^*(g^{\otimes}) = 33$. However, the collaborative norm that we observe is extracting only a small fraction of the potential gains from coordination compared to the most efficient collaborative norm, which, as table 3 shows, would entail subjects in the H type node choosing an effort level equal to 100, and subjects in the P or F type nodes choosing 60. Thus, the average effort levels that subjects

¹⁷See, in particular, their low Nash treatment where the Nash contribution is 20% and the Pareto optimum is 80%: subjects' contributions start close to 60% and decline to just below 40%.

FIGURE 4.—DISTRIBUTION OF EFFORTS CHOSEN IN THE LAST 10 ROUNDS BY TYPE OF POSITION IN NETWORK g^{21} 

Top: H (Left) and B (Right) type. Center: F (Left) and C (Right) type. Bottom: P type. Vertical lines indicate predicted Nash play (black), mean (dashed gray), and median (gray) efforts.

converge to are much closer to Nash than to the most efficient collaborative norm. An interpretation is that the $g^{\otimes}$ network introduces asymmetry across nodes, which makes the coordination on a collaborative norm more challenging. Continuing with the loose analogy with public good game experiments, this is in agreement with the finding that contribution levels decrease in public good games where there

are asymmetries across participants (see, e.g., Rapoport & Suleiman, 1993).

Result 1: *In the $g^{\ominus}$ network, subjects establish and maintain a collaborative norm that entails choosing efforts higher than the Nash prediction. The collaborative norm is still present, but it is weaker, in the asymmetric $g^{\otimes}$ network. The norm*

disappears in the more complex and asymmetric $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks.

If subjects are unable to sustain a collaborative norm in the more complex and asymmetric networks, a potential fall back option is to play the Nash equilibrium effort levels. At the same time, the setup of this game is rather complex given the rich structure of the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks as well as the number of discrete effort levels subjects can choose from, so it is not an easy task to figure out or learn the equilibrium.

Our second finding is that subjects converge to the Nash equilibrium predictions in the more complex $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks. Table 3 shows that in $\mathbf{g}^{15}$ the average effort in the last 10 rounds is statistically indistinguishable from the Nash predictions independently of the type of position. The average effort by subjects assigned to the H node is 39.2, and we cannot reject the hypothesis that this is the same as the Nash effort $e_H^*(\mathbf{g}^{15}) = 38$. Similarly, the average efforts in the last 10 rounds in the F and P positions are 29.9 and 27.9, respectively, and we cannot reject hypothesis $H2(iii)$ that they are the same as the Nash predictions $e_F^*(\mathbf{g}^{15}) = e_P^*(\mathbf{g}^{15}) = 28$. The center right and bottom panels of figure 3 show the distribution of efforts in the last 10 rounds in the H , F , and P type of nodes, respectively: efforts are approximately normally distributed with mean/median at the Nash equilibrium prediction.

The Nash point predictions in $H2(iv)$ for the $\mathbf{g}^{21}$ network are also mostly validated by the data. Table 3 shows that the average efforts in the last 10 rounds in the B and H positions are 79.4 and 79, respectively, and we cannot reject hypothesis $H2(iv)$ that they are the same as the Nash predictions $e_B^*(\mathbf{g}^{21}) = 78$ and $e_H^*(\mathbf{g}^{21}) = 77$. Similarly, the average efforts in the last 10 rounds in the C and P positions are 40.8 and 34.6, respectively, and we cannot reject hypothesis $H2(iv)$ that they are the same as the Nash predictions $e_C^*(\mathbf{g}^{21}) = 38$ and $e_P^*(\mathbf{g}^{21}) = 33$. A notable exception is type F node where the average effort by subjects in the last 10 rounds is 39, which is significantly higher (WSR, $p = 0.03$) than the Nash prediction $e_F^*(\mathbf{g}^{21}) = 33$. We discuss this exception below in more detail.

Figure 4 shows the distribution of efforts in the last 10 rounds. They tend to be approximately normally distributed with mean/median coinciding with the Nash equilibrium prediction, aside from position F where the mean is higher than the Nash prediction. In the H and B type nodes, there is a fraction of subjects that pick efforts close to or equal to 100, possibly due to the vicinity of the Nash prediction to the upper boundary of the strategy space.

At first sight it seems surprising that subjects are able to converge on Nash equilibrium play in complex settings such as $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$. This is, however, consistent with experimental findings in other contexts. Erev and Rapoport (1998) and Rapoport et al. (2002) show that participants in a market entry game converge to equilibrium predictions in groups of 12–20 players. They argue that participants adopt a reinforcement

learning strategy, which theoretically predicts convergence to equilibrium. Bramoullé et al. (2014) prove that the game examined in this paper can be reformulated as a potential game, and therefore theory predicts that players adopting a reinforcement learning strategy would converge to Nash equilibrium. Moreover, Erev and Rapoport (1998) show that the convergence finding occurs only in treatments where subjects have information about their own but not other participants' payoffs, which is the same minimal information feedback design in our experiment.

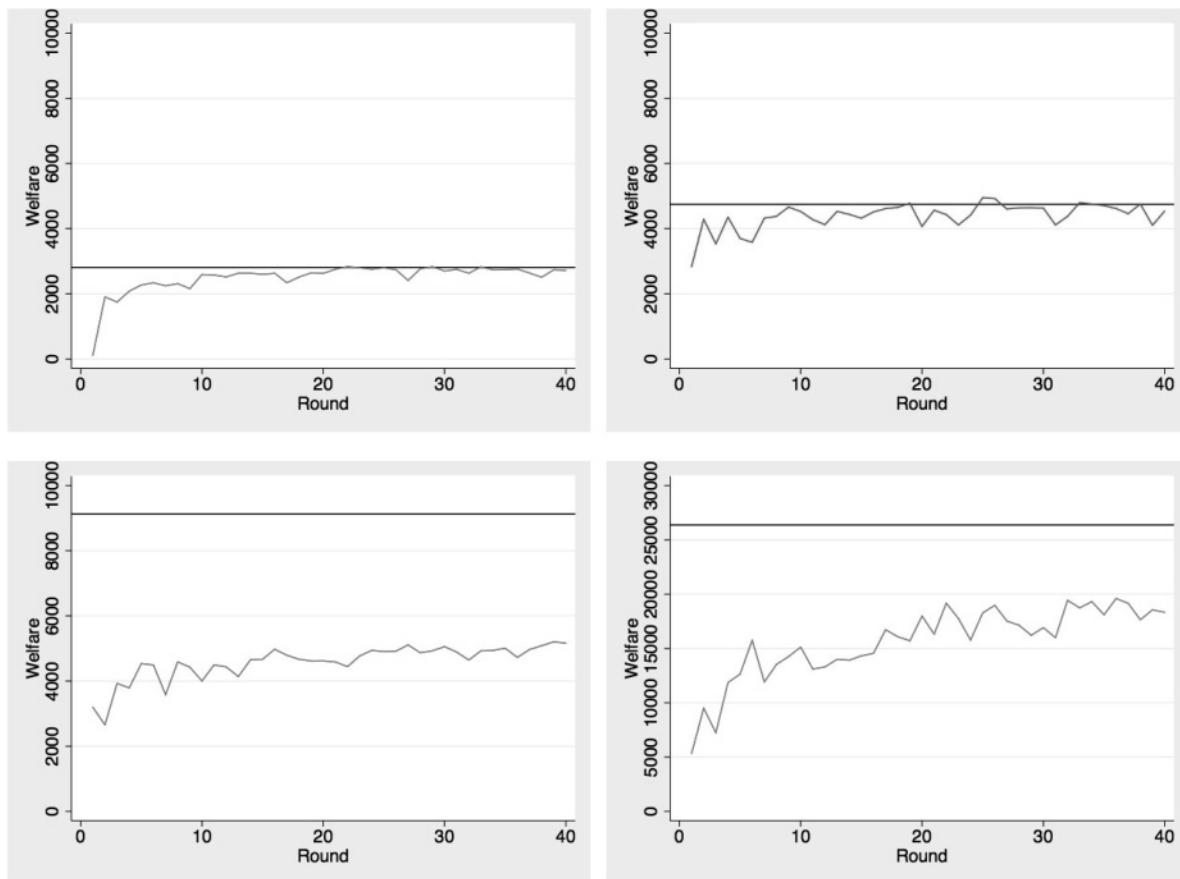
A consequence of the subjects' inability to establish a collaborative norm in the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks is that the aggregate welfare is, in comparative terms, lower than in the $\mathbf{g}^{\circ}$ and $\mathbf{g}^{\otimes}$ networks relative to the theoretical aggregate welfare achievable if everyone were to play Nash. Figure 5 shows the evolution of the aggregate welfare, that is, the sum of subjects' payoffs, for each of the 4 networks. In the $\mathbf{g}^{\circ}$ and $\mathbf{g}^{\otimes}$ networks, subjects converge to an aggregate welfare that is indistinguishable from the theoretical aggregate welfare if everyone played Nash. On the other hand, the aggregate welfare in the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks is significantly lower than the theoretical aggregate welfare if everyone played Nash. Notice that the strategic complementarities in the payoff function mean that deviations from equilibrium effort will have a nonlinear impact on payoffs.¹⁸ Consequently, the variability in subjects' play lowers aggregate welfare so the average aggregate welfare is not above the one achievable at Nash in the $\mathbf{g}^{\circ}$ and $\mathbf{g}^{\otimes}$ networks despite the establishment of a collaborative norm, and, similarly, it is not equal to the one achievable at Nash in the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks despite the subjects converging to Nash play on average.

Result 2: In the $\mathbf{g}^{15}$ and $\mathbf{g}^{21}$ networks, subjects converge to the Nash point predictions on almost all node types.

Our third finding is that there is evidence that subjects focus on the local rather than the global features of the network to make their decisions. The first piece of supporting evidence is that the ranking of subjects' effort decisions in different types of nodes matches *all* the predictions in $H3$. Table 4 shows the average difference in effort levels of subjects across the different types of nodes in the $\mathbf{g}^{\otimes}$, $\mathbf{g}^{15}$, and $\mathbf{g}^{21}$ networks. As we have hypothesized in section III, subjects who choose their efforts depending on the local structure would pick higher efforts the higher the degree is of the node to which they are assigned. In the $\mathbf{g}^{\otimes}$ and $\mathbf{g}^{15}$ networks, the predictions in $H3(i)$ and $H3(ii)$ of subjects playing based on the local structure match the Nash predictions, and table 4 shows that the data validate these predictions. Similarly, in the $\mathbf{g}^{21}$ network, subjects in the B and H node types choose effort levels higher than subjects in the other node types in agreement with both

¹⁸ As an example, consider $\mathbf{g}^{\circ}$. In equilibrium, everyone plays $e(\mathbf{g}^{\circ}) = 25$ and aggregate welfare is 1,875. Now suppose three individuals deviate to $e_{low}(\mathbf{g}^{\circ}) = 15$ and three individuals deviate to $e_{high}(\mathbf{g}^{\circ}) = 35$ with each individual having neighbors that play the other two efforts. Average effort is clearly unchanged, but welfare is now 1,694.8.

FIGURE 5.—EVOLUTION OF WELFARE LEVEL DURING THE 40 ROUNDS



Top: g^0 (Left) and g^0 (Right) treatment. Bottom: g^{15} (Left) and g^{21} (Right) treatment. Lines indicate predicted Nash (black) and mean (gray) welfare levels.

TABLE 4.—DIFFERENCES IN AVERAGE EFFORT ACROSS DIFFERENT POSITIONS FOR ALL THE DATA

		g^0		g^{15}		g^{21}			
		P	F	P	H	P	C	F	
g^0	H	14.0**							
g^{15}	H		9.2**	9.7**					
	F			0.5					
g^{21}	B				0.6	37**	29.8**	32.5**	
	H					37.6**	30.4**	33.2**	
	P						-7.2**	-4.5**	
	C							2.8	

the Nash predictions and $H3$. However, subjects who play according to the degree will deviate from Nash play for moderately high levels of the complementarity effect in specific networks, and we designed the g^{21} treatment to examine such a case.

In the g^{21} network, there are three node types where the Nash predictions ranking of effort levels differs from the ranking in $H3$, and the data fully validate the predictions generated by play based on local network structure. Subjects playing according to the degree would pick the same effort

level in node types F and C , which have degree 2, and they would pick a higher effort level in node F compared to the P node type that has degree 1, while the Nash predictions are $e_C^*(g^{21}) > e_F^*(g^{21})$ and $e_F^*(g^{21}) = e_P^*(g^{21})$. We have already seen in table 3 that subjects' play in the F and C node types is indistinguishable from the Nash predictions, while it is higher than Nash (WSR, $p = 0.03$) in the P node type in line with the predictions of play based on local network structure. Table 4 further validates the predictions in $H3(iii)$: the effort levels of subjects in the F and C node types are indistinguishable, and subjects choose a higher effort level in node F compared to the P node type (WSR, $p = 0.03$). Moreover, we also cannot reject the hypothesis that subjects' play in node type F is the same as the Nash prediction $e_C^*(g^{21}) = 38$ for C .

The second piece of supporting evidence is a panel data analysis of the determinants of subjects' efforts in table 5. All estimations include random effects at subject level and session fixed effects. We do not cluster errors at the session level because it is generally deemed inappropriate with a low number of observations per cluster (Wooldridge, 2003). A concern with our analysis is therefore that the results do not account for potential correlation of observations in a session. While this is an inevitable drawback of a network experiment with large groups, the results in table 5 are consistent with

TABLE 5.—DETERMINANTS OF SUBJECTS' EFFORTS

	$g^{\otimes}$	g^{15} (all)	g^{15} ($\{F, P\}$)	g^{21} (all)	g^{21} ($\{F, C, P\}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Degree	2.828*** (0.176)	2.973*** (0.212)		4.353** (1.411)	4.946*** (1.355)		
Bonacich				10.446*** (2.413)	6.643 (5.294)		
F position						−1.860 (1.482)	
P position			−0.586 (1.118)			−6.806*** (1.047)	−4.946*** (1.355)
C position							1.860 (1.482)
Round	−0.052* (0.024)	−0.063 (0.026)	−0.201*** (0.457)	0.199*** (0.034)	−0.132*** (0.039)	−0.132*** (0.039)	−0.132*** (0.039)
Age	0.117 (0.087)	−0.046 (0.074)	0.034 (0.092)	−0.357* (0.144)	−0.212 (0.129)	−0.212 (0.129)	−0.212 (0.129)
Gender	2.011 (1.702)	2.809 (1.757)	4.377* (2.183)	3.309 (2.853)	4.895 (2.549)	4.895 (2.549)	4.895 (2.549)
Trust	1.935 (1.702)	−0.320 (1.721)	1.492 (2.145)	4.546 (2.971)	3.545 (2.652)	3.545 (2.652)	3.545 (2.652)
Risk	0.214 (1.745)	1.667 (2.158)	0.495 (2.682)	7.123* (3.331)	1.702 (2.979)	1.702 (2.979)	1.702 (2.979)
Sessions	Y	Y	Y	Y	Y	Y	Y
Constant	16.771*** (5.053)	27.878*** (4.961)	27.878*** (6.125)	14.143 (7.694)	24.443* (10.185)	47.088*** (6.630)	45.228*** (6.679)
Obs.	2,160	2,160	720	2,840	1,654	1,654	1,654
Subjects	54	54	54	72	72	72	72
Wald χ^2	292.37	242.96	41.44	2,210.78	75.78	75.78	75.78
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Tobit panel estimation with random effects at subject level and session fixed effects. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the nonparametric analysis above, which accounts for these correlations. Moreover, the results are robust to including clustering of standard errors.¹⁹

Specifications (1) and (2) analyze the full data for the $g^{\otimes}$ and g^{15} treatments, respectively: the common regressors to all the specifications are subjects' gender, age, trust, and risk aversion as captured by the risk elicitation test in the post-experimental questionnaire. In these networks, degree and Bonacich centrality are perfectly collinear and highly significant predictors of subjects' efforts. Specification (3) restricts the analysis to the F and P nodes on g^{15} , which have the same degree and Bonacich centrality. As expected and consistently with the nonparametric analysis, there is no difference in effort choices between these two positions.

The most interesting specifications to test $H3$ are (4)–(7) for the g^{21} network. In specification (4) with all the data both degree and Bonacich centrality are significant predictors of subjects' efforts. This is unsurprising because they make the same prediction for the majority of positions in g^{21} . Specifically, in the case of g^{21} , node types H and B have both high degree and centrality. In specifications (5) we repeat the panel data analysis excluding from the sample node types H and B , and keeping node types F , C , and P where the degree

and Bonacich centrality metrics differ. We find that degree remains highly significant while Bonacich is completely insignificant. This is evidence that subjects are basing their decision on their position in the local rather than the global network structure: in a network where degree and Bonacich are not perfectly correlated, degree is highly predictive of subjects' choices, while Bonacich centrality has no predictive power once the degree is included as a regressor.

There are two separate effects that lead degree to be a better predictor of subjects' choices than Bonacich centrality. Specification (6) repeats the panel data analysis with dummies for the F and P positions, and with the C position as a baseline. The F position dummy is not significant, which indicates that the first reason degree is more predictive is that there is no difference in effort levels between the F and C positions as predicted by degree and in contrast to the $e_C(g^{21}) > e_F(g^{21})$ Bonacich prediction. Specification (7) repeats the panel data analysis with dummies for the C and P positions. The P position dummy is negative and highly significant, which indicates that the second reason degree is more predictive is that there is a difference in effort levels between the F and P positions as predicted by degree and in contrast to the $e_P(g^{21}) = e_F(g^{21})$ Bonacich prediction.

A third piece of supporting evidence for the local features of the network structure as the main determinant of subjects' choices is qualitative in nature. In the postexperimental questionnaire, we asked subjects the following open-ended question: "Please briefly describe how you picked your

¹⁹See Wooldridge (2003) for a discussion of the minimum number of observations per cluster to use clustered standard errors. The replication of the results in table 5 with clustered standard errors is available from the authors upon request.

activity level during the experiment.” Subjects were required to input an answer in a text box, and we employed an RA to categorize the answers. Out of the subjects who answered the question²⁰ for the g^{15} and g^{21} networks (89.7%, 113 out of 126), two-thirds of them (64.6%) replied that they chose the effort depending on the number of connections of the node to which they were assigned. This was the most popular answer, followed by “trial and error” (14.2%), “maximize own profits” (9.7%), and “depending on what others were choosing” (7.1%). No subject mentioned the number of connections of their neighbors in the answer, which is an important component of Bonacich centrality.

Result 3: *We find qualitative and quantitative evidence that subjects base their choices on the local rather than the global structure of the network. In all networks, subjects’ efforts are ranked according to the degree of the node to which they are assigned. In the node types of the g^{21} network where the degree has different predictions than Nash, the degree is highly predictive of subjects’ behavior while Bonacich centrality is insignificant. Finally, the degree of the node they are assigned to is subjects’ most popular response to an open-ended question of how they make their decisions.*

An alternative explanation for deviations from equilibrium predictions is that the strategic risk of exerting high effort varies across nodes. In particular, strategic risk should be inversely related to degree because a low degree means having only one or two neighbors, and therefore a mistake in play by one of them has a large impact on one’s payoff. In g^{21} , for instance, strategic risk considerations would predict that subjects should be more conservative in their effort choices in F compared to H . In contrast, as table 3 summarizes, subjects exert effort close to equilibrium in H [78.95 average, $e_H(g^{21}) = 77$], but qualitatively higher than equilibrium in F [38.95 average, $e_H(g^{21}) = 33$]. Additionally, table 5 shows that risk preferences are not a significant predictor of subjects’ effort choices.

Subjects base their decision on the local structure despite always having at their disposal information on the whole network as well as their position in it as they are making their choice. Gallo and Yan (2015) show that the availability of network information changes subjects’ decisions in a network formation game, but this does not seem to play a first-order role in the context of this game. An alternative experimental design choice would have been to give subjects information about everyone’s choice of efforts and payoffs, and not just their own payoffs and neighbors’ efforts. This alternative feedback could have nudged them to focus their attention on the whole network. We decided, however, against this in order to suppress imitation play of subjects copying the effort choices of the participants receiving the highest payoff in a given position. The presence of imitation dynamics would

have been a confounding factor to testing the equilibrium predictions, and therefore we followed the standard practice in the experimental literature to give subjects only the information necessary to compute their own payoff. A fruitful area of future inquiry is to investigate the robustness of our findings to giving subjects more information about others’ actions and/or payoffs.

A natural question is whether the role of local structure in determining choices is consequential for deviations from equilibrium predictions in real networks. The key intuition is that deviations are likely to be observed in networks where there is a lot of variation in the connectivity of the neighbors of poorly connected nodes. In the g^{21} example, positions P , F , and C are all poorly connected, but F ’s neighbors are all poorly connected while both C and P have at least one highly connected neighbor. There is abundant empirical evidence that many social networks have a neighbors’ degree distribution that is highly skewed with a few highly connected neighbors and many poorly connected ones,²¹ which suggests that the deviations observed in g^{21} typify deviations that we expect to observe in real social networks. A general network metric that is a useful guide for the likelihood of deviations is degree assortativity.²² In highly assortative networks, poorly connected nodes are mostly connected with each other so there is little variation in their neighbors’ connectivity and therefore few deviations from equilibrium. Similarly, in highly disassortative networks, low degree nodes are mostly linked with highly connected ones leading, again, to little variation. In networks that are (close to) nonassortative, however, there will be a lot of variation in the connectivity of poorly connected nodes’ neighbors, and therefore we would expect more widespread deviations from equilibrium behavior.

V. Conclusion

In this paper, we have examined experimentally how social network structure mediates the tension between equilibrium play and the establishment of a more efficient norm by investigating a game of strategic complements played on different networks.

We find that subjects are able to coordinate on a collaborative norm when the network is simple and symmetric such as the circle, and, to a lesser extent, the wheel network. In contrast, in the more complex networks of 15 and 21 nodes, on average subjects converge to the Nash equilibrium play on almost every node. Given the richness of the network structure and the size of the strategy space, this result provides a strong validation of the theoretical results in Ballester et al. (2006) and it shows how position in the network can be a key determinant of equilibrium play. These results are consistent

²⁰It was compulsory to answer the question, but some subjects decided to decline to provide an answer by, for example, inputting a hyphen in the text box.

²¹See Newman et al. (2006) for a comprehensive review.

²²The assortativity coefficient is the Pearson correlation coefficient of degree between pairs of linked nodes; see Jackson (2008) for a formal definition.

with previous experimental work on public good games that shows that asymmetry across subjects leads to a decrease in the level of contributions. In future work, it would be interesting to explore systematically which structural features of the network leading to asymmetries across subjects have the largest detrimental impact on the coordination on efficient outcomes.

We also provide evidence that subjects base their decisions on the local, rather than the global, network structure. If we limit the analysis to the set of nodes in the 21-node network whose local features are not highly correlated with their overall position in the network, degree is a significant predictor of subjects' play, but Bonacich centrality, which determines equilibrium play, is not. In future work, it would be interesting to investigate whether focusing on local network features is a common way for individuals to cope with the challenging task of processing complex network information, independently of the game they are playing. Evidence on additional network structures and/or games would allow the identification of the specific boundedly rational decision rule(s) individuals deploy to use information about degree in their decisions. These finding would spur further theoretical work—in many games played on networks, it is challenging to solve for the equilibrium because strategies relate to the overall network structure in intricate ways, but this relation may simplify significantly if it is limited to the local network.

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