Network Formation in Large Groups*

Syngjoo Choi† Sanjeev Goyal‡ Frédéric Moisan§

March 27, 2019

Abstract

We conduct an experiment to understand the principles that govern network formation. The design of the experiment builds on a model of linking and efforts taken from Galeotti and Goyal [2010]. In order to reduce cognitive complexity facing human subjects and facilitate learning, we develop a new experimental platform that integrates a network visualization tool using an algorithm of Barnes and Hut [1986] with an interactive tool of asynchronous choices in continuous time.

Our experiment provides strong support for macroscopic predictions of the theory: there is specialization in linking and efforts across all treatments. Moreover, and in line with the theory, the specialization is more pronounced in larger groups. Thus subjects abide by the law of the few.

Information on payoffs provided to subjects affects their behavior and yields differential welfare consequences. In the treatment where subjects see only their own payoffs, in large groups, the most connected individuals compete fiercely—they exert large efforts and have small earnings. By contrast, when a subject sees everyone's payoffs, in large groups, the most connected individuals engage in less intense competition—they exert little effort and have large earnings. The effects of information are much more muted in small groups.

JEL: C92, D83, D85, Z13.

*The paper was supported by the FET-Open Project IBSEN (contract no. 662725), the Keynes Fund and by Creative-Pioneering Researchers Program (Seoul National University).

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

‡Faculty of Economics and Christ's College, University of Cambridge. Email: sg472@cam.ac.uk

§Faculty of Economics, University of Cambridge. Email: fm442@cam.ac.uk

1 Introduction

Large scale social networks are a defining feature of contemporary society. Empirical research suggests that such networks exhibit a law of the few: effort provision is concentrated in a very small subset of individuals and the distribution of links is also very unequal.[1] Given the prominence of these networks, it is important to understand the principles underlying their formation.

As efforts and links are costly, individuals would naturally compare the trade-offs. So our starting point is the economic theory of network formation.[2] Galeotti and Goyal [2010] present a model with costly efforts and linking. Linking with another individual gives access to that individual's efforts and also the efforts of his neighbours. They show that every robust equilibrium of their game exhibits the law of the few. This model has been tested in the laboratory with small groups of subjects. The results are very mixed. For instance, in an interesting recent paper, van Leeuwen et al. [2018] find that the hub-spoke structure predicted by the theory does not arise in the laboratory. These experimental findings raise a question mark about the validity of the economic mechanisms underlying the model.

A common element of existing network formation experiments is that the number of subjects is small, typically ranging between 4 and 8. Moreover, most of the experiments require subjects to make simultaneous choices in discrete time. In a real world setting, groups are very large and individuals typically choose effort and linking at different points in time. The individual decision problem is complicated because the attractiveness of links depends on the efforts of individuals *and* also on the efforts by the neighbours of these individuals. As group size grows, these informational requirements become more demanding. So it is quite unclear if we can extend the findings from the small group experiments to more realistic settings. The work of Friedman and Aprea [2012] suggests that continuous time experiments offer subjects more opportunities to learn on how to make decisions and that they may offer better prospects for convergence than discrete time experiments. Our paper builds on this insight.

A large-scale continuous-time experiment on network formation generates a great deal of information that is in principle relevant for decision making. This may be cognitively too

[1]See, for example, Barabási and Albert [1999], Goyal et al. [2006], and Jackson and Rogers [2007].

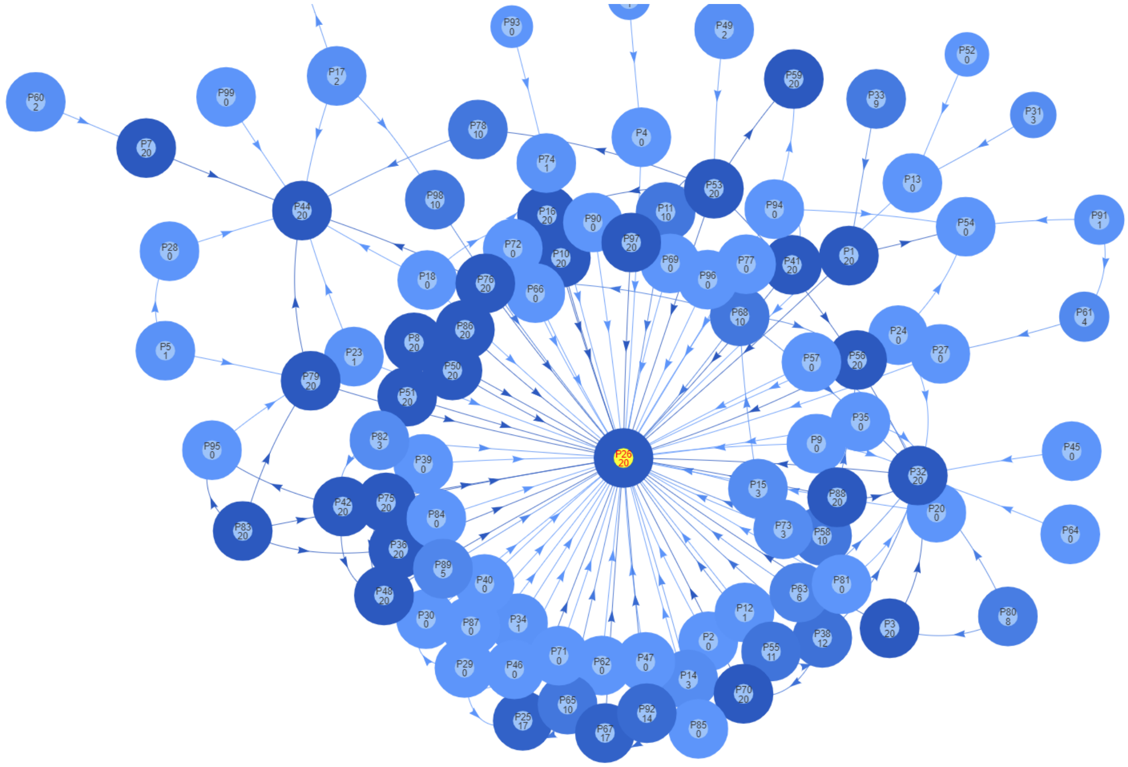
[2]For early contributions see Bala and Goyal [2000] and Jackson and Wolinsky [1996]. For a survey, see Bramoulle and Rogers [2016].

demanding for individuals and can undermine the rationale for controlled experimentation. In order to handle such concerns, we develop a new experimental platform. Three aspects of the platform are worth noting. Firstly, it includes a network visualization tool that uses the Barnes-Hut approximation algorithm (Barnes and Hut [1986]). This algorithm allocates nodes and edges in a two-dimensional space to improve visual clarity of network presentation. Secondly, we integrate this tool for network visualization with the interactive tool of dynamic choices. This feature allows individuals to form and remove links and change effort levels instantly. The integration enables us to update rapidly evolving networks in real time on the computer screen. Finally, the platform is flexible in information provision both with regard to what subjects know about the network and what they know about the actions and payoffs of different subjects.

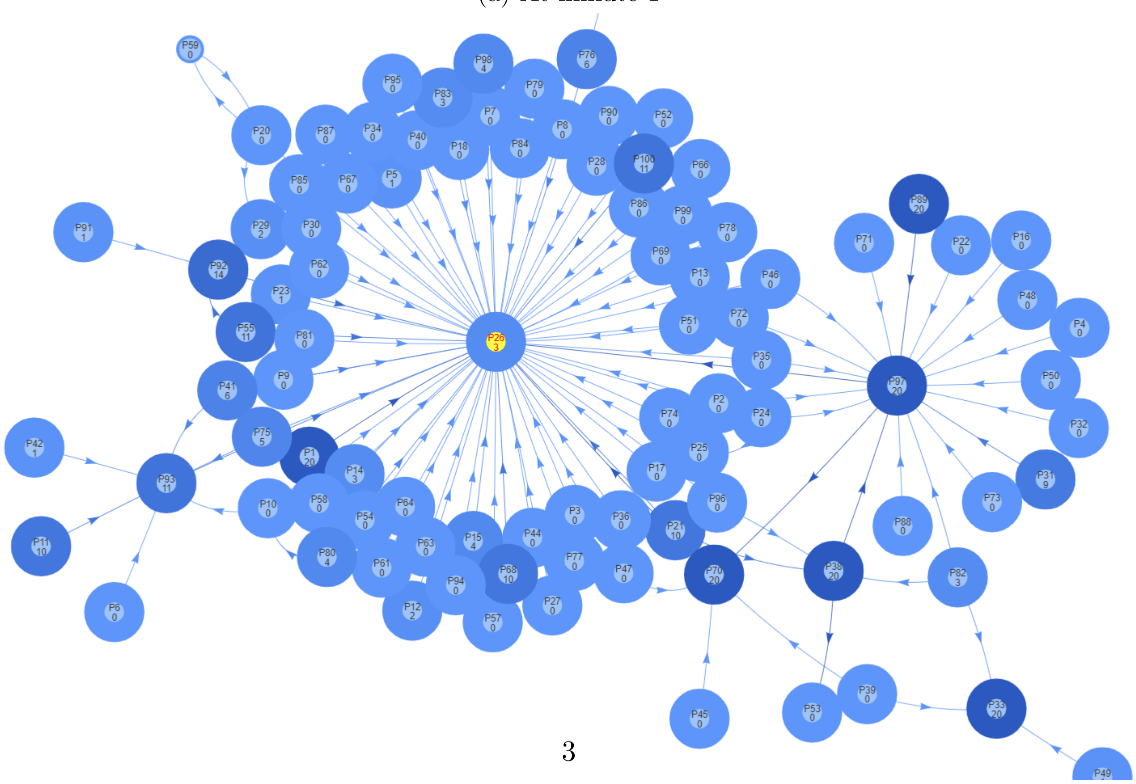
We consider four group sizes $4, 8, 50, 100$ and each of these groups plays the linking and effort game over 6 minutes. There are two information treatments: in the baseline treatment, subjects observe only their own payoffs, while in the payoff information treatment a subject observes the payoffs of everyone. Taken together, we therefore have a 4×2 design. This design enables us to vary the strategic uncertainty and cognitive complexity facing subjects and therefore offers us a natural way to test the theory.

We start with the baseline information treatment. To get an overall impression of the dynamics of linking and effort, Figures 1 and 2 present snap shots taken from the experiment with a hundred subjects. Initially, at minute 1, subject P26 emerges as a hub with the maximum effort 20. There are other subjects who make maximal effort (such as P97). At minute 3, P26 continues to be a hub but has substantially lowered her effort. Due to this shading of effort, she starts to lose some of her links to subject P97, who has kept her effort at 20. The transition becomes clearer in Figure 2a at the 5 minute mark, when the initial hub subject P26 has lost most of her links to the emerging hub P97. Figure 2b confirms that this transition is stable until the end of the game. These figures highlight two macroscopic patterns: there is specialization in linking and efforts and there is a positive correlation between links and efforts. The figures also bring out individual level dynamics: a few individuals exert large efforts and this leads to intense competition to become a hub. This rivalry leads to the emergence of a "pure influencer" outcome. We now examine the data from the experiments more systematically.

Our first set of findings concern the macroscopic patterns. In all four group sizes, there is a tendency toward specialization in linking and efforts, but this tendency expresses itself in the clearest form in the large groups (especially in the hundred subject treatment).

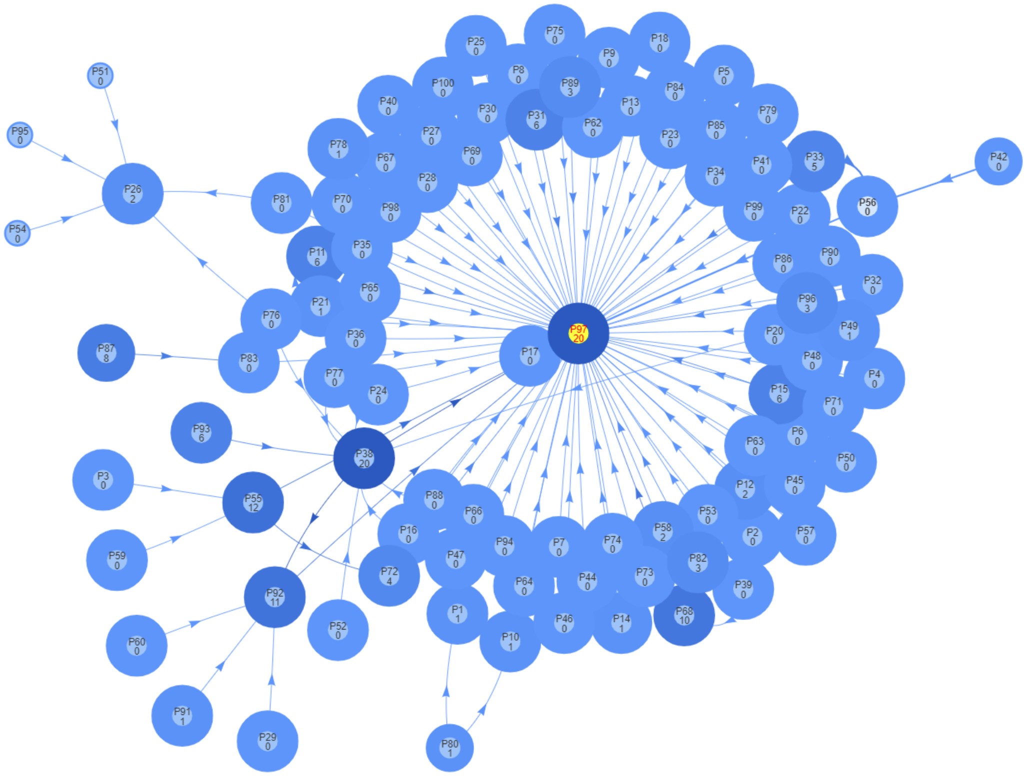


(a) At minute 1

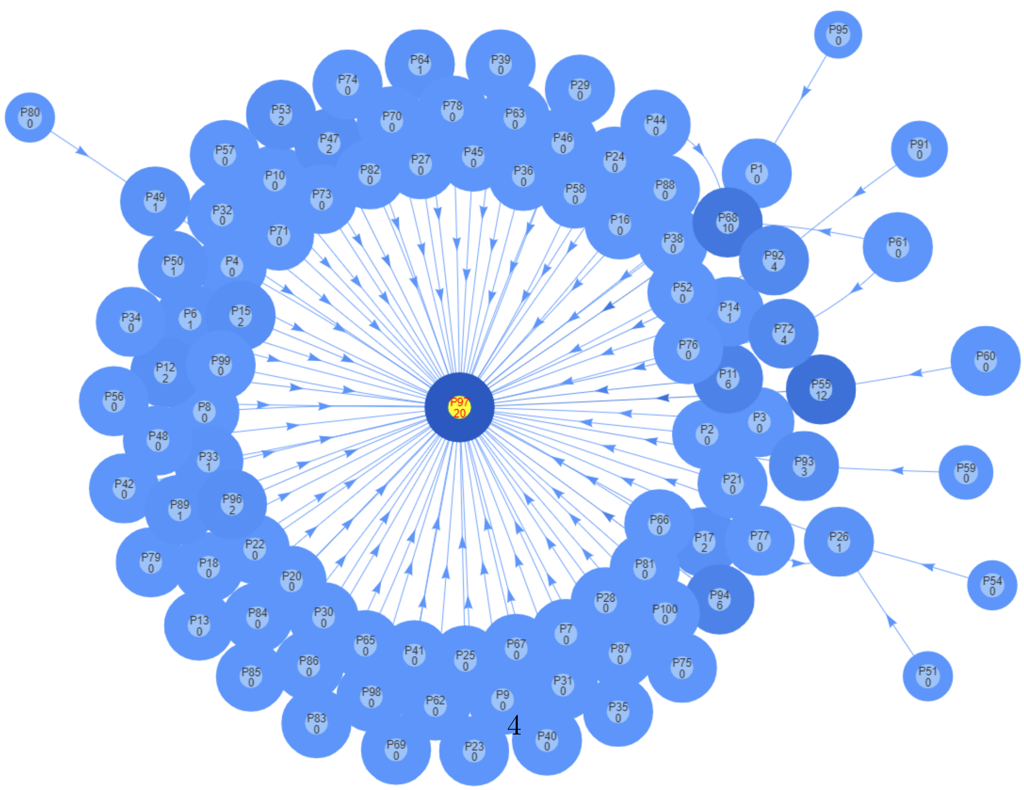


(b) at minute 3

Figure 1: Snap shots of a dynamic game



(a) At minute 5



(b) At minute 6

Figure 2: Snap shots of a dynamic game (cont.)

Another finding is that, across all group sizes, there is a positive correlation between connectedness and effort: this supports the pure influencer outcome.

Our second set of findings are about the individual behavior that supports these macroscopic patterns. In all four group sizes, highly connected individuals exert large efforts. However, the level of efforts and the closeness of the efforts between the few most connected individuals varies with group size. In particular, in small groups the efforts of the most connected individual are close to the equilibrium prediction of the static model. By contrast, in the large groups of fifty and a hundred subjects, the most connected subject chose efforts that are excessive and much above the equilibrium prediction. Moreover, in small groups the efforts of the most connected and the second most connected individual are far apart, while they are fairly similar in the large groups. This suggests that a larger group size intensifies the level of competition.

So the big effect of group size is on efforts and competition dynamics: why do individuals seek to become hubs? The natural motivation would be a desire to increase payoffs. To our surprise, we find that individuals who seek to become the hub by making large efforts (and by forming multiple links) typically have low earnings. Indeed, in many cases they earn much less than the peripheral players. This poses a puzzle.

Could it be that subjects fail to understand the payoff implications of large efforts and linking? We explore this idea by considering another setting of the experiment in which subjects are shown the payoffs of everyone. Provision of payoff information on everyone can facilitate a comparison of payoff performances among subjects, which in turn makes it easy for subjects to understand the payoff implications of their own choices. Availability of such information may also alter dynamic adjustments of individual behavior due to different sources such as imitation and sophistication (Schlag [1998], Huck et al. [1999], and Camerer [2003]).

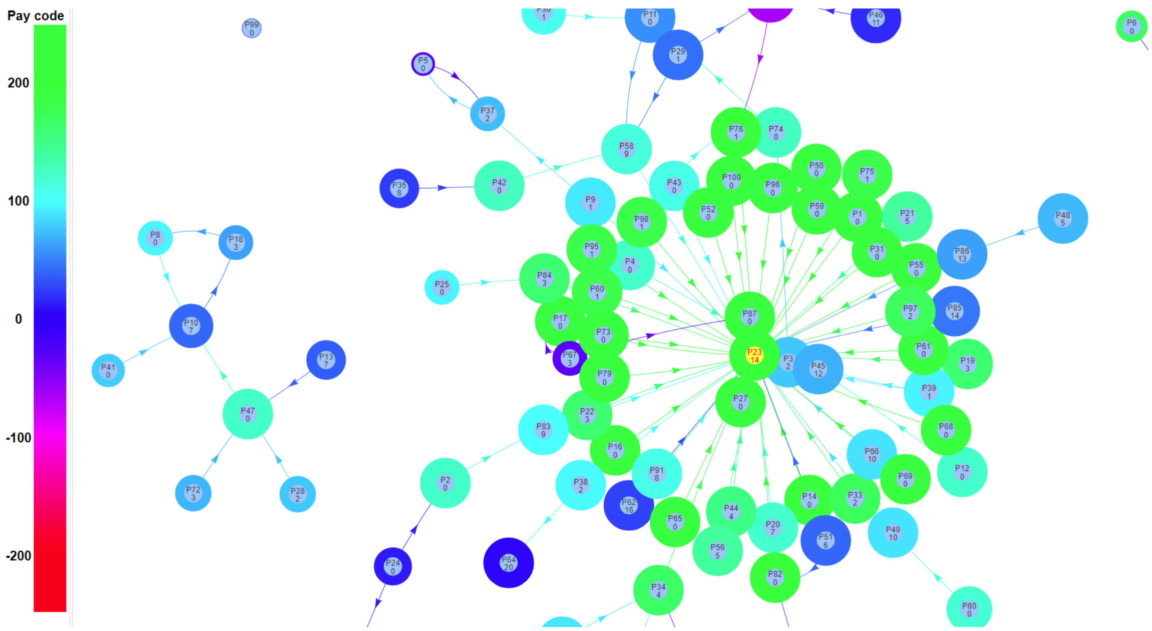
Providing subjects with information on everyone's payoffs has large effects. To get a first impression of these effects, Figures 3 and 4 present snap shots taken in the payoff information treatment with a hundred subjects. Observe that the specialization in linking continues to hold in this setting. However, there is a major change in the behavior of individuals seeking to become a hub: the most connected individual (P23) starts at a high effort 14, but then shades her efforts. The key difference with the baseline is that the challengers do *not* respond by making excessive efforts. As a result, the efforts by the most connected individual keep declining (and the number of links formed by her is also close to zero). This has two important implications. The outcome is closer to a "pure connector outcome" in some groups and, in most groups, the most connected individual earns much more than the peripheral individuals.

We now summarize the general findings of the payoff information treatment. Our first observation is that even with payoff information, in all four group sizes, there is a tendency toward specialization in linking and in efforts, and that this tendency is stronger in the large groups. This finding taken together with the findings of the baseline treatment suggests that subjects abide by the law of the few.

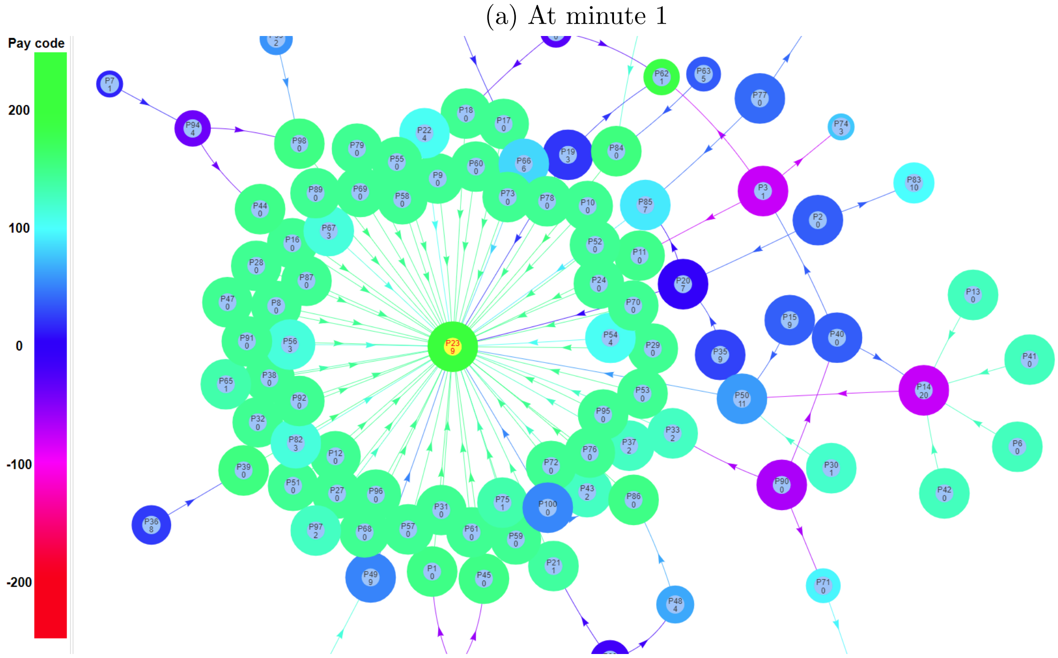
The second observation is that in the payoff information treatment, in small groups there is a strong positive correlation while in large groups there is a weak correlation between connectedness and effort. In some large groups the most connected individual puts in 0 effort and this leads to the pure connector outcome (as in Figures 3 and 4), while in others there emerges the pure influencer outcome. The selection of the pure connector outcome is the major departure from what we observed in the baseline treatment. This motivates a closer examination of the individual level behavior in the two information treatments.

We find that, in the payoff information treatment, across the four group sizes, the efforts of the most connected individual tend to be close to the equilibrium prediction in the small groups but are substantially lower in the large groups. A comparison between the baseline and payoff information treatment reveals that payoff information interacts with group size in shaping behavior. We are led to the view that, under the baseline treatment, in large groups, cognitive constraints may be driving the excessive efforts and the high linking of the most connected individuals. When highly connected individuals are shown information on everyone's payoffs, this cognitive constraint is relaxed and individuals appear to understand the adverse payoff implications of excessive efforts. This discourages a challenger from making high efforts in large groups. Interestingly, as a consequence, in large groups, it allows an incumbent hub to lower efforts greatly and obtain much higher payoffs. This suggests that, with payoff information, a larger group size reinforces incumbency power and reduces competition.

We now place our paper in the context of the experimental literature on network formation. Prominent early papers include Callander and Plott [2005], Goeree et al. [2009], Falk and Kosfeld [2012]; recent papers include Rong and Houser [2012], van Leeuwen et al. [2018] and Goyal et al. [2017]. The principal novelty of our paper is that we study network formation in large groups of up to 100 subjects. This necessitates a methodological change in the way we assess the experimental evidence: existing papers have focussed on exact

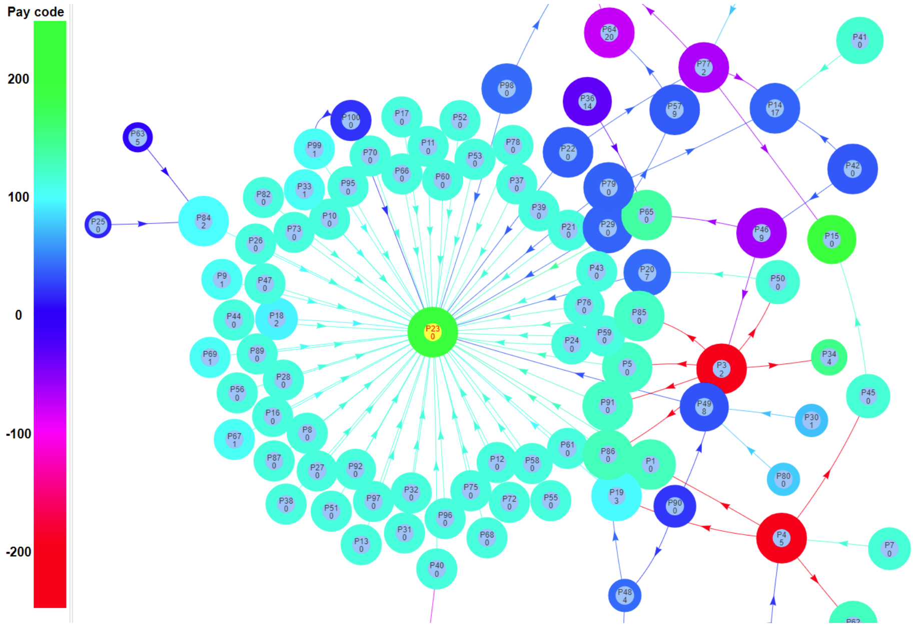


(a) At minute 1

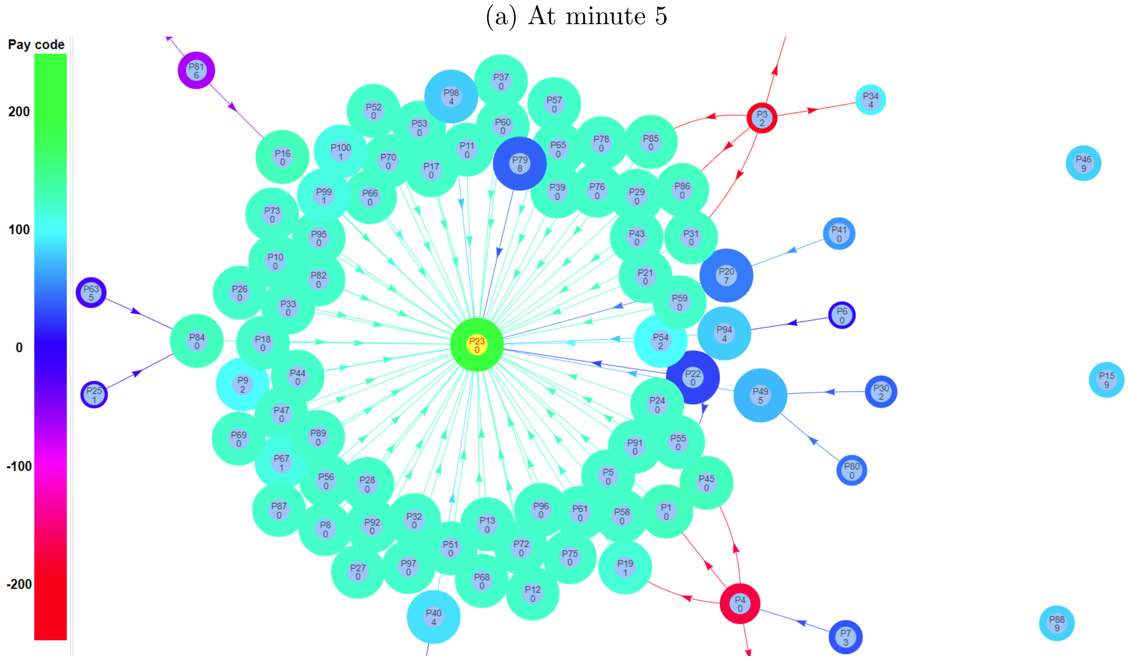


(b) at minute 3

Figure 3: Snap shots with payoff information



(a) At minute 5



(b) At minute 6

Figure 4: Snap shots with payoff information (cont.)

predictions of the theory: e.g., the emergence of star network. By contrast, we take a statistical approach and study the distributions of degree and effort. This builds a bridge between the strategic models of network formation and the large body of work on complex and large networks. Existing papers use small groups and find mixed evidence in support of the structural predictions of the theory, see e.g. Berninghaus et al. [2006], Falk and Kosfeld [2012], Goeree et al. [2009] and van Leeuwen et al. [2018]. By contrast, we find that, under a variety of circumstances, in small and large groups, with and without payoff information, there is a strong tendency toward specialization in linking and efforts. This specialization becomes progressively more acute in the large groups. Thus our experiments suggest that subjects abide by the law of the few.[3]

Our paper also contributes to the experimental literature of continuous time games. Existing studies are built on a recent development of experimental software, called ConG, allowing economic experiments in continuous time (Pettit et al. [2014]) and have focused on small group interaction (see e.g., Friedman and Aprea [2012]; Calford and Oprea [2017]). The novelty of our paper is that we develop an experimental software that enables us to study large group interaction in continuous time. In order to overcome information overload of evolving networks and relax subjects' cognitive bounds in information processing, our software integrates the network visualization tool with the interactive tool of asynchronous choices in real time. This is achieved by adopting an enhanced communication protocol between the server and subjects' computers. It allows us to run both network visualization and asynchronous dynamic choices in real time without communication congestion and lagged responses, even when participants are interacting remotely from different physical locations. Due to these technical advances for large-scale continuous time experiments, we are able to document empirical findings that are especially relevant for large groups such as the law of the few and the interaction between group size and payoff information.

2 Theory

We present a model of linking and efforts taken from Galeotti and Goyal [2010].

Let $N = \{1, 2, \ldots, n\}$ with $n \geq 3$. Each player $i \in N$ simultaneously and independently chooses a level of information acquisition $x_i \in X$ and a set of links g_i with others to access

[3] There is a also a small literature on experiments in which players choose partners and then play a coordination game, see e.g., Riedl et al. [2016], Kearns et al. [2012]. The focus here is on how linking shapes behavior in the coordination game. This is quite different from the motivation of the current paper.

their information such that $g_i = (g_{i1}, \ldots, g_{ii-1}, g_{ii+1}, \ldots, g_{in})$, and $g_{ij} \in \{0,1\}$ for any $j \in N \backslash \{i\}$. Let $G_i = \{0,1\}^{n-1}$. We define the set of strategies of player i as $S_i = X \times G_i$, and the set of strategies for all players as $S = S_1 \times \ldots \times S_n$. A strategy profile $s = (x, g)$ specifies efforts by each player, $s = (x_1, x_2, \ldots, x_n)$, and the network links made by every player, $g = (g_1, g_2, \ldots, g_n)$. The network g is a directed graph. The closure of g is an undirected network denoted by $\bar{g}$ where $\bar{g_{ij}} = \max(g_{ij}, g_{ji})$ for every $i, j \in N$. The undirected link between two players reflects bilateral information exchange between them. We define $\eta_i(g) = |\{j \in N : g_{ij} = 1\}|$ as the number of links i has formed. For any pair of players i and j in g, the geodesic distance, denoted by $d(i, j; \bar{g})$, is the length of the shortest path between i and j in $\bar{g}$. If no such path exists, the distance is set to infinity. We define $N_i^l(\bar{g}) = \{j \in N : d(i, j; \bar{g}) = l\}$ as the set of players at distance l from i in $\bar{g}$.

Given a strategy profile $s = (x, g)$, the payoffs of player i are:

$$\Pi_i(x, g) = f(x_i + \sum_{l=1}^{n-1} a_l(\sum_{j \in N_i^l(\bar{g})} x_j)) - cx_i - \eta_i(g)k \tag{1}$$

where c denotes the constant marginal cost of efforts, k the cost of linking with another player, and a_l reflects the spillover across players who are at distance l. So if $j \in N_i^l(\bar{g})$, then the value of agent j's information to i is given by $a_l x_j$. We assume that $a_l \geq a_{l+1}$, for all $l \in \{1, .., n-2\}$. In the paper, we will focus on the special case where $a_1 = 1$, $a_2 \in (0,1)$, and $a_l = 0$, for all $l \geq 3$. The benefit function $f(y)$ is twice continuously differentiable, increasing, and strictly concave in y. For simplicity, also assume that $f(0) = 0$, $f'(0) > c$, and $\lim_{y \to \infty} f'(y) = m < c$. Under these assumptions there exists a number $\hat{y} \in X$ such that $f'(\hat{y}) = c$.

There are no general equilibrium characterization results available for this model; the analysis of Galeotti and Goyal [2010] focuses on polar cases in which $a_1 = 1$ and $a_l = 0$, for all $l \geq 2$ and the case where $a_l = 1$, for all l. Here we are allowing for gradual decay in valuation with distance in network; a case which appears to be the natural one. The following result characterizes equilibrium when linking costs are relatively large.

Proposition 1. *Suppose payoffs are given by (1), $a_1 = 1$, and $a_2 \in (0,1)$. Then there exists a $\hat{k}$, such that for $k \in (\hat{k}, c\hat{y})$ the following is true. The equilibrium network is a periphery sponsored star. There exist two possible effort equilibrium configurations:*

- *the pure influencer outcome: the hub invests $\hat{y}$ and everyone else invests* 0.

- *the pure connector outcome: the hub invests* 0 *and everyone else invests* $\frac{\hat{y}}{1+(n-2)a_2}$.

The proof is presented here for easy reference.

Proof. The first step is to observe that in equilibrium every individual must access at least $\hat{y}$. This is true because if someone is accessing less than $\hat{y}$, then due to the concavity of the $f(.)$ function, she can simply increase her utility by raising effort so that the total access equals $\hat{y}$.

The second step is to show that players will form one link or zero link, for sufficiently large linking costs. Observe that an isolated individual will choose $\hat{y}$. So it follows that in a network with connections, no one will ever choose more than $\hat{y}$. Note that if link costs are close to $c\hat{y}$ then it is not profitable to form links with two individuals who each choose $\hat{y}$. So the only situation in which an individual, A, may choose two or more links arises if an individual accesses significantly more than $\hat{y}$ through each link. Consider a link between A and B. Iterating on optimal effort, it is true that if B chooses $\hat{y}$ then every neighbor of B must choose 0. So A accesses more than $\hat{y}$ only if B chooses strictly less than $\hat{y}$. If a neighbour of B chooses a positive effort then it must be the case then this person must meet the first order condition on optimal efforts: her total efforts invested and accessed must equal $\hat{y}$. As this person is a neighbour of B, it follows that A cannot access more than $\hat{y}$ via the link with B. So, A will form at most one link in equilibrium.

The third step considers effort configurations. Take the situation in which some individual (say) A chooses $\hat{y}$. It is optimal for everyone else to choose effort 0 and form a link with this person. And it is clearly optimal for A to choose $\hat{y}$ faced with zero efforts by everyone else.

To conclude the proof, we need to show that the pure connector outcome is the only possible equilibrium in a situation where no player chooses $\hat{y}$. Observe first that the pure connector outcome is an equilibrium so long as $k < c\frac{\hat{y}(n-2)a_2}{1+(n-2)a_2}$. Observe that $c\frac{\hat{y}(n-2)a_2}{1+(n-2)a_2}$ converges to $c\hat{y}$, as n gets large.

Now we rule out any other possible equilibrium. The key step here is to show that any equilibrium network must have diameter less than or equal to 2. Suppose the diameter of a component is 3 or more. We know from step 2 that the component must be acyclic. So consider two furthest apart leaf nodes. A variant of the 'switching' argument, developed in Bala and Goyal [2000], shows that one of the two leaf players have a strict incentive to deviate. So every component must have diameter 2. Given that the network is acyclic, this implies it must be a star. It is now possible to apply standard agglomeration arguments to deduce that multiple components cannot be sustained in equilibrium.

Finally, the hub player must choose zero. Suppose not. By hypothesis the hub chooses less than $\hat{y}$. Given that a_1 and $a_2 < 1$, both the hub and the spokes cannot be accessing exactly $\hat{y}$. A contradiction that implies that the hub must choose zero effort.

□

In the pure influencer equilibrium, we witness an extreme version of the 'law of the few': a single person receives all the links formed in society and also carries out all the efforts. The pure connector equilibrium retains the specialization in links: a single person receives all links. However, now the efforts are fairly evenly spread out. Interestingly, in both equilibria the creation of links is basically egalitarian – $n-1$ players form one link each. For large k values, the payoff distribution is only slightly unequal in the pure influencer equilibrium. However, the pay-off inequality can be very large in the pure connector equilibrium (especially if k is large and a_2 is small). We note that the pure connector equilibrium holds only for a sufficiently large group size n, i.e., $n \geq 2 + \frac{k}{a_2(c\hat{y}-k)}$.

We now present the specific function $f(.)$ used in the experiment and the rest of the numerical details.

$$f(y) = \begin{cases} y(29-y) & \text{if } y \leq 14 \\ 196 + y & \text{else} \end{cases} \tag{2}$$

In the experiment we assume that efforts are integers and set a maximum bound, $\overline{x} = 20$. So the efforts set is given by $X = [0, 20]$. And we will assume that $c = 11$ and $k = 95$ and $a_2 = 1/2$. In this context, it can be checked that $\hat{y} = 9$. There exists a pure influencer equilibrium in which a single individual chooses 9 and all other individuals choose 0 and form a link with the positive effort player. In principle, there exists a pure connector equilibrium in which the periphery players each choose $18/n$, for any $n \geq 50$.[4] In our experiment, however, given the integer constraints, this equilibrium is no longer feasible (for any $n \geq 50$, $0 < 18/n < 1$ is not an integer). In this context, in the treatments with 50 and 100 subjects, the periphery sponsored star where 18 peripheral individuals choose 1 and the rest of the subjects choose 0 constitutes an 'approximate' equilibrium (for

[4]The pure connector equilibrium does not hold in the experimental setting for any $n < 50$.

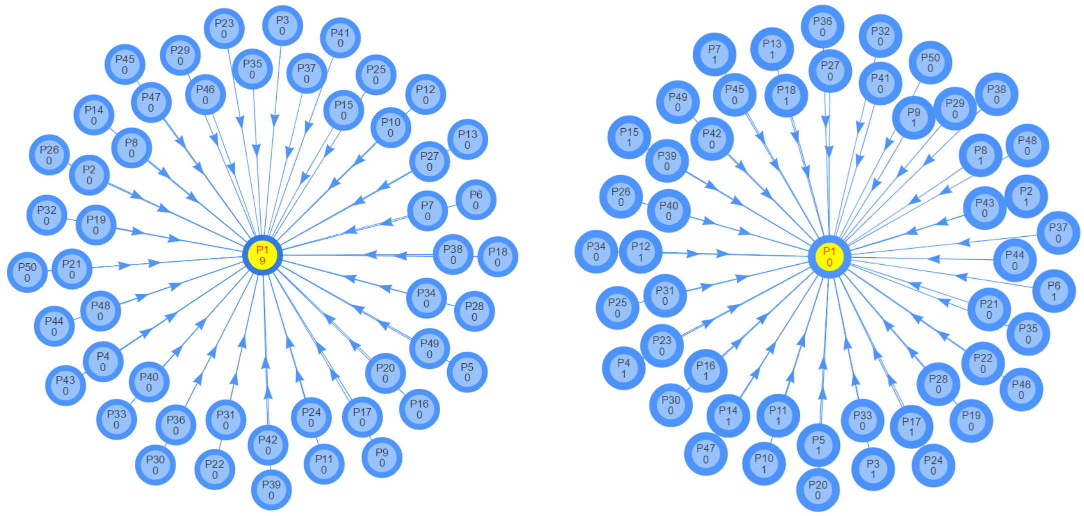


Figure 5: Pure influencer and pure connector equilibrium, $n = 50$

details see Online Appendix A).[5] Figure 5 illustrates the pure influencer equilibrium and the pure connector approximate-equilibrium.

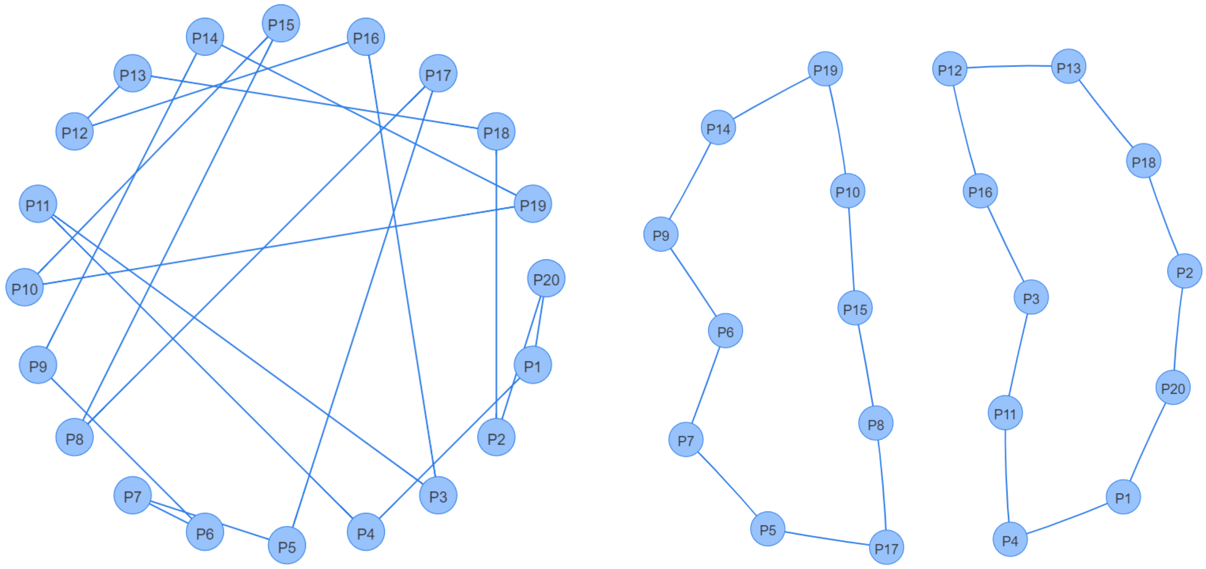
To summarize, in the pure influencer equilibrium, the hub chooses effort 9, while the spokes choose 0. The spokes form one link with the hub. The hub earns 81, while the spokes earn 85. In the pure connector equilibrium, the hub chooses effort 0, eighteen spokes choose 1 each, while the other spokes choose 0. The hub earns 198, the active spokes 74, and the inactive spokes 85.

3 Experiment

3.1 Challenges and methodology

The goal of this paper is to understand the mechanisms that shape network formation and assorted activity in large groups. As the complexity of subjects' decision making increases in scale, large-scale experiments on network formation pose several major challenges. We discuss these challenges and explain how our experimental software and design address each of them.

[5]The periphery player who chooses effort 1 and forms a link with the hub earns 79.25. This person could earn 81 by deleting the link and instead choosing effort level 9.



(a) Fixed visualization

(b) Adaptive visualization

Figure 6: Examples of network visualization

Network visualization. Existing studies of network formation in economics have considered small group sizes such as 4 or 8 people in a group and visualized evolving networks with fixed positions of nodes (e.g., Goyal et al. [2017]; van Leeuwen et al. [2018]). When the group size increases, such a representation of networks with fixed positions of nodes makes it very difficult for subjects to perceive network features adequately. For example, consider a group of 20 people with fixed positions of nodes in a circle as depicted in Figure 6a. While the exact nature of the network is hardly perceptible by observing Figure 6a, the same network structure can be represented in a transparent manner in Figure 6b.

For subjects to learn what to do, they must have a good idea of the evolving networks. An appropriate tool for visualizing networks is thus critical in running the experiment in continuous time. This leads us to develop an experimental software including an interactive network visualization tool that allows the network to automatically reshape itself based on its evolving structure. We use the Barnes-Hut approximation algorithm [Barnes and Hut, 1986] for grouping nodes in a network that are sufficiently nearby and adjust their relative positions on the subject's computer screen. It enables us to apply repulsion forces between nodes so that they are sufficiently separated from one another, attractive forces to nodes that are directly linked with each other, and gravity to all the nodes with respect to a central origin on the screen such that nodes not linked with each other remain within reasonable distance from each other. The network visualization in Figure 6b was made using this algorithm. In our large-scale experiment, this visualization tool improves graphical clarity of evolving networks and helps subjects distinguish between those who are more connected and those who are less connected. More details regarding the specifics of this visualization tool (including model parameters characterizing attraction and repulsion forces) can be found in Online Appendix B. It is important to emphasize that this tool allows interaction between the subject and the network: while the nodes are subject to the above attraction and repulsion forces, they can also be freely manipulated by the participant through the usual drag-select functionality. The creation and removal of links is also interactive through double-clicking on corresponding nodes. This network visualization tool is built on the open source Javascript library *vis.js*.

Learning and dynamics. We wish to allow subjects ample opportunities to learn about the environment of decision making, other subjects' behaviors, and how to respond optimally to them. In view of the strategic complexity alluded to above, the issue of learning and behavioral convergence is particularly complicated. To address these issues, and to make the learning opportunities as comparable across group sizes as possible, we run the experiment in continuous time with near real time updating—of all actions and linking by everyone—for every subject.[6] Continuous time experiments can also offer better prospects for convergence than discrete time experiments (see e.g., Friedman and Aprea [2012]).

In our experiment, the game is played in continuous time for 6 minutes during which every subject was free to asynchronously adjust their actions of efforts and linking. Because subjects face a complex problem of decision making and need some time to figure out the game and coordinate their actions, a trial time of one minute is provided (during which subjects start choosing their actions with no monetary consequence). After the trial period is over, the subsequent 5 minutes are payoff relevant and one second is randomly chosen to determine subjects' earnings in the game. This information is publicly known to subjects.

Running the continuous time experiments in large groups poses some technical challenges. First, every action made by a subject on her computer must be updated instantly on the computer screens of all other participants through the server computer. Network vi-

[6] Although the experimental software allows for real time updating of actions, we voluntarily introduce some latency in our experiment to avoid any possible confusion caused by some overload of activity on the subjects' screen. More precisely, the network depicted on any subject's screen is updated every 5 seconds or whenever the subject makes a decision.

sualization must be also correspondingly updated in real time. As the group size increases, the total amount of information flows across the computer network increases drastically. This can cause communication congestion and lagged responses. Another challenge with such a large scale experiment is that it is constrained by the limited capacity of existing laboratories. Large groups that cannot fit into a single lab therefore require remote interactions between subjects in different geographical locations (that is, different labs). In order to handle both of these technical challenges, we use a Websocket protocol with enhanced two-way communication between the server and subjects' computers. It fits into the environment of asychronous choices in real time and updating such information only when necessary. Our Websocket technology relies on the Javascript run-time environment *Node.js.* [7]

Network information. In addition to the issue of network visualization, we are also concerned about the network information each individual subject have access to. To get a sense of the range of possibilities, consider two extreme scenarios: one, subjects only observe their own neighbors in the current network, and two, subjects get to see the entire network. The information and cognitive load implied by the latter scenario grows rapidly in size of the group. In view of this potential trade-off between transparency of network change and information and cognitive overload, we choose to inform each subject of a local structure of the network within a (geodesic) distance 3 from the subject.

So given a fixed network, for every subject, we can partition the entire group of subjects into two mutually exclusive subgroups: those who are located within distance 3 from the subject, and those who are located outside this set. Figure 7 depicts an illustration of network visualization and information shown in the experiment with 50 subjects. The left side of Figure 7 shows the group of subjects within distance 3 (and all their links with other subjects within distance 3). The right side of Figure 7 collects the group of subjects further than distance 3 (with no information about their links in the network). In addition to network information, subjects are informed about every subject's effort—presented as a number within the corresponding node along with that subject's ID. The total access to information of a node is captured by the size of that node.

Information on Payoffs. We now turn to information on payoffs: clearly subjects need to be able to see their own payoffs in order to learn the profitability of different linking

[7]Since it only requires an internet connection and is compatible with most existing web browsers (e.g., Google Chrome, Mozilla Firefox, Internet Explorer), this technology makes no specific restriction on the physical location of every participant.

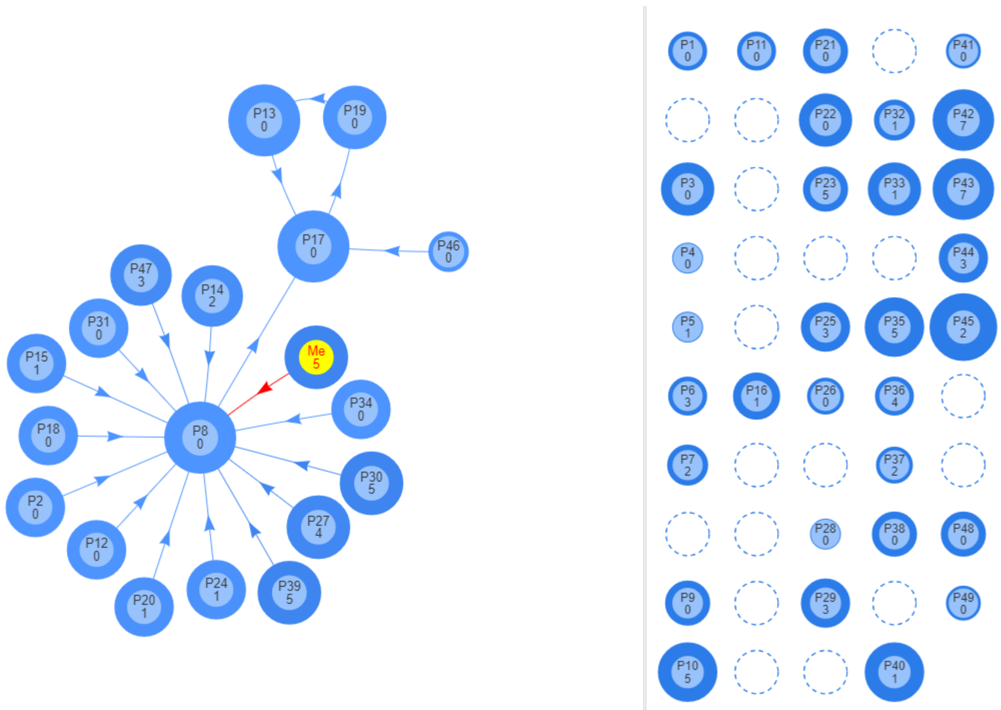


Figure 7: Network information

and effort options.[8] What about information on payoffs of other individuals?

The literature of learning in games provides some guidance on this question (see, e.g., Camerer [2003] for a survey). In adaptive models such as reinforcement learning and experience-weighted attraction learning (Camerer and Ho [1999]), players ignore information on payoffs of other individuals. In other models such as imitation learning (Schlag [1998]) and sophisticated learning (Camerer et al. [2002]), players would behave differently if the payoffs of others are known. In the recent body of network experiments (e.g., Goeree et al. [2009] and Falk and Kosfeld [2012]), researchers have tended not to show subjects the payoffs of others. However, when information on others' payoffs is available in particular in large groups where it is difficult to infer such information, subjects may follow a different behavioral rule. In fact, the experimental literature documents that human subjects may behave differently when information on the payoffs of other individuals is available (e.g., Huck et al. [1999]).

Building on these strands of research, it is possible to argue that in games with small groups of subjects, showing the payoffs of others may not be a first order issue, as subjects can compute these payoffs themselves in a fairly straightforward manner, should the need arise. However, in a dynamic game with a hundred subjects—and with the network and efforts configuration constantly evolving—an individual may find it much harder to compute the payoffs of other subjects. The knowledge of others' payoffs may become an important concern for experimental design for a couple of reasons. The first reason pertains to learning dynamics: observing the others' payoffs could potentially assist subjects in better appreciating the trade-offs associated with different courses of action. The second reason pertains to fairness considerations. The two equilibria described in Proposition 1 exhibit very different levels of payoff inequality across players. The pure-influencer equilibrium exhibits a minor payoff difference between the hub player and the spoke players, whereas the pure-connector equilibrium yields a much larger payoff difference between the hub player and the spokes players. These payoff differences may shape behavior of subjects. These considerations motivate treatments in which we vary the level of information on others' payoff.

In the baseline treatments subjects are shown their own payoffs but *not* the payoffs of other subjects. A subject is also shown the efforts and access to information for all other subjects, as shown in Figure 7. In principle, therefore, a subject can infer the gross

[8]Details about the costs and benefits are provided to the subjects to facilitate their comprehension of their own payoff, as illustrated in Online Appendix D

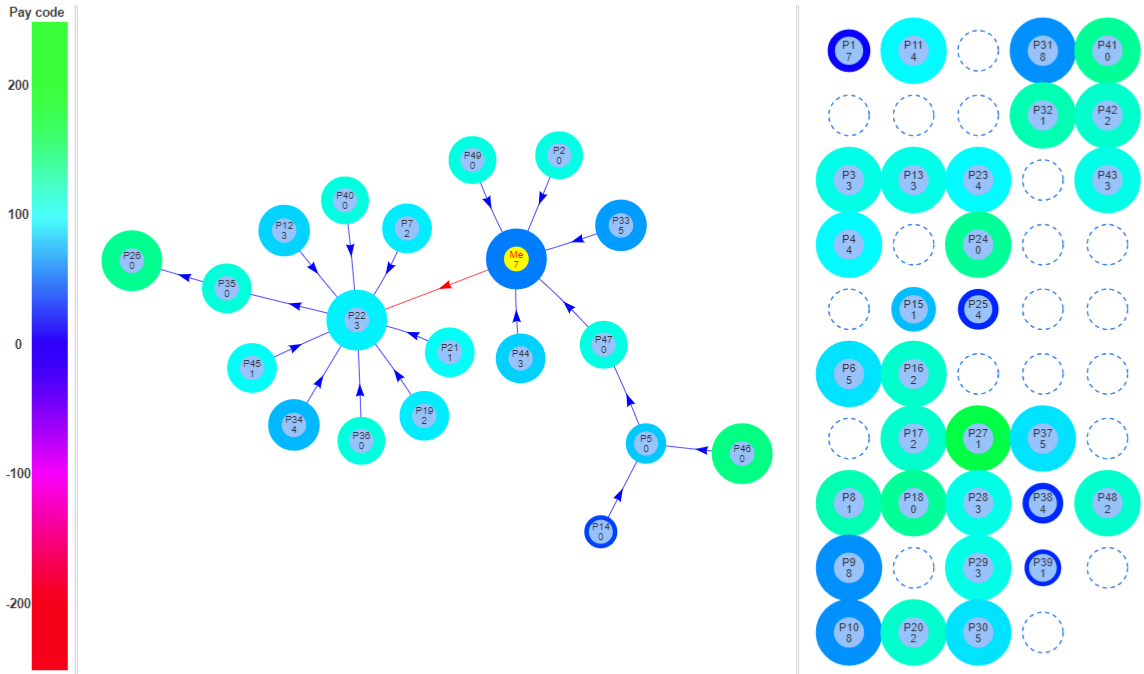


Figure 8: Screen shot of the Payoff Information Treatment

payoffs of any other subject by observing these pieces of information. But we believe that such inference would be challenging for subjects during a large scale continuous-time game, where the network and effort levels are evolving rapidly. In the payoff information treatments, we add information about every player's payoff through a set of color codes as illustrated by Figure 8. More precisely, the border of each node in the network is characterized by some color, which varies from green (high positive payoff) to red (high negative payoff) depending on the player's corresponding earnings. The scale of the color code is constantly provided on the computer screen as in the left part of Figure 8.

3.2 Treatments and design details

The experiment varies the group size $N \in \{4, 8, 50, 100\}$ and the visibility of others' payoff. Table 1 summarizes the 4×2 treatment structure of our experiment.

All the treatments are based on the same payoff function, as defined in equation (1). Recall that the marginal cost of effort is set to $c = 11$. This implies an optimal effort of

		Group size			
		$N = 4$	$N = 8$	$N = 50$	$N = 100$
Others' payoff information	**NO**	**Baseline4**	**Baseline8**	**Baseline50**	**Baseline100**
	YES	**PayInfo4**	**PayInfo8**	**PayInfo50**	**PayInfo100**

Table 1: Experimental Treatments

$\hat{y} = 9$ in the static model. The cost of linking is fixed to be $k = 95$. We restrict effort x as any positive integer value not exceeding 20, i.e., $\overline{x} = 20$. Finally, we set $a_1 = 1$, $a_2 = 0.5$, and $a_l = 0$, for all $l \geq 3$.

At any instant in the 6 minutes game, every subject can form or remove a link with another subject by simply double-clicking on the corresponding node in the computer screen. If the subject forms a link with another subject on the right side of the screen (i.e., someone who is in more than 3 geodesic distance away), that subject along with his neighbors and neighbors' neighbors would be transferred to the left side of the computer screen. In a case where the subject removes a link with another subject on the left side of the screen, that subject would be transferred to the right side of the computer screen if they become more than 3 geodesic distance apart in the network and would remain in the left side of the screen otherwise.

During the experiment, each subject can also choose any level of effort by moving a slider varying from 0 to 20 by increments of 1. This slider is provided on top of the decision screen along with other payoff-relevant information including the subject's gross earnings (i.e., the benefit $f(x)$ where x is the total amount of information the subject has access to), cost of effort, cost of linking, and resulting earnings (i.e., payoff $\Pi_i(x_g)$). Further information on the screen is provided in Online Appendix D.

3.3 Experimental procedures

The experiment was conducted in the Laboratory for Research in Experimental and Behavioural Economics (LINEEX) at the University of Valencia and in the Laboratory for Experimental Economics (LEE) at the University Jaume I of Castellón . All the treatments except for $N = 100$ treatments were conducted at the LINEEX. The experimental sessions of $N = 100$ treatments were conducted through the internet connection between

LINEEX and LEE (the number of subjects was then evenly distributed across both locations). Subjects in the experiment were recruited from online recruitment systems of the two laboratories. Each subject participated in only one of the experimental sessions. After subjects read the instructions, the instructions were read aloud by an experimenter to guarantee that they all received the same information. While reading the instructions, the subjects were provided with a step by step interactive tutorial which allowed them to get familiarized with the experimental software and the game. Subjects interacted through computer terminals and the experimental software was programmed using HTML, PHP, Javascript, and SQL. Sample instructions and interactive tutorials are available in Online Appendix C.

There were in total 18 sessions: 1 session of 16 subjects for each of the Baseline4 and PayInfo4 treatments, 1 sessions of 32 subjects for each of the Baseline8 and PayInfo8 treatments, 4 sessions of 50 subjects for each of the Baseline50 and PayInfo50 treatments, and 3 sessions of 100 subjects for each of the Baseline100 and PayInfo100 treatments. In each experimental session, subjects were (randomly) matched into a fixed group (if there are more than one group in a session) and interacted with the same subjects throughout the experiment. Therefore, there are 4 independent groups for each of the $N = 4$, $N = 8$, and $N = 50$ treatments and 3 independent groups for each of the $N = 100$ treatments. A total of 1096 subjects participated in the experiment.

The experiment consists of 6 rounds of the continuous-time game, each of which lasted for 6 minutes with the first minute as a trial period and the subsequent 5 minutes as the game with payment consequence. At the end of each round every subject was informed, using the same computer screen, of a time moment randomly chosen for payment, detailed information on subjects' behavior at the chosen moment including a network structure and all subjects' efforts, and the resulting earning of the subject. While each group of people was fixed in a session, subjects' identification numbers were randomly reassigned at the beginning of every round in order to reduce potential reputation effects. The first round was a trial round with no payoff relevance and the subsequent 5 rounds were effective for subjects' earnings. In analyzing the data, we will focus on subjects' behavior and group outcomes from the last 5 rounds. At the beginning of the experiment, each subject was endowed with an initial balance of 500 points and added positive earnings to or subtracted negative earnings from that initial balance. Subjects' total earnings in the experiment amounted to the sum of earnings across the last 5 rounds and the initial endowment. Earnings were calculated in terms of experimental points and then exchanged into euros at the rate of 100 points being equal to 1 euro. Each session lasted on average 90 minutes, and subjects earned on average about 18 euros, including a 5 euros show-up fee.

At the end of the experiment, subjects took incentivized tasks to elicit social preferences and risk preferences. They are a modified version of Andreoni and Miller [2002] and Holt and Laury [2002], respectively. In addition, subjects answered a brief version of the Big Five personality inventory test adapted from Rammstedt and John [2007], a comprehension test related to the experimental game, and a debriefing questionnaire including demographic information. More details about them can be found in Online Appendix E.

3.4 Connecting theory and experiment

Our goal is to understand the principles that shape linking and assorted activity in large groups. The static theory we have presented above predicts specialization in both linking and effort. But there remain residual complications: for instance, there there are multiple equilibria and these equilibria display considerable diversity in terms of efforts, linking, and payoffs across individuals. Over and above this, in large groups, the individual decision problem is complicated and it is far from clear if subjects will be able to navigate this complexity. These considerations motivate a design with ample opportunity to experiment and to learn. Given the large scale, we are then led naturally to an experimental design in continuous time. This dynamic game in continuous time creates the possibility of signalling, cheap talk, and reputation building; these forces go beyond the original static game. It is therefore important to emphasize a more general methodological point: the aim is to examine the economic implications of the trade-off between costs of linking and the costs of personal efforts. The static model clarifies implications of these trade-offs for networks and efforts. If these arguments are robust, then subjects should abide by the predictions of the theory in an experimental setting that incorporates real world elements more accurately. Keeping this in mind, for the purposes of the experiment, we take the following 'high level' view of the theory:

1. *Law of the Few*: a small fraction of individuals receive most of the links and carry out most of the efforts. An increase in group size leads to greater specialization in linking and efforts.

2. *Strategic uncertainty*: there exist multiple equilibria; these equilibria exhibit differences in actions, linking and payoffs across individuals.

4 Results: Baseline Treatments

We highlighted the three key points from the snap shots in Figures 1 and 2: (i) extreme specialization in linking and efforts; (ii) very large efforts and intense competition among a few subjects to become the hub; and (iii) the emergence of pure influencer outcome. In this section we examine the experimental data systematically. We start with a presentation of the macroscopic outcomes. We will observe that there are interesting group size effects. This motivates a study of individual level behavior and competition dynamics.

For simplicity in all the data analyses that follow, the data used from every round of the game consists of 360 observations (snapshots of every subject's choices in the group) selected at regular time intervals of one second. Although some information about choice dynamics between two time intervals may be lost, we consider the possible impact of such a simplification as negligible to our analyses. Moreover, unless stated otherwise, all analyses are focused on data from the last 5 minutes of each round of the game.

4.1 Macroscopic Patterns

For any individual, the indegree is the number of incoming links from other individuals. Consider the Lorenz curve of indegrees at any point in time: it plots the cumulative fraction of subjects, ranked from least connected to most connected, against the cumulative fraction of total indegrees. Such Lorenz curves are then averaged across seconds of the last five minutes, across rounds, and across groups in each treatment. Figure 9 presents these average Lorenz curves and the corresponding Gini coefficients of indegree across different group sizes. We observe that specialization in linking is present in every group size but that it becomes more pronounced as the group size increases. This is clearly reflected in the Gini coefficient: it is 0.61 for Baseline4, 0.70 for Baseline8, 0.86 for Baseline50, and 0.89 for Baseline100. By organizing the group-level average data, we conduct t-test for the null hypothesis on the equality of Gini coefficients between a small group ($N = 4$ or $N = 8$) and a large group ($N = 50$ and $N = 100$). We reject it with 5% significance level.

Next, we examine more closely the details of dynamics of specialization in linking. Two simple statistics are the time fraction (number of seconds out of 5 minutes) in which the individual is most connected and her mean indegree ratio. For the latter, we consider each individual's indegree and compute the sum of indegrees across individuals at every second in the five minutes. We compute each individual's indegree ratio defined as her indegree divided by the sum of indegrees at every second. We then take the average of an

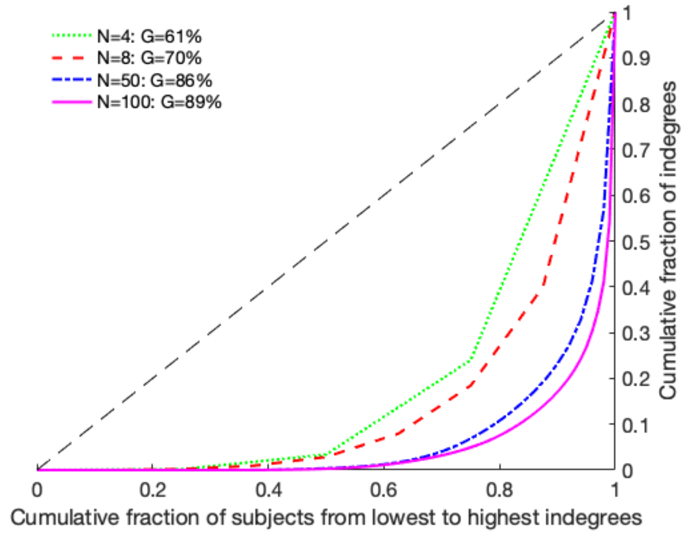
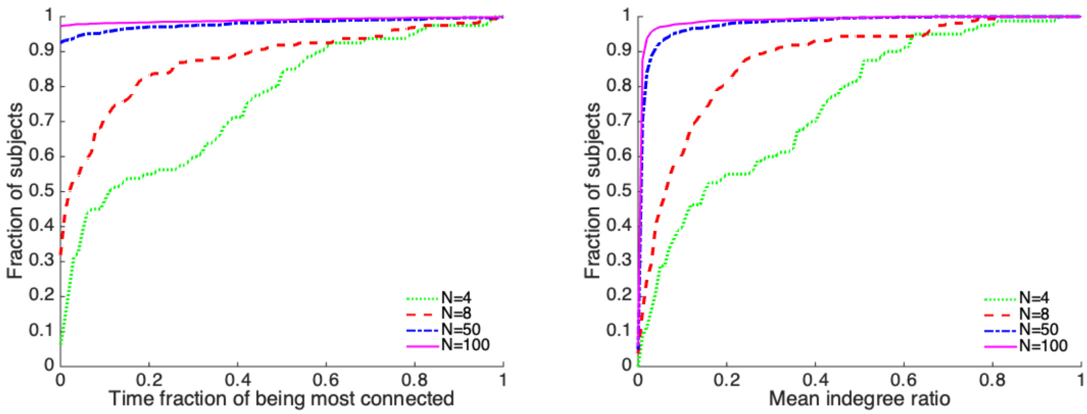


Figure 9: Lorenz curves and Gini coefficients of indegrees

individual's indegree ratio (across 5 minutes) to have her mean indegree ratio. With each of these two variables, we compute its cumulative distribution in a round and consider the average across rounds and groups.

Figure 10 shows the cumulative distributions of time fraction of being most connected and mean indegree ratio. The fraction of subjects who *never* become the most connected player are very high for the large group treatments—0.97 for Baseline100 and 0.93 for Baseline50; this fraction is significantly lower for the smaller groups—0.31 for Baseline8 and 0.06 for Baseline4. It suggests that only a few subjects had any chance of being most connected in the large group treatments, whereas most of the subjects in the small group treatments experienced moments when they were most connected. Similarly, the fraction of subjects whose mean indegree ratio is low increases significantly in group size. For instance, relative frequencies of subjects with mean indegree ratio being less than or equal to 0.05 are 0.29 for Baseline4, 0.45 for Baseline8, 0.93 for Baseline50, and 0.97 for Baseline100.[9] For each variable, the distribution for a small group treatment first order dominates the distribution for a large group treatment at the usual significance level (p-value < 0.01 from

[9]This compares well with the predictions in the periphery sponsored star: the fraction of subjects with 0 mean indegree ratio would be 75% for $N = 4$, 88% for $N = 8$, 98% for $N = 50$, and 99% of the players for $N = 100$.



(a) Time fraction (b) Mean Indegree Ratio

Figure 10: Distributions of linking

the Kolmogorov-Smirnov test)

We turn to examine the macroscopic features of efforts. We start again by drawing the Lorenz curve for efforts and compute the Gini coefficient at every second of the five minutes. We then average them across seconds of the game, across rounds, and across groups. Figure 11 shows these average Lorenz curves and Gini coefficients, across different group sizes. Specialization in efforts is present in every group size and it is more pronounced in larger groups. This is reflected in the Gini coefficient of efforts: 0.48 for Baseline4, 0.58 for Baseline8, 0.75 for Baseline50, and 0.75 for Baseline100. The difference between Gini coefficient in the small group treatment ($N = 4$ and $N = 8$) and that in the large group treatment is statistically significant (p-values < 0.01 from t-test with the group-level data).

In order to look into the details of specialization in efforts in the continuous time game, we consider a variable of mean effort ratio as we did for linking: an individual's effort ratio at every second is defined as her effort divided by the sum of efforts across individuals at that second. We compute the mean of effort ratios across the five minutes for each individual. With this variable, we compute its cumulative distribution in any round and consider the average across rounds and groups. Specialization in efforts becomes substantially more pronounced in large groups. The fraction of subjects whose mean effort ratio is low increases significantly in group size. For instance, relative frequencies of subjects with mean effort ratio being less than or equal to 0.05 are 0.19 for Baseline4, 0.42 for Baseline8, 0.91 for Baseline50, and 0.99 for Baseline100. The distribution of mean effort

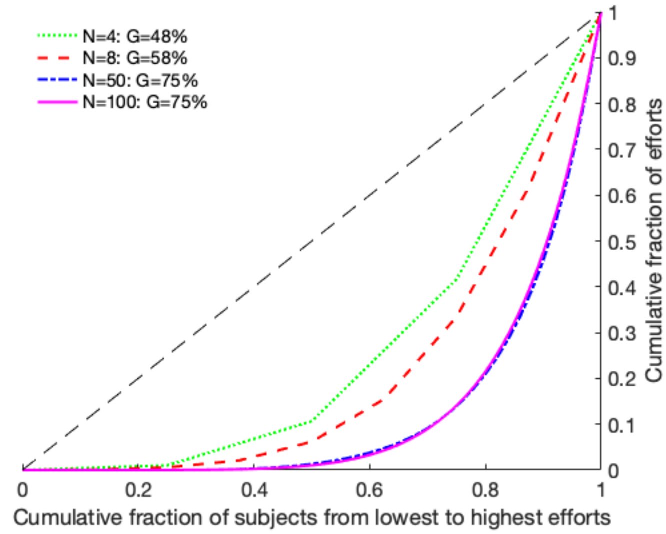


Figure 11: Lorenz curves and Gini coefficients of Efforts

ratio for a small group treatment first order dominates that for a large group treatment at the usual significance level (p-value < 0.01 from the Kolmogorov-Smirnov test).

Result 1 *Specialization in linking and efforts is present in all group sizes and becomes significantly higher as group size increases.*

Next, we turn to investigate the relation between indegrees, efforts and payoffs. Recall from Proposition 1, that there are two equilibria, corresponding to the pure influencer and the pure connector outcomes. In the former there is a positive correlation between efforts and indegrees and a (weak) negative relation between indegrees and payoffs. By contrast, in the latter equilibrium, there is a negative correlation between indegrees and efforts, and a positive correlation between indegrees and payoffs. We run linear regression analysis of mean indegree ratio on efforts and a median regression of (median) payoffs on mean indegree ratio (with controlling demographic information, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality). We use the median regression analysis to minimize the impact of outliers in payoffs. [10] Table 2 presents

[10] In Online Appendix F.1 we report the same regression analysis by replacing mean indegree ratio with time fraction of being most connected. The regression results with both variables are quite similar.

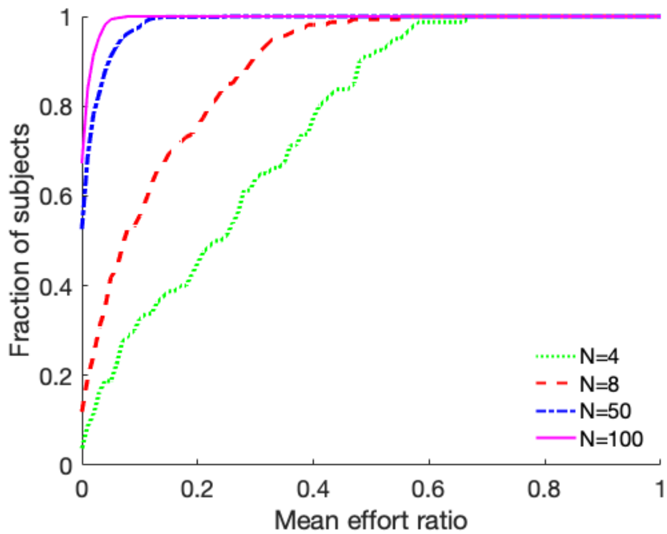


Figure 12: Distribution of Efforts

a set of regression results for each of the four baseline treatments. Robust standard errors, clustered by individual subject, are reported in parenthesis.

This regression brings out the positive correlation between efforts and indegree: this relation is statistically significant and positive in each of the baseline treatments. The regression coefficients for efforts is smaller in the large group treatments than in the smaller groups. This is partly because the range of effort is wider in the large group treatments while the range of the time fraction of being most connected is similar across the treatments as we will see in the next subsection. Next, we note that the association between indegree and payoffs is weak and insignificant in both small group sizes, Baseline4 and Baseline8 treatments. There is, however, a strong negative and significant correlation between linking and payoff in the large group sizes. A one percent increase in mean indegree ratio is associated with 2.72 decrease in median payoff for the Baseline50 treatment and a 2.37 decrease in median payoff for the Baseline100 treatment. We summarize the group size effects on the relation among effort, linking and payoff as follows.

Result 2 *There is a positive correlation between effort and indegrees in all group sizes. The correlation between indegrees and payoffs is insignificant in the small groups and significantly negative in the large groups.*

Table 2: Regression analysis in the baseline treatments

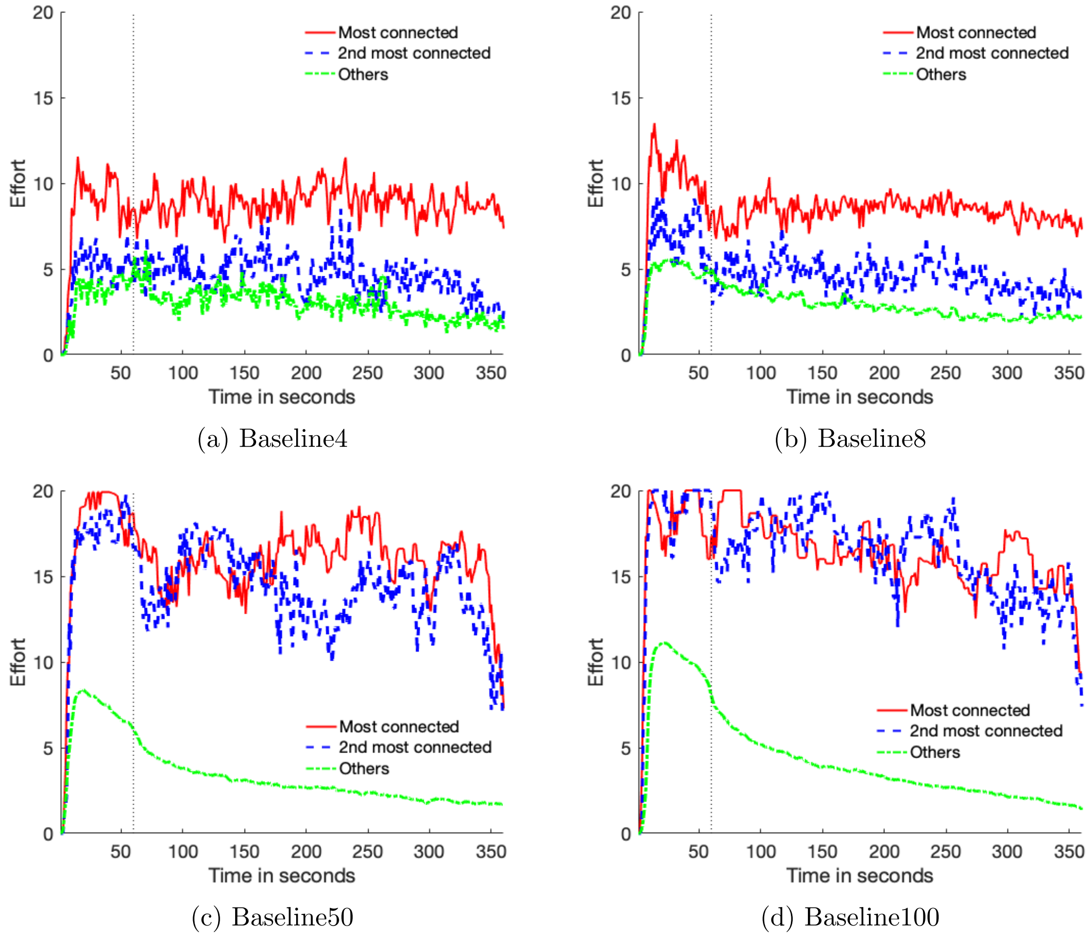
	Mean indegree ratio (%)				Median payoff			
	$N = 4$	$N = 8$	$N = 50$	$N = 100$	$N = 4$	$N = 8$	$N = 50$	$N = 100$
Effort	5.10***	3.67***	0.89***	0.44***				
	(0.33)	(0.55)	(0.12)	(0.07)				
Mean Indegree ratio (%)					0.05	0.03	-2.72***	-2.37*
					(0.17)	(0.12)	(0.38)	(1.31)
Number of observations	80	160	1000	1500	80	160	1000	1500
R-squared	0.769	0.508	0.407	0.210	0.117	0.089	0.145	0.090

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

4.2 Individual Behavior and Competition Dynamics

This section seeks to understand the macroscopic patterns observed—especially the effects of the group size—by examining individual behaviour. The snap shots in Figures 1 and 2 suggest that there are different types of subjects with distinct dynamics of efforts during the game—the two most connected subjects who are competing with each other and the rest of the subjects.

We start with an examination of the dynamics of efforts made by the three different types of subjects identified at every second of the experiment—most connected, 2nd most connected, and the others. Figure 13 presents the average time series of effort for each of the group sizes. The end of the trial minute is represented by the vertical dotted line. We observe very sharp increase in effort by the most connected individual as we move from group size 8 to 50. The other interesting feature of the data is the relative levels of effort between the top two connected individuals: in the small groups there is a persistent gap between their efforts; in the large groups there is a very small gap in effort levels between the top two connected individuals. On the other hand, the average level of effort made by the others is low in all group sizes and steadily decreases over time. These time series patterns suggest that an increase in group size leads to much greater competition to become



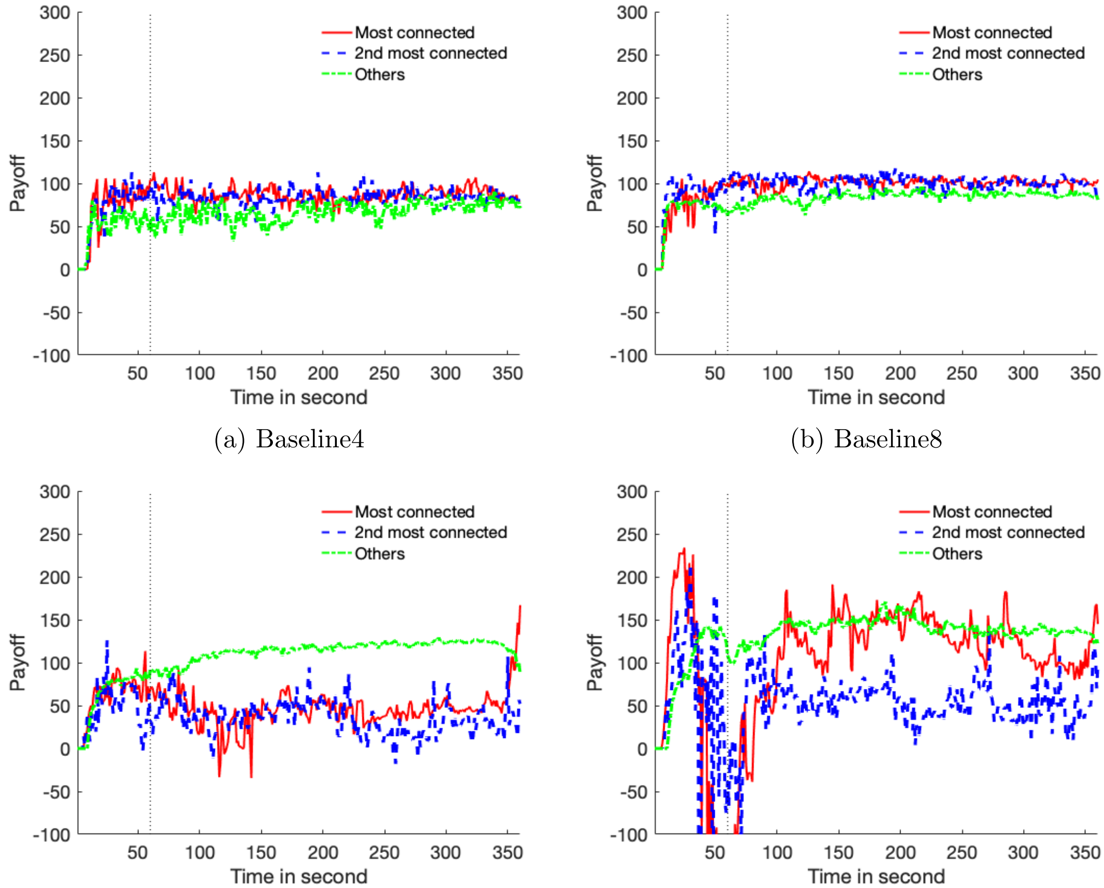
(a) Baseline4 (b) Baseline8

(c) Baseline50 (d) Baseline100

Figure 13: Time series of efforts for the three different types of subjects

a hub.

We next look at the dynamics of median payoffs obtained by the three different types of subjects in Figure 14. The two most connected subjects do not perform better than the other subjects in the large groups. In particular, the 2nd most connected subjects in both Baseline50 and Baseline100 obtain persistently lower payoffs over time than those of the other subjects. This is a consequence of the high efforts. The most connected subjects in the Baseline50 also get persistently lower payoffs than the other subjects except for the last 10 seconds. In the Baseline100, they earn as much as the others for brief periods but the average payoffs are lower than others' payoffs. By contrast, in small groups, the payoffs



(a) Baseline4 (b) Baseline8

(c) Baseline50 (d) Baseline100

Figure 14: Time series of median payoffs for the three different types of subjects

earned are stable and very similar among the three different types of subjects.

In order to make a statistical assessment on the treatment effects on subjects' behavior, we conduct linear regression analyses of mean efforts and oudegree (the number of links) made by each type of subjects—most connected, 2nd most connected, and the others—on the dummy of large groups ($N = 50$ or 100). In this analysis, we define the types of subjects with the ranking of the fraction of time (across the five minutes) in which a subject is most connected in a round.[11] The most connected individual is the subject who receives the

[11] Figure 21 in Online Appendix F.2 presents histograms showing the time fraction of different efforts over 5 minutes for the three different types of subjects across group sizes in the baseline treatment. The two most connected subjects in the large groups chose the maximum effort level, 20, for the majority of time,

most links for the largest fraction of time. The 2nd most connected individual is similarly defined. We refer to the rest of subjects as the ‘others’.

Table 3 reports the regression results after controlling for round dummies, demographic information, comprehension test score, experimental measures of risk aversion and altruism, and personality. Robust standard errors clustered by individual subject are reported. Average efforts and outdegrees for each type of subjects in the small groups ($N = 4$ and 8) are also reported for comparison.

We observe statistically significant and large treatment effect on efforts and outdegree. The most connected subject chose 68% more effort and about one link more in the large groups as compared to the small groups. The 2nd most connected subject made 173% more effort in the large groups than in the small groups. These patterns confirm that competition is more intense in the large groups.[12]

The scale effect on subjects' behavior have large effects on payoffs. Table 4 reports median regression results on the effects of scale on individual median payoffs.[13] As expected, the two most connected subjects earned substantially less in the large groups than in the small groups: 27% less for the most connected subject, albeit less strongly significant, and 55% less for the 2nd most connected subject. [14] And thanks to the intense competition of the two most connected subjects, the other subjects earned 44% more in the large groups than in the small groups.

We now summarize the findings on individual behavior, the competition dynamics, and payoffs.

Result 3 *An increase in group size intensifies the competition between the two most connected subjects. It leads to a significant increase in efforts and outdegree and results in a decline of their payoffs in large groups, relative to the other subjects.*

whereas they in the small groups chose significantly less with the mode of the most connected subject's effort being around the equilibrium effort level, 9

[12]Tables 9 and 10 in Online Appendix F.1 report the replications of Table 3 by splitting the two large groups. The results remain similar with each of the large groups.

[13]Due to outliers of payoffs, we conduct median regression analysis with median payoffs.

[14]Tables 11 and 12 in Online Appendix F.1 report the replications of Table 4 by splitting the two large groups. The negative effects of large group on median payoffs for the two most connected subjects are stronger in $N = 50$ than in $N = 100$.

Table 3: Scale effects on effort and outdegree in the baseline treatments

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
Large group	6.00***	9.04***	0.62*	1.03***	0.75*	0.24***
	(1.05)	(1.10)	(0.32)	(0.35)	(0.40)	(0.05)
Average in small group	8.77	5.24	2.65	0.20	0.62	0.90
Number of observations	75	75	2590	75	75	2590
R-squared	0.59	0.64	0.04	0.38	0.41	0.03

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 4: Scale effects on payoffs in the baseline treatments

	Median payoff		
	most connected	2nd most connected	others
Large group	-23.75*	-44.94**	37.12***
	(13.25)	(18.13)	(2.90)
Median in small group	86.50	81.00	85.00
Number of observations	75	75	2590
R-squared	0.19	0.23	0.08

Notes: Robust standard errors are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

5 Payoff Information

We found that, as the group size grows, individuals compete fiercely to become hubs. This leads them to invest very large amounts and, as a result, their earnings suffer. Indeed, in some cases the hubs actually make negative earnings![15] This is a striking and unexpected outcome. In this section we examine the sources of these negative earnings. An obvious concern is that the game becomes very complex with the increased number of players and so individuals may not understand the payoff implications of different choices. To explore this line of thought we consider a design in which subjects are shown the payoffs of everyone. This section investigates the effects of information of others' payoffs on subjects' behavior and outcomes and its interaction with the scale effects.

5.1 Macroscopic Patterns

Figure 15 begins by presenting the average of Lorenz curves and Gini coefficients of indegree across seconds of the last five minutes of the game, across rounds, and across groups in the payoff information treatment. We again observe the aggregate effect of scale on indegree distribution in the payoff information treatment, albeit to a lesser degree compared to the baseline treatments. The Gini coefficients are larger in the large group sizes than in the small group sizes: 61% for PayInfo4, 77% for PayInfo8, 84% for PayInfo50, and 81% for PayInfo100. Comparing these statistics from the baseline treatments, we observe an increase of Gini coefficient in PayInfo8 relative to Baseline8 and a decrease of this in PayInfo100 relative to Baseline100. In spite of this, we observe a statistical difference in this measure of specialization of linking between PayInfo4 and each of PayInfo50 and PayInfo100 (p-value < 0.01 from t-test with the group-level average data). These scale effects are also seen in the cumulative distributions of the time fraction of being most connected and mean indegree ratio (see Online Appendix F.2).

Next, we turn to examine the macroscopic patterns of efforts in the payoff information treatments. Figure 16 presents the average of Lorenz curves and Gini coefficients of efforts, across the last five minutes of the game, across rounds, and across groups. The scale effects we see are similar to what we observed for the baseline treatment. The Gini coefficient increases in group size: 38% for PayInfo4, 57% for PayInfo8, 74% for PayInfo50, and

[15] We observe that 25% (13%) of the 1st most connected subject's sample in the Baseline50 (Baseline100) earned negative earnings. There is no incidence of negative earnings for the most connected subject in the small group treatments. Negative earnings are often made by excessive efforts and multiple links.

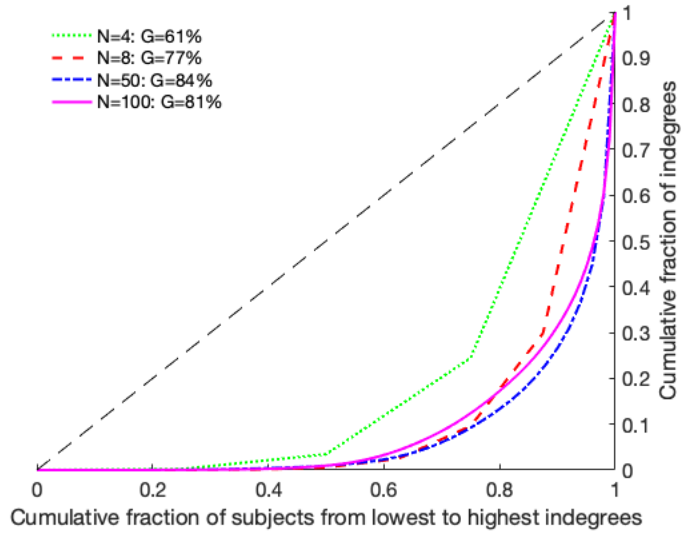


Figure 15: Lorenz curves and Gini coefficients of indegrees: Payoff Information treatments

74% for PayInfo100. We observe a statistical difference in this measure of specialization of efforts between PayInfo4 and each of PayInfo50 and PayInfo100 (p-value < 0.01 from t-test with the group-level average data) and between PayInfo8 and PayInfo50 (p-value < 0.04). We also observe similar scale effects with the cumulative distributions of mean effort ratio (see Online Appendix F.2).

Next, we turn to the relation between efforts and linking and the relation between linking and payoff in the payoff information treatments. As in the baseline treatments in Section 4.1, we run linear regression analysis of mean indegree ratio on efforts, and median regression analysis of median payoffs on mean indegree ratio with the same set of control variables. Table 5 presents a set of regression results for each of the four payoff information treatments. Robust standard errors, clustered by individual subject, are reported in parenthesis.

Firstly, starting with the regression results in the large group payoff information treatments, we find that the relation between efforts and linking is significant but relatively weak. On the other hand, the relation between linking and payoff in the large group treatments is strongly positive. Overall we interpret that showing information on others' payoff makes subjects choose efforts cautiously and leads to the relation between linking

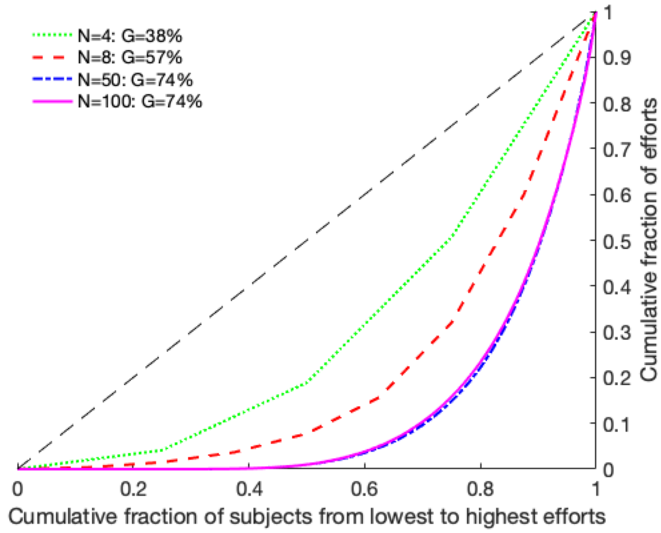


Figure 16: Lorenz curves and Gini coefficients of Efforts: Payoff Information treatment

Table 5: Regression analysis when information on others' payoff is observable

	Mean indegree ratio (%)				Median payoff			
	$N = 4$	$N = 8$	$N = 50$	$N = 100$	$N = 4$	$N = 8$	$N = 50$	$N = 100$
Effort	6.68***	4.80***	0.40***	0.23***				
	(0.52)	(0.61)	(0.09)	(0.06)				
Mean indegree ratio					0.45***	0.10	1.81***	4.43***
					(0.12)	(0.16)	(0.11)	(0.62)
Number of observations	80	160	1000	1500	80	160	1000	1500
R-squared	0.726	0.540	0.064	0.055	0.551	0.070	0.078	0.002

Notes: Robust standard errors, clustered at the level of interaction between individual subject and round, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

and payoff which is predicted by the pure-connector equilibrium.

We next look at the regression results in the small group payoff information treatments. As in the baseline treatments, we find a strong and positive association between efforts and linking in the small group payoff information treatment. This pattern is in line with the corresponding prediction of the pure-influencer equilibrium. When we analyze the relation between linking and payoff, we observe a weak and insignificant relation between linking and payoff in the PayInfo8 treatment, which is in line with that of the pure-influencer equilibrium. We observe a significant but weaker relation between linking and payoff in the PayInfo4 treatment.

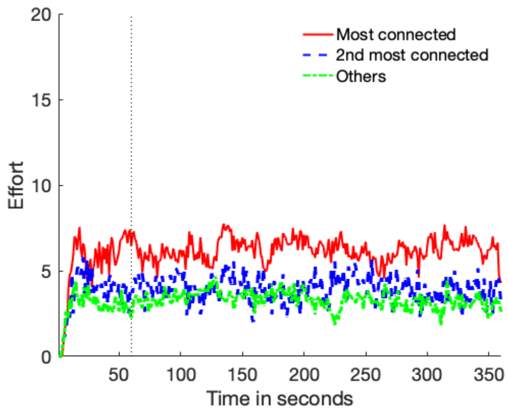
These observations are summarized as follows.

Result 4 *(i) Specialization in linking and efforts continues to hold in the payoff information treatments. (ii) In the small groups, the correlation between linking and effort is strongly positive, while the correlation between linking and payoff is weak. (iii) In the large groups there is a strongly positive correlation between linking and payoffs, while the correlation between efforts and linking is weak.*

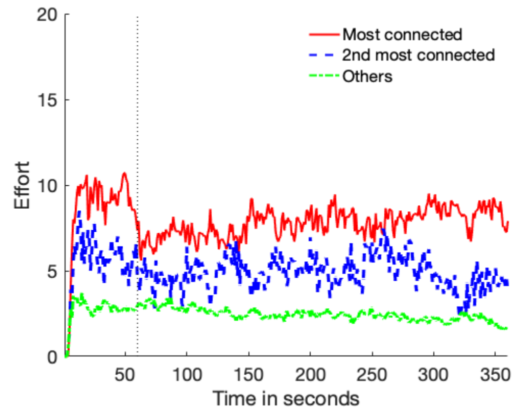
A comparison of this result with Result 2 under the baseline treatment reveals that payoff information has strong treatment effects. Specifically, we note that the negative correlation between indegrees and payoffs is reversed and now there is a positive correlation between indegrees and payoffs. This change support the view that subjects tend to make more cautious choices and move away from a pure influencer outcome towards a pure connector outcome. We now examine the individual level data to understand better how this comes about.

5.2 Individual Behavior and Competition Dynamics

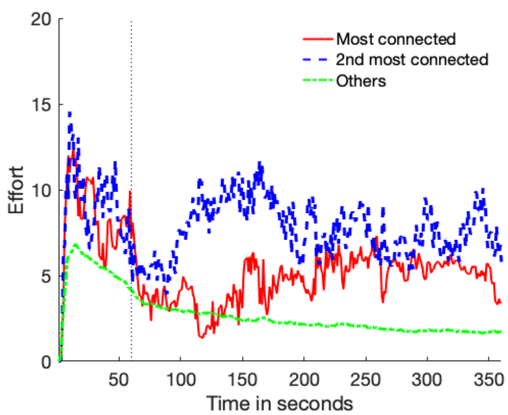
As before, we seek to understand the macroscopic patterns in terms of individual choices on efforts and links. We start with Figure 17 that presents the time series of average efforts (the end of the trial minute is represented by the vertical dotted line) for the three different types of subjects identified at every second in each of the group sizes. Compared to Figure 13 in the baseline treatments, we observe that competition dynamics in the large group payoff information treatments is quite different: the time series of efforts made by two most connected subjects are substantially lower when information on others' payoffs is visible. By contrast, in the small groups, the dynamics of efforts is similar across the



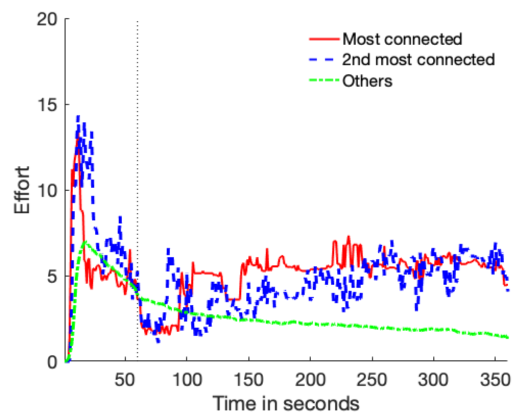
(a) PayInfo4



(b) PayInfo8



(c) PayInfo50

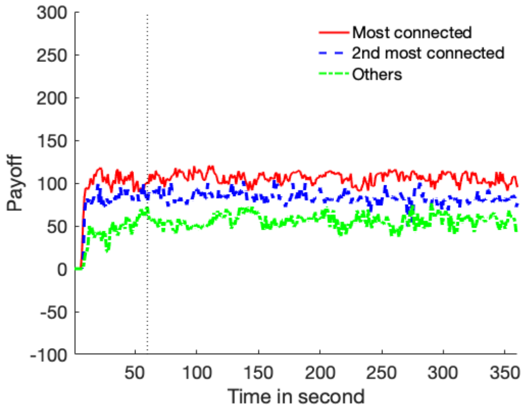


(d) PayInfo100

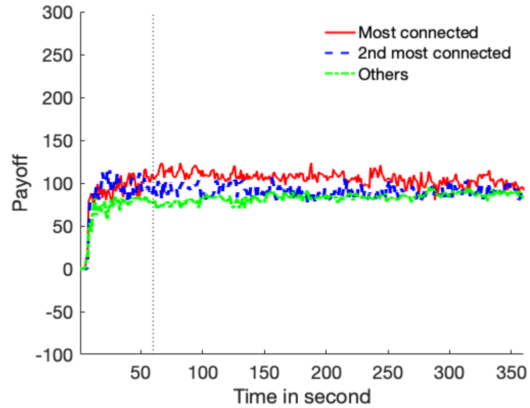
Figure 17: Time series of efforts in the payoff information treatment

payoff information treatment and the baseline. The behavior of 'other' subjects is similar across the two information treatment and across different group sizes.

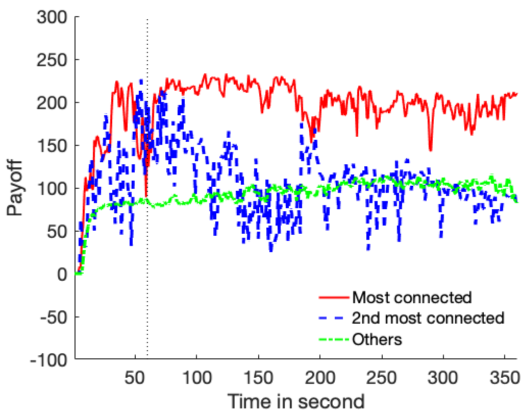
Figure 18 presents time series of median payoffs for the three types of subjects in the payoff information treatment. We would like to compare this figure with Figure 14 that summarizes the outcomes in the baseline treatments: this comparison reveals that there is a sharp increase in the payoffs of the most connected subjects in the large groups. In the small groups, the payoffs are similar across the two information treatments. Putting together the observations from Figure 17 and Figure 18, we are led to conclude that the availability of information on others' payoffs leads to lower efforts by the two most connected subjects



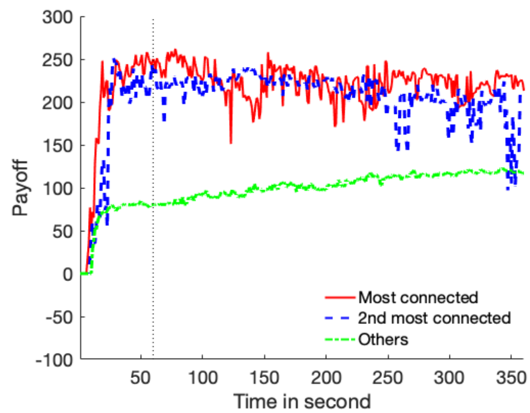
(a) PayInfo4



(b) PayInfo8



(c) PayInfo50



(d) PayInfo100

Figure 18: Time series of median payoffs in the payoff information treatment

and this in turn creates large payoff gains for them.

We next conduct linear regression analyses of mean efforts and outdegree made by each type of subjects on the dummies of payoff information and large group ($N = 50$ or 100) and their interaction dummy. As was done in Table 3, we define each type using the time fraction of being most connected in the 5 minutes.[16]

[16]Figure 22 in Online Appendix F presents histograms showing the time fraction of different efforts over 5 minutes for the three different types of subjects across group sizes in the payoff information treatment. We observe a drastic change of efforts in the large groups: in the payoff information treatments, the two most connected subjects substantially lower their level of efforts and the unique mode of the distribution is at zero effort. On the other hand, we observe little change of efforts in the small group sizes by showing information on others' payoffs.

Table 6 report the regression results with controlling for round dummies, demographic information, comprehension test score, experimental measures of risk aversion and altruism, and personality. Average efforts and outdegrees for each type of subjects in the large groups ($N = 50$ or 100) baseline treatment are also reported for comparison. The coefficient of the interaction dummy captures the difference-in-differences effect for the treatments of large group and payoff information. On the other hand, the coefficient of the payoff information describes the payoff information effect in the small groups.

In large groups, we observe a significantly negative effect of payoff information on efforts. Compared to the corresponding subject type in the large group baseline treatments, the most connected subject makes 61% less effort and the 2nd most connected subject makes 68% less effort. The rest of subjects also made 28% less effort in the large group payoff information treatments.[17] Hence, all the subjects in the large groups lowered their efforts when information on others' payoffs is available. In contrast, in the small groups, subjects' efforts did not respond to the availability of information on others' payoffs.

We then proceed to check the effect of payoff information on subjects' payoffs. Table 7 reports the median regression results of payoffs on the dummies of payoff information and large group as well as their interaction with the same set of control variables as in Table 6. We observe substantial impacts of payoff information on subjects' earnings in the large groups. The median payoffs increase by 202% and 260%, respectively, for the most connected subject and the 2nd most connected subject. In contrast, we observe a 11% drop of the payoffs for the other subjects.[18]

Result 5 *(i). In the small groups, subjects do not change efforts and linking behavior significantly in response to the availability of information on others' subjects. (ii). In the large groups, the two most connected individuals make substantially lower efforts in the payoff information treatment as compared to the baseline treatment. This results in large payoff gains for them.*

We are led to the view that when groups are large, it is difficult for a subject to keep track of the payoff implications of different choices. Where information on payoffs of others

[17] Tables 14 and 15 in Online Appendix F.1 replicate Table 6 by considering $N = 50$ and $N = 100$ separately. The negative effect of payoff information remain similar in each case.

[18] Tables 16 and 17 in Online Appendix F.1 report the replication of Table 7 by considering the cases of $N = 50$ and $N = 100$ separately. The results remain overall similar although the negative effect of payoff information for the most connected subject in $N = 100$ is only about 61% increase and imprecised estimated.

Table 6: Treatment effects on effort and outdegree

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
Payoff info	-0.75	0.52	0.00	-0.05	0.24	0.05
	(0.77)	(0.70)	(0.36)	(0.84)	(0.18)	(0.07)
Large group	6.30***	8.41***	0.62**	1.14	0.94***	0.25***
	(1.04)	(1.19)	(0.30)	(0.93)	(0.33)	(0.05)
Payoff info × Large group	-9.24***	-9.00***	-0.91**	2.34	-0.80**	-0.01
	(1.41)	(1.63)	(0.39)	(2.42)	(0.39)	(0.07)
Average in large group baseline	15.12	13.22	3.22	1.90	1.32	1.12
Number of observations	150	150	5180	150	150	5180
R-squared	0.53	0.51	0.05	0.43	0.34	0.04

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 7: Treatment effects on payoffs

	Median payoff		
	most connected	2nd most connected	others
Payoff info	6.71	-12.75***	-10.56***
	(11.54)	(4.53)	(1.97)
Large group	-30.33*	-42.76**	36.20***
	(17.08)	(17.34)	(1.90)
Payoff info × Large group	119.24***	120.76***	-14.07***
	(29.18)	(29.02)	(2.30)
Median in large group baseline	59.00	47.00	126.50
Number of observations	150	150	5180
R-squared	0.09	0.17	0.09

Notes: Robust standard errors are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

is not directly shown, some subjects are willing to make large efforts in order to attract links from others. In doing so, these subjects appear not to understand that these large efforts lead to much lower payoffs. However, when information on others' payoffs is made directly observable, individuals become more cautious in their effort decisions. By contrast, in small groups, it seems that subjects are able to keep track of the payoff implications of their effort more accurately and the impact of showing information on everyone's payoffs has relatively small impact on subjects' effort behavior.

6 Conclusion

There is a large body of research that describes the structure of large empirical networks. This work highlights the richness of the structures. By contrast, the economic theory of network formation emphasizes the emergence of highly stylized structures—such as the star network. This apparent difference has hampered the welfare analysis of networks. Moreover, experimental tests of the theory have tended to reject the exact predictions on network structure. This creates a gap between the growing empirical literature and the theory of networks.

In this paper our aim has been to bridge this gap. To this end, we conduct large scale experiments on network formation. The design of the experiments builds on a model of linking and efforts taken from Galeotti and Goyal [2010]. The principal insight of the theory is that individual choices leads to a *law of the few*. The distinctive feature of our experiments is that we allow for up to 100 subjects to make choices in continuous time under laboratory conditions. The paper presents a new experimental platform that integrates a network visualization tool (that uses the Barnes-Hut approximation algorithm (Barnes and Hut [1986])) with an interactive tool of dynamic asynchronous choices.

Our experiments provide strong support for macroscopic predictions of the theory: there is specialization in linking and efforts across all treatments. Moreover, and in line with the theory, the specialization is more pronounced in larger groups. Thus subjects abide by the law of the few.

Information on payoffs provided to subjects affects their behavior and yields interesting welfare consequences. In the treatment where subjects see only their own payoffs, in large groups, the most connected individuals compete fiercely—they exert large efforts and have small earnings. By contrast, when a subject sees everyone's payoffs, in large groups, the most connected individuals engage in less intense competition—they exert little effort and have large earnings. The effects of payoff information are much more muted in small groups. This leads us to the view that when groups are large, cognitive constraints become a factor. As a result, some subjects are willing to make large efforts in order to attract links from others, even though such high efforts may result in lower earnings.

References

J. Andreoni and J. Miller. Giving according to garp: An experimental test of the consistency of preferences for altruism. *Econometrica*, 70(2):737–753, 2002.

V. Bala and S. Goyal. A non-cooperative model of network formation. *Econometrica*, 68 (5):1181–1231, 2000.

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

J. Barnes and P. Hut. A hierarchical o(n log n) force-calculation algorithm. *Nature*, 324: 446–449, 1986.

S. K. Berninghaus, K.-M. Ehrhart, and M. Ott. A network experiment in continuous time: The influence of link costs. *Experimental Economics*, 9(3):237–251, 2006.

A. G. Bramoulle, Y. and B. Rogers. *Oxford Handbook on Economics of Networks*. Oxford University Press, 2016.

E. Calford and R. Oprea. Continuity, inertia, and strategic uncertainty: A test of the theory of continuous time games. *Econometrica*, 85:915–935, 2017.

S. Callander and C. Plott. Principles of network development and evolution: An experimental study. *Journal of Public Economics*, 89:1469–1495, 2005.

C. Camerer. *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton University Press, 2003.

C. Camerer and T. H. Ho. Experience-weighted attraction learning in normal form games. *Econometrica*, 67:827–874, 1999.

C. Camerer, T. H. Ho, and J.-K. Chong. Sophisticated experience-weighted attraction learning and strategic teaching in repeated games. *Journal of Economic Theory*, 104: 137–188, 2002.

A. Falk and M. Kosfeld. Its all about connections: Evidence on network formation. *Review of Network Economics*, 11:Article 2, 2012.

D. Friedman and R. Aprea. A continuous dilemma. *American Economic Review*, 102(1): 337–63, 2012.

A. Galeotti and S. Goyal. The law of the few. *The American Economic Review*, 100(4): 1468–1492, 2010.

J. K. Goeree, A. Riedl, and A. Ule. In search of stars: Network formation among heterogeneous agents. *Games and Economic Behavior*, 67(2):445–466, 2009.

S. Goyal, J. Moraga, and M. van der Leij. Economics: an emerging small world? *Journal of Political Economy*, 114(2):403–412, 2006.

S. Goyal, S. Rosenkranz, U. Weitzel, and V. Buskens. Information acquisition and exchange in social networks. *Economic Journal*, 127:2302–2331, 2017.

C. A. Holt and S. K. Laury. Risk aversion and incentive effects. *American Economic Review*, 92(5):1644–1655, 2002.

S. Huck, H.-T. Normann, and J. Oechssler. Learning in cournot oligopoly-an experiment. *Economic Journal*, 109:C80–C95, 1999.

M. Jackson and A. Wolinsky. A strategic model of social and economic networks. *Journal of Economic Theory*, 71:44–74, 1996.

M. O. Jackson and B. W. Rogers. Meeting strangers and friends of friends: How random are social networks? *American Economic Review*, 97(3):890–915, 2007.

M. Kearns, S. Judd, and Y. Vorobeychik. Behavioral experiments on a network formation game. *ACM EC 2012*, 2012.

J. Pettit, D. Friedman, C. Kephart, and R. Oprea. Software for continous game experiments. *Experimental Economics*, 17:631–648, 2014.

B. Rammstedt and O. P. John. Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german. *Journal of research in Personality*, 41(1):203–212, 2007.

A. Riedl, I. M. Rohde, and M. Strobel. Efficient coordination in weakest-link games. *The Review of Economic Studies*, 83(2):737–767, 2016.

R. Rong and D. Houser. Emergent star networks with ex ante homogeneous agents. 2012.

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

B. van Leeuwen, T. Offerman, and A. Schram. Continuity, inertia, and strategic uncertainty: A test of the theory of continuous time games. *Forthcoming to Journal of the European Economic Association*, 2018.

ONLINE APPENDICES

A Theory

The following proposition shows that, under discrete values of personal effort, a sufficiently high cost of linking implies a pure influencer equilibrium (for any group size n) and an approximate pure connector equilibrium (for a sufficiently large group size).

Proposition 2. *Suppose payoffs are given by (1), $a_1 = 1$, $a_2 \in (0, 1)$, $\hat{y} \in X = \{0, 1, 2, \ldots, \overline{x}\}$, and $c(\hat{y} + a_2 - 1) < k < c\hat{y}$.*

- *(a) Every Nash equilibrium $s^* = (x^*, g^*)$ is such that g^* is a periphery sponsored star structure where the hub is a pure influencer investing $\hat{y}$ and every spoke invests 0.*
- *(b) If $n \geq 2 + \frac{\hat{y}-1}{a_2}$, there exist pure connector ϵ-equilibria where the hub invests 0 while m spokes invest 1 and others invest 0 (with m s.t. $(m-1)a_2 < \hat{y} \leq 1 + (m-1)a_2$).*

Proof. It follows from Proposition 1 that the pure influencer equilibrium always hold, regardless of n. Moreover, the pure connector equilibrium holds only if $n \geq 2 + \frac{k}{a_2(c\hat{y}-k)}$, in which case it requires every spoke to personally invest $\frac{\hat{y}}{1+(n-2)a_2}$. Since $c(\hat{y} + a_2 - 1) < k$ implies $\hat{y} < \frac{k}{c} + 1$, we have that $n \geq 2 + \frac{k}{a_2(c\hat{y}-k)} > 2 + \frac{\hat{y}-1}{a_2}$, and consequently $\frac{\hat{y}}{1+(n-2)a_2} < 1$ for any $n \geq 2 + \frac{\hat{y}-1}{a_2}$. However, since the lowest positive effort that can be made in the game is 1, no more than $m = \frac{\hat{y}-1}{a_2} + 2$ players (with $m < n$) can benefit from making such minimum positive effort. In this case, each of those positive investors accesses $(m-1)a_2$ from forming a link and therefore earns $f(1 + (m-1)a_2) - c - k$, which is strictly less than if they unilaterally deviate by forming no link and investing $\hat{y}$ since $c(\hat{y} + a_2 - 1) < k$ can be rewritten as $(m-1)a_2 < \frac{k}{c}$. As a result, the pure connector outcome is an ϵ-equilibrium whenever $\epsilon > f(\hat{y}) - f(1 + (m-1)a_2) - c(\hat{y} - 1)$ where m is the number of investing spokes such that $(m-1)a_2 < \hat{y} \leq 1 + (m-1)a_2$. □

B Network visualization

The experimental software uses the well known Barnes-Hut approximation algorithm as introduced by Barnes and Hut [1986], which provides a low complexity simulation technique to compute the forces applied to any node as influenced by every other node in a network. Such forces are computed through three distinct sources:

- All other nodes from the network: all nodes apply a repulsion force F_r to each other to avoid overlaps and allow a sparse visualization of the network. This force is the only used by Barnes and Hut [1986].

- Connected nodes (with direct links only) in the network: nodes that are linked with each other apply attractive forces F_s towards each other to allow for visual proximity of connected nodes.

- Point of origin O: nodes are applied a gravitational force F_{cg} to a center of origin to pull the entire network towards the center of the screen. In particular, such a force allows disconnected components to be within reasonable distance from each other, and therefore more easily visualized on the screen.

In summary, nodes are attracted by gravity and other nodes they are linked with, and repulsed by other nodes they are not directly linked with.

The Barnes-Hut algorithm consists in first constructing a quad-tree by recursively dividing the visual space into same size groups such that every node can eventually be associated with exactly one group based on its visual position (leaf of the tree). Any such group may however associate several nodes such that the aggregated forces applied from those nodes can be approximated through a unique force (as if the group of nodes were a single node). More precisely, starting from the largest group of the Barnes-Hut quad-tree (the root), the algorithm assesses the distance between a given o and the center of mass of that group of nodes: if the distance is sufficiently large (according to a given exogenous threshold), then the group of nodes is considered as a single node, else the process is iterated by considering subgroups from the tree (nodes sufficiently close to o will therefore be considered independently). Such approximation is known to considerably reduce computational complexity for computing forces applied to every node. The root of the Barnes-Hut quad-tree represents the whole visual space.

More formally, we define the distance between a node o and a node m (or group of nodes represented as a single node m) as $dist(o, m)$. The repulsion force applied to node o by m is determined as

$$F_r(o, m) = \frac{K_g.M_m}{dist(o, m)^3} \tag{3}$$

Where K_g captures the gravitational constant such that $K_g < 0$ to obtain the repulsion effect. In Equations (3), it is assumed that the mass of every node is 1. However, the mass M_m may be larger when representing a group of nodes (M_m represents the number of nodes in that group, as described by the Barnes-Hut algorithm). Similarly, the attraction force applied to node o by m corresponds to

$$F_s(o,m) = \frac{K_s}{dist(o,m)}.\begin{cases} 0 & \text{if } o \text{ and } m \text{ are not linked} \\ (L - dist(o,m)) & \text{if } o \text{ forms a link with } m \\ (dist(o,m) - L) & \text{if } m \text{ forms a link with } o \end{cases} \tag{4}$$

Where L defines the resting length of an edge, and K_s the spring gravity constant such that $K_s > 0$ to obtain the attraction effect. Note from Equation (4) that the force applied on two linked nodes is symmetric, i.e., both nodes are equally attracted by each other. Finally, we define the central gravity force applied to node o as

$$F_{cg}(o) = \frac{K_{cg}}{dist(o,O)} \tag{5}$$

Where O represents the position of the point of origin, and K_{cg} the central gravity constant such that $K_{cg} > 0$ to obtain the attraction effect.

The net force vector applied to any node o resulting from the above three forces is then:

$$F_x(o) = d_x(o,O).F_{cg}(o) + \sum_{m \in N \setminus \{o\}} d_x(o,m).(F_r(o,m) + F_s(o,m)) \tag{6}$$

$$F_y(o) = d_y(o,O).F_{cg}(o) + \sum_{m \in N \setminus \{o\}} d_y(o,m).(F_r(o,m) + F_s(o,m)) \tag{7}$$

The above static properties describe the net forces that are applied in the network, given the positions of all nodes and the links between nodes. The resulting dynamic update of the network is achieved by computing the corresponding velocity of nodes on both coordinate axes. More precisely, the velocity applied to a node o at a time t on both coordinate axes (x and y) is determined as follows:

$$V_x(o,t) = max(V_{max}, (F_x(o) - D.V_x(o,t-1)).T + V_x(o,t-1)) \tag{8}$$
$$V_y(o,t) = max(V_{max}, (F_y(o) - D.V_y(o,t-1)).T + V_y(o,t-1)) \tag{9}$$

Where D represents the damping factor determining how much of the velocity from the previous physics simulation iteration carries over to the next iteration, T the time step for the discrete simulation, and V_{max} the maximum velocity of nodes (used to increase time to stabilization). We assume no initial velocity, i.e., $V_x(o,0) = V_y(o,0) = 0$. Given such velocity, the position update of a node o at any time t directly follows:

$$x(o,t) = x(o,t-1) + V_x(o,t).T \tag{10}$$
$$y(o,t) = y(o,t-1) + V_y(o,t).T \tag{11}$$

The discrete simulation terminates and node o stabilizes whenever the associated velocity (on both coordinate axes) becomes sufficiently low with respect to some given threshold (V_{min}). More precisely, the convergence rules are:

$$V_x(o,t) < V_{min} \tag{12}$$
$$V_y(o,t) < V_{min} \tag{13}$$

Model parameter setting used in the experiment:

- $K_g = -2000$
- $K_s = 0.04$
- $K_{cg} = 0.3$
- $L = 95$
- $D = 0.09$
- $T = 0.5$
- $V_{min} = 0.3$
- $V_{max} = 10$

C Experimental instructions

[In the following instructions, N is to be replaced with any value from $\{3, 7, 49, 99\}$ *depending on the treatment]*

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

You can earn money by earning points during the experiment. The number of points that you earn 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:

100 points = 1 Euro

The money you earn will be paid out in cash at the end of the experiment. The other participants will not see how much you earned.

Details of the experiment

The experiment consists of 6 (six) independent rounds of the same form. The first round is for practice and does not count for your payment. The next 5 rounds will be counted for your payment.

At the beginning of each round, you will be grouped with N other participants. This group will remain fixed throughout the 6 rounds. Each of the participants will be randomly assigned an identification number of the form "Px" where x is a number between 1 and N. Those numbers will be randomly changed across every round of the experiment. The actual identity of the participants will not be revealed to you during or after the experiment. The participants will always be represented as blue circles on the decision screen. You are always represented as a yellow circle identified as "ME".

Each round will last **6 (six) mins: the first minute will be a trial period, only the latter 5 minutes will be relevant for the earnings**. Your earnings in a given round will be based on everyone's choice **at a randomly selected moment in the last 5 mins of the round**. In other words, any decision made before or after that randomly chosen moment will not be used to determine your points. This precise moment will be announced to everyone only at the end of the round, along with the corresponding behaviour and earnings.

At the beginning of the experiment, you are given an initial balance of 500 points. Your final earnings at the end of the experiment will consist of the sum of points you earn across the 5 last rounds plus this initial capital (the first round will be used to familiarize yourself with the game and will have no influence on your earnings). Note that if your final earnings (i.e., the sum of your earnings across the 5 last rounds plus the initial endowment) go below 0, your final earnings will be simply treated as 0.

In each round, every participant will have choose two types of actions:

- **How many any units to buy/invest**: You may buy at most 20 units. Each unit costs you **11 points**.
- **Add/delete links with other participants**: You are linked with another person if you form a link with that person or that person forms a link with you (or both). You do not pay any fee for links formed by others. The people that you are linked with (regardless of whether you or they form the links) are called your neighbours. You automatically have access to **all units bought by your neighbours** as well as **half of the units bought by your neighbours' neighbours** (see below for an example). Each link you form costs you **95 points**.

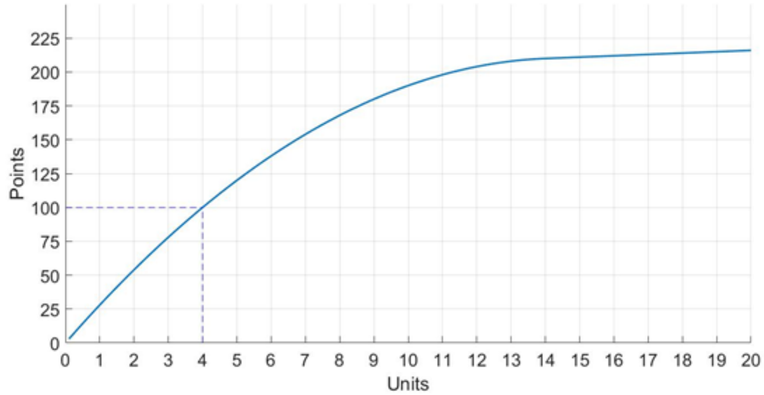
You may revise your choices at any moment before the round ends. During a round, you will also be informed about every other participant's most recent decision (units bought and formed links), which will be updated every 5 seconds or whenever you change your own choice.

At any moment, the total number of units you have access to (i.e., units you bought + units bought by your neighbours + units bought by your neighbours' neighbours) generates points for you according to the following figure (for example, accessing 4 units generates 100 points, as shown by the dotted lines):

Moreover, having access to 20+m units generates 216+m points.

The computer screen will be split into two parts:

- **The middle side of the screen presents you and your local neighbourhood**. More precisely, you will see your neighbours, the neighbours of your neighbours,



and the neighbours of neighbours' neighbours. In other words, you will see the participants that are up to 3 links away from you.

- **The right side of the screen presents participants outside of your local neighbourhood**.
- **The left side of the screen presents the code for the players' net earnings in the network**. *[Payoff information treatment only]* The inner circle of each node from the middle or right part side of the screen is characterized by some color, which varies from **green** (high positive net payoff) to **red** (high negative net payoff) depending on the player's corresponding net earnings.

Each node is described by their identification number "Px" and the number of units that they buy. Identification numbers "Px" are randomly assigned in every round. Therefore, every player is likely to have a different ID in different rounds. In the initial state of the network, nobody buys any unit and no link is formed.

Tutorial

Please follow this simple tutorial simulating a simple virtual scenario on the computer screen. In this tutorial you are interacting with 9 other players. In the initial state, you are not linked with anyone and you do not buy any units: you start at 0 points.

1. The slider allows you to choose how many units you wish to buy yourself. For example, buying 4 units costs you 44 points (= 4 units $\times$ 11 points, in red on the

screen) and generates 100 points (according to the figure from the previous page, in green on the screen).

2. Initially, the nodes on the right side of the screen represent all other players (in this simulation, those players are not real people). The size of node reflects the total number of units bought by that node and the units accessed via the network. For example, P1-P4 are the largest nodes because these players have access to the most units.

3. You may choose to form a link with any player by simply double clicking on the corresponding node. For example, forming a link with P4 reveals that P1, P2, and P3 each form a link with P4, and P9 forms a link with P1. Forming a link with P4 costs you 95 points (in red on the screen), but it also gives you access to 8.5 units (7 from P4 + 0.5×1 from P1 + 0.5×1 from P2 + 0.5×1 from P3), which generates 174 points (according to the above figure, describing the benefit function in green on the screen). If you do not buy any additional unit yourself, your resulting net payoff is **79 points (= 174 points − 1 link × 95 points)**.

4. After forming a link with P4, you observe that some nodes remain unobserved (P5, P6, P7, and P8 on the right side). However, forming an additional link with P9 (by double clicking on the corresponding node) reveals that those nodes all form a link with P9. You were not allowed to observe them before because they were 4 nodes away from you (for example, P5 were connected to you via P4, P1, and P9). You can now observe them because they are only 2 nodes away from you (for example, P5 is connected to you via P9 only). Remember that you can only see players that are at most 3 nodes away. Assuming you still do not buy any unit yourself, your resulting net payoff is **16 points (= 206 points from accessing 12.5 units − 2 links × 95 points)**.

5. Alternatively, you may choose to remove a link that you previously formed by double clicking on the corresponding node. For example, after forming links with P4 and P9, removing the link with P4 leads to players P2 and P3 becoming unobserved again, as they are now more than 3 nodes away from you.

6. Note that varying the amount of units you buy directly affects the sizes of the nodes you are linked with as well as their neighbours. Indeed, the amount of units they

each have access to includes the units you buy (the larger this amount, the larger the node).

7. You may also shape the visual structure of the network by dragging nodes as it pleases you.

Summary

Here is a brief description of information available on the decision screen:

1. The timer indicates elapsed time since the beginning of the round. Any round lasts **6 mins**. A moment will be randomly selected **in the last 5 mins** to determine everyone's payoff. The time displayed will turn red when entering this interval.

2. **Only decisions made at the randomly selected moment in the round** matter to directly determine the earnings. The payoff may be negative at the end of a round. However, starting from a balance of 500 pts, any negative total of points at the end of the 5 rounds will be equivalent to 0 point.

3. The amount of units you have access is equal to the sum of **(1)** the units bought by you, **(2)** the units bought by your neighbours, and **(3)** half of the units bought by your neighbours' neighbours.

4. You are represented as the yellow node, and your ID is "ME".

5. Every other node's ID is represented as "Px" (inside the node) where x is a number. Every node has a unique ID, which is randomly reassigned in every round.

6. The size of each node determines **how many units that node has access to** (units bought personally plus units accessed from others, directly and indirectly).

7. The amount of units **bought personally by** a player is mentioned inside the corresponding node.

8. *[Payoff information treatment only]* The color of each node determines **that node's net earnings** according to the code depicted on the left side of the screen.

D Network game interface

The decision making interface used in the experiment is similar across all treatments. More specifically, Figure 19 illustrates a (fictitious) example of a subject's computer screen in Treatment **Baseline100**. The top part of the screen depicts information about the timer indicating how much time has lapsed in the current round (the timer turns red when payoffs become effective, i.e., after more than 1 minute), the subject's own effort, which can be modified via the slider, and a comprehensive description of the subject's own payoff. Information about payoffs include gross earnings (output of function $f(.)$), the cost of effort (own effort multiplied by c), the cost of linking (number of links multiplied by k), and the net earnings (costs substracted from gross earnings). The bottom part of the screen shows detailed information about the network (the subject's node is highlighted in yellow): the subject's local network is represented on the left, other players outside of the subject's local network are found on the right. Note that a scrolldown feature is available for the subject to explore every player outside of his/her local network. Baseline treatments with smaller group sizes use the very same interface (the scrolldown feature is not available then because all players are then directly visible on the screen).

Similarly, Figure 20 illustrates a (fictitious) example of a subject's computer screen in Treatment **PayInfo100**. The only difference with the decision screen from Figure 19 is about the wider range of colors used to represent the border of each node depicted in the network. Any given node's color is directly associated with that node's corresponding payoff, according to the scale presented on the left part of the screen. payoff-information treatments with smaller group sizes use the very same interface.

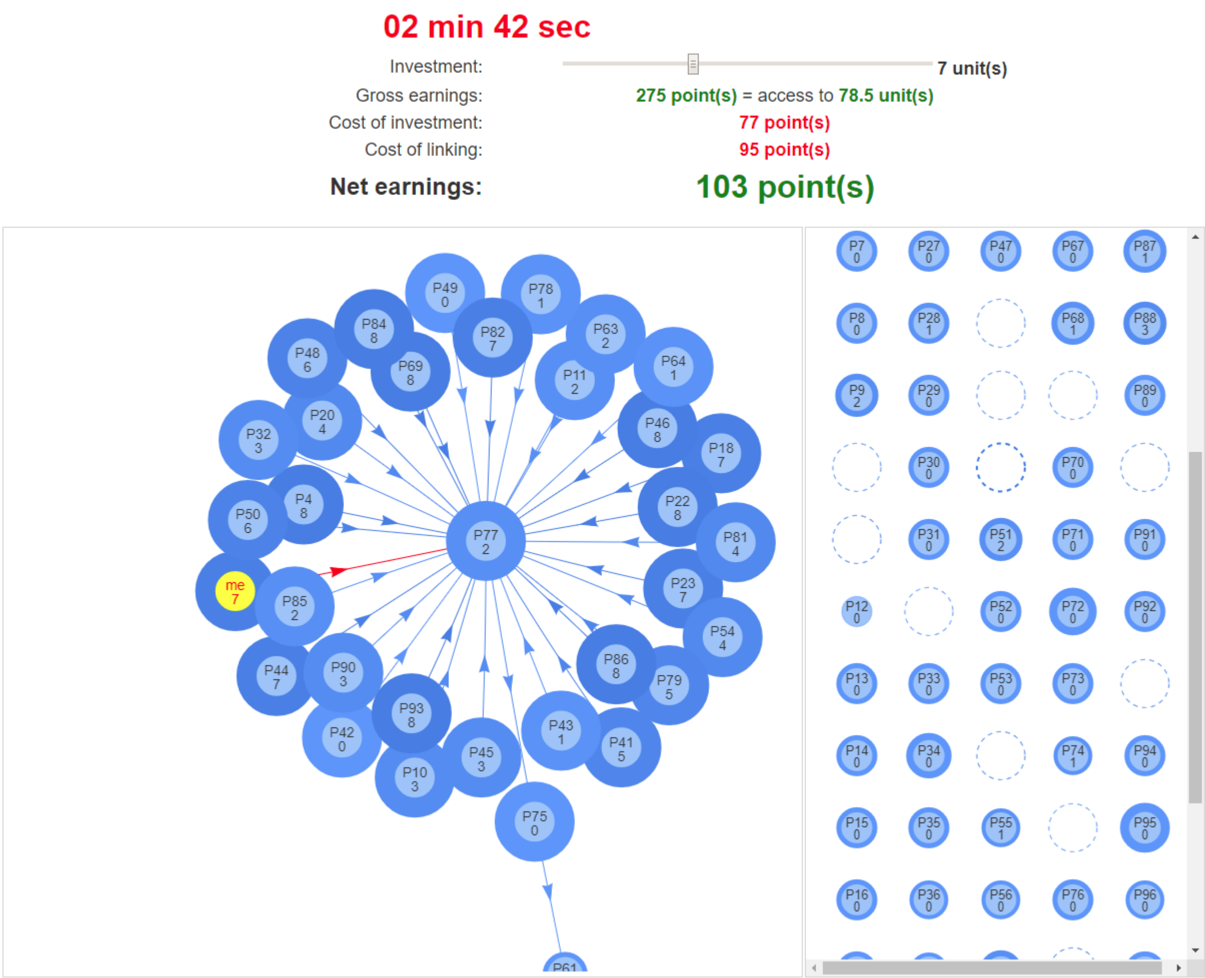


Figure 19: Example of decision screen for Treatment **Baseline100**

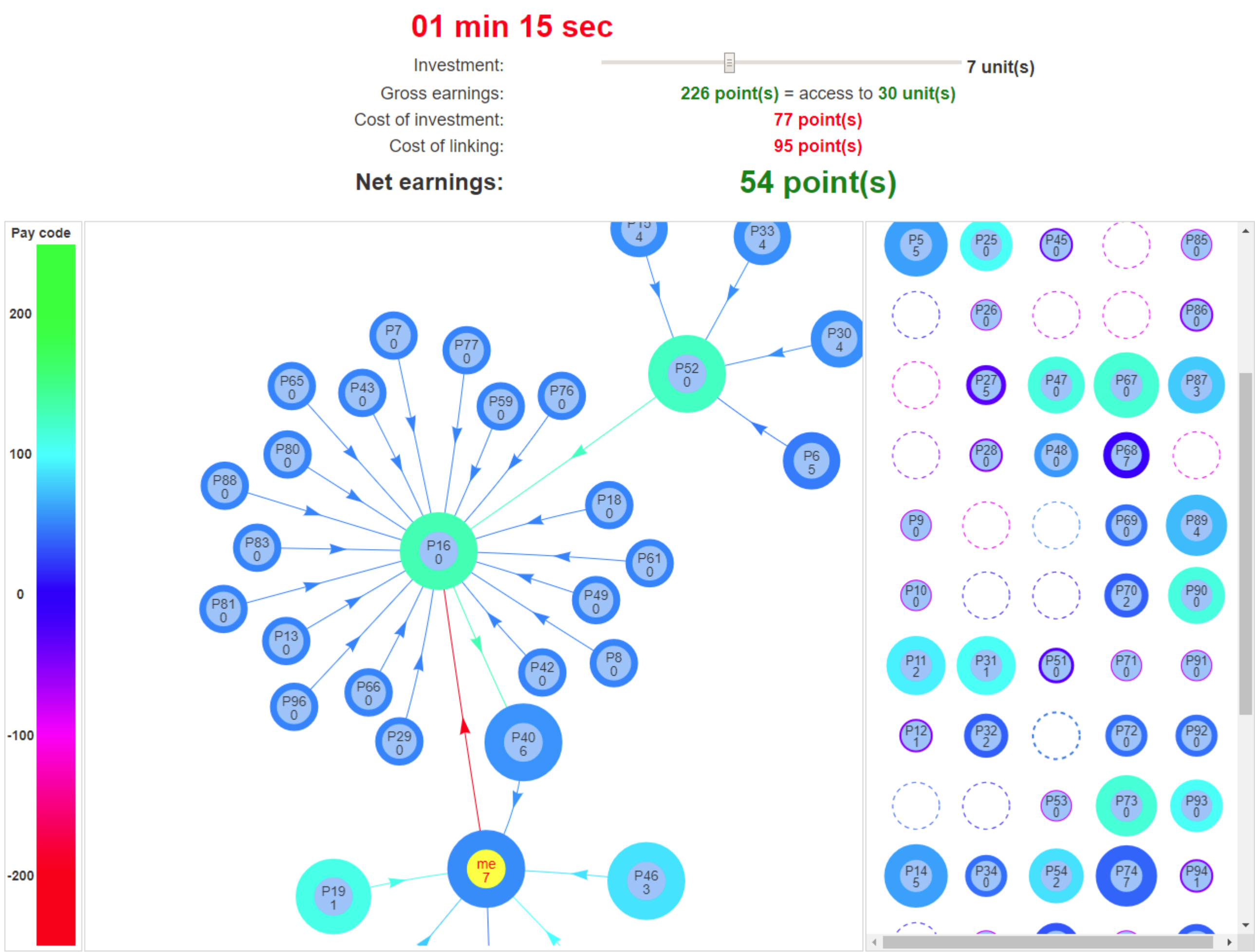


Figure 20: Example of decision screen for Treatment **PayInfo100**

E Questionnaires

At the end of the experiment, subjects answered a set of surveys aiming at measuring various types of individual differences. More precisely, incentivized measures of comprehension in network game, social preferences, and risk preferences were used. Finally non incentivized personality measures were used before which subjects filled up a debriefing questionnaire that includes demographics information.

E.1 Comprehension check

In order to assess the subjects' comprehension of the network game played during the experiment, we provided 5 questions, each of which with a unique correct answer. Each correct answer was rewarded with 0.1 euro for the subject.

The following first 2 questions were used across all treatments (correct answers are "11 pts" to question 1, and "95 pts" to question 2).

Question 1: In the previous game, how many points did investing one unit cost you?

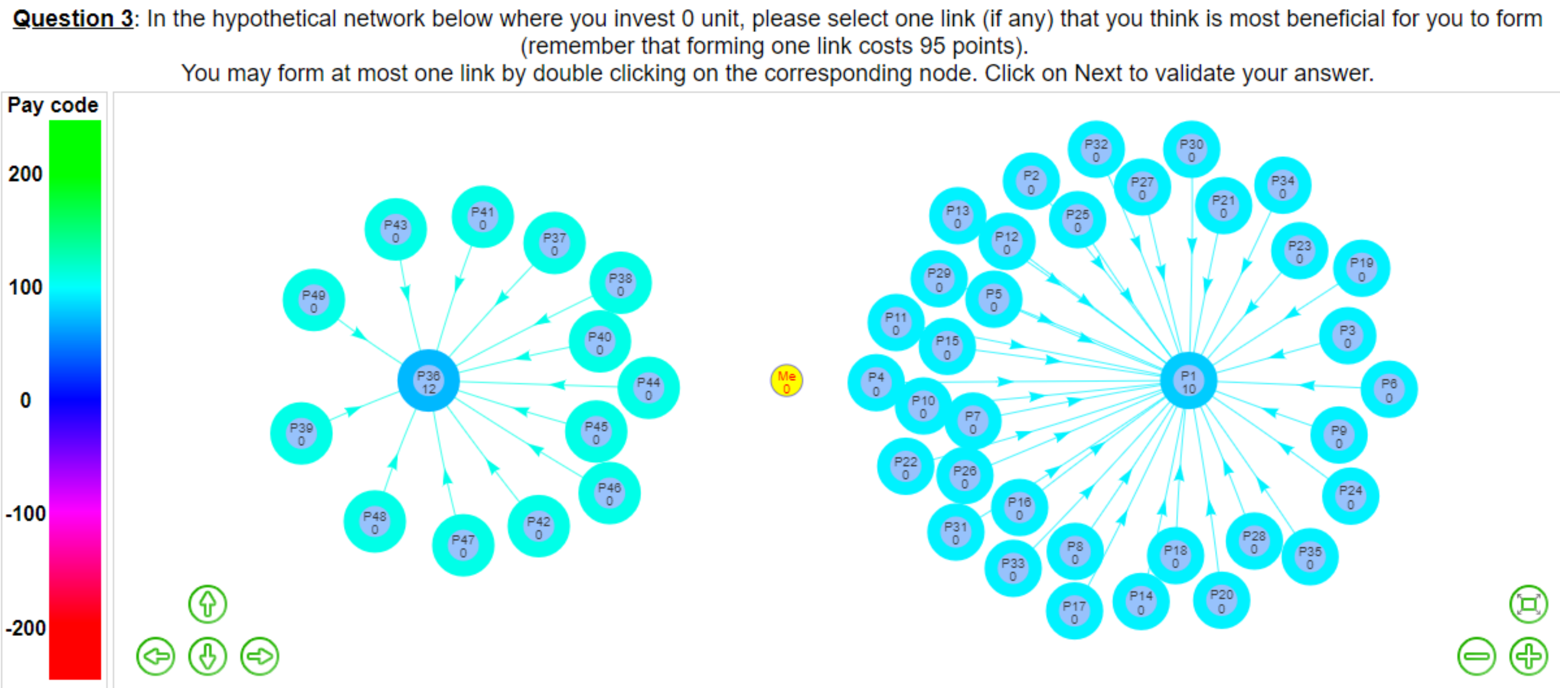
- 1 pts
- 11 pts
- 21 pts
- 31 pts
- 41 pts
- 51 pts
- more than 51 pts

Question 2: In the previous game, how many points did forming a link cost you?

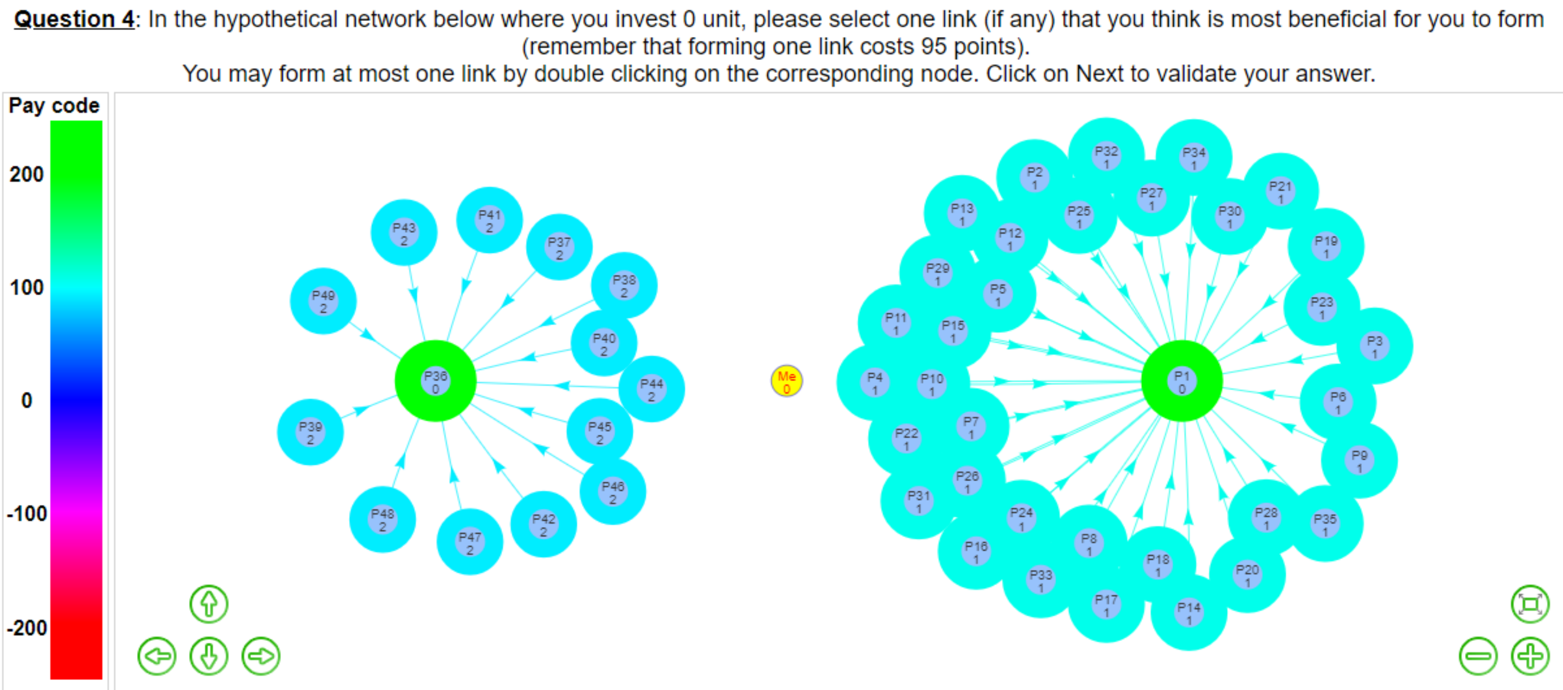
- 0 pt
- 25 pts
- 45 pts
- 65 pts
- 95 pts
- 115 pts
- more than 115 pts

The third question depicted below was used in the payoff information treatment with $n = 50$ (the correct answer is "P36"). This question was adapted in all other treatments by matching the number of nodes to the group size in the experiment, and by removing the colors in the baseline treatments.

The following questions 4 and 5 below were also used in the payoff information treatment with $n = 50$ (correct answers are "P1" for both questions 4 and 5). These questions were

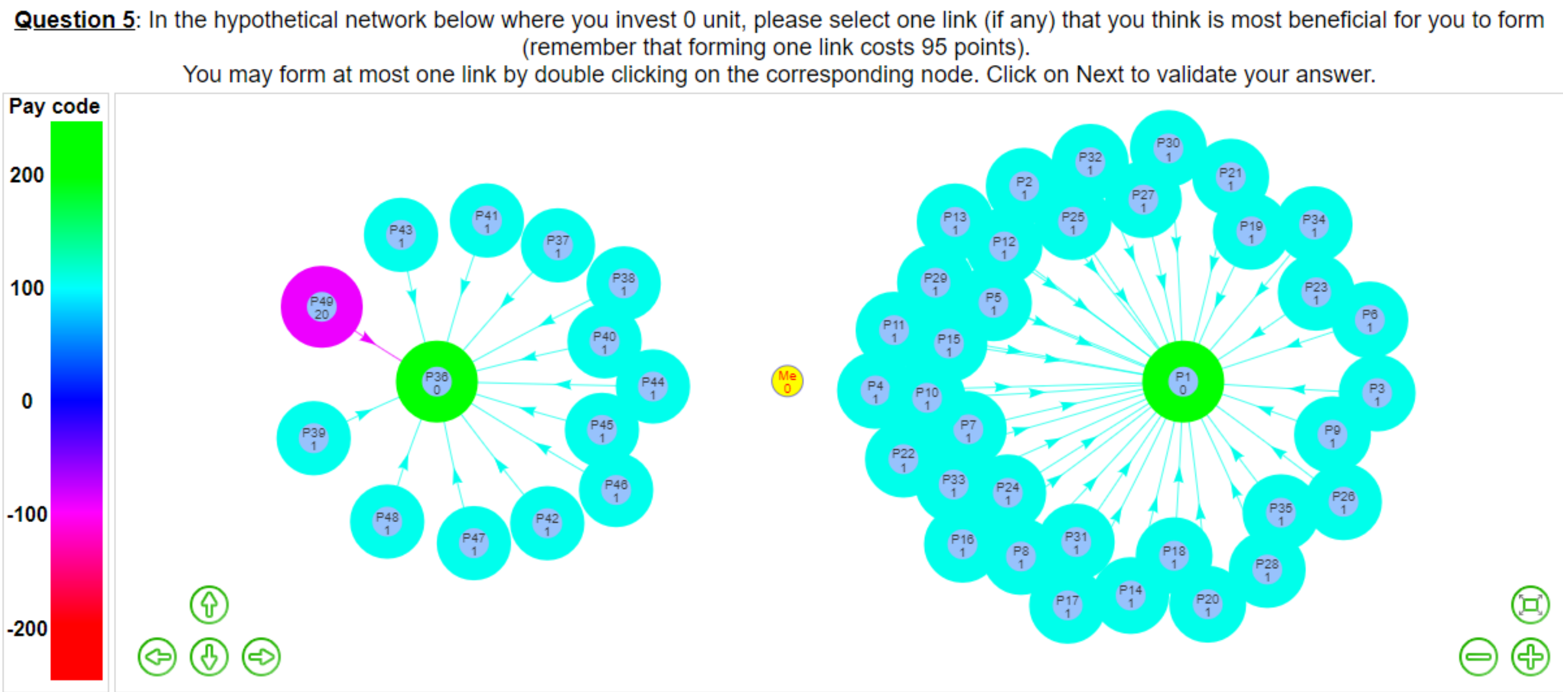


however adapted only in other treatments where $n > 4$ by again matching the number of nodes to the group size in the experiment. The reason for filtering the small group treatments (with $n = 4$) is that the limited number of nodes did not allow representing the corresponding scenarios. As before, these questions were also adapted to the baseline treatments by simply removing the colors to match the design of the actual game that subjects played.



E.2 Social preferences

The social preferences measure was adapted from Andreoni and Miller [2002] and involved a series of five money allocation tasks between the decision maker and some anonymous external participants of another experiment at the LINEEX lab (corresponding payments were therefore made to these external passive participants). The five tasks used in our experiment were represented through sliders as shown in the following figure:

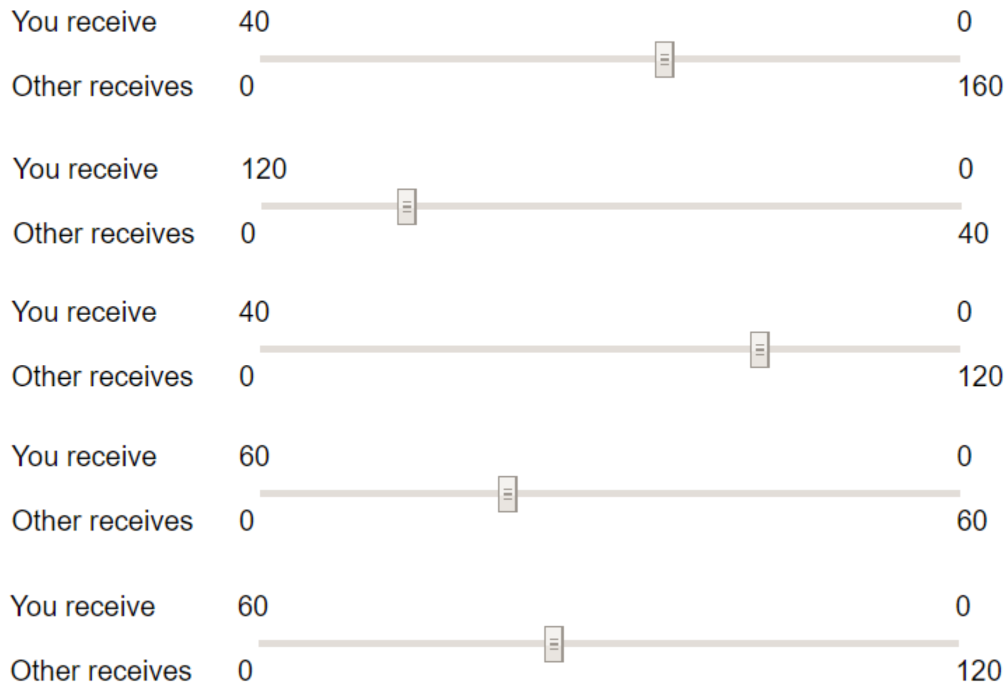


Note however that each question was presented in a different screen, and the order of presentation was randomized for every subject. Furthermore, 50 points were worth 1 euro both the subject, and the other anonymous external participant. Detailed instructions provided to the subjects, as well as a screenshot highlighting one of the above five questions are described below.

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

E.3 Risk preferences

The risk preference measure was adapted from Holt and Laury [2002] and consisted of a series of five binary choices between lotteries, presented as in the figure below.



E.4 Personality test

Non incentivized measures were used through a simplified version of the Big Five personality inventory test adapted from Rammstedt and John [2007], as shown below.

Question 1

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

You receive 17
Other receives 93

You receive	40	0
Other receives	0	160

Next

You are now asked to make 5 independent choices between two lotteries. According to **Lottery A**, you can win 2.00€ with a certain probability **p**, and 1.60€ otherwise. According to **Lottery B**, you can instead win 3.85€ with the same probability **p**, and 0.10€ otherwise. For each of the following 5 choices, which only differ in the value of the probability **p**, please select the lottery that you prefer. At the end of the study, we will randomly select one of your 5 preferred lotteries to determine your payment in this question.

	Lottery A			Lottery B
Choice 1:	2.00€ with probability 20/100, 1.60€ with probability 80/100	○	○	3.85€ with probability 20/100, 0.10€ with probability 80/100
Choice 2:	2.00€ with probability 35/100, 1.60€ with probability 65/100	○	○	3.85€ with probability 35/100, 0.10€ with probability 65/100
Choice 3:	2.00€ with probability 50/100, 1.60€ with probability 50/100	○	○	3.85€ with probability 50/100, 0.10€ with probability 50/100
Choice 4:	2.00€ with probability 65/100, 1.60€ with probability 35/100	○	○	3.85€ with probability 65/100, 0.10€ with probability 35/100
Choice 5:	2.00€ with probability 80/100, 1.60€ with probability 20/100	○	○	3.85€ with probability 80/100, 0.10€ with probability 20/100

Next

How well do the following statements describe your personality?

I see myself as someone who...	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little	Agree strongly
1. ... is reserved					
2. ... is generally trusting					
3. ... tends to be lazy					
4. ... is relaxed, handles stress well					
5. ... has few artistic interests					
6. ... is outgoing, sociable					
7. ... tends to find fault with others					
8. ... does a thorough job					
9. ... gets nervous easily					
10. ... has an active imagination					

Next

F Appendix tables and figures

F.1 Regression tables

F.2 Appendix figures

Table 8: Regression analysis in the baseline treatments: time fraction

	Time fraction of being most connected (%)				Median payoff			
	$N = 4$	$N = 8$	$N = 50$	$N = 100$	$N = 4$	$N = 8$	$N = 50$	$N = 100$
Effort	5.53***	4.66***	1.27***	0.55***				
	(0.40)	(0.65)	(0.23)	(0.12)				
Time fraction					0.04	0.03	-1.29***	-0.28
					(0.13)	(0.10)	(0.26)	(0.79)
Number of observations	80	160	1000	1500	80	160	1000	1500
R-squared	0.729	0.516	0.265	0.115	0.119	0.090	0.127	0.055

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions includes a constant, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 9: Scale effects on effort and outdegree in the baseline treatments

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
$N = 50$	6.61***	7.27***	0.32	0.99***	0.74	0.15***
	(1.08)	(1.41)	(0.32)	(0.28)	(0.52)	(0.06)
Average in small group	8.77	5.24	2.65	0.20	0.62	0.90
Number of observations	60	60	1120	60	60	1120
R-squared	0.61	0.59	0.04	0.49	0.47	0.04

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 10: Scale effects on effort and outdegree in the baseline treatments

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
$N = 100$	6.64***	11.06***	0.88***	2.03**	0.72*	0.30***
	(1.54)	(1.10)	(0.32)	(0.77)	(0.38)	(0.05)
Average in small group	8.77	5.24	2.65	0.20	0.62	0.90
Number of observations	55	55	1630	55	55	1630
R-squared	0.62	0.83	0.04	0.53	0.46	0.06

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 11: Scale effects on payoffs in the baseline treatments

	Median payoff		
	most connected	2nd most connected	others
$N = 50$	-40.81***	-51.09**	28.82***
	(10.20)	(23.61)	(1.73)
Median in small group	86.50	81.00	85.00
Number of observations	60	60	1120
R-squared	0.39	0.23	0.11

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 12: Scale effects on payoffs in the baseline treatments

	Median payoff		
	most connected	2nd most connected	others
$N = 100$	16.54	-25.41*	53.20***
	(29.95)	(14.54)	(2.77)
Median in small group	86.50	81.00	85.00
Number of observations	55	55	1630
R-squared	0.20	0.38	0.14

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 13: Regression analysis when information on others' payoff is observable: time fraction

	Time fraction of being most connected (%)				Median payoff			
	$N = 4$	$N = 8$	$N = 50$	$N = 100$	$N = 4$	$N = 8$	$N = 50$	$N = 100$
Effort	7.75***	5.55***	0.49**	0.34*				
	(0.68)	(0.84)	(0.21)	(0.20)				
Time fraction					0.35**	0.10	1.13***	1.74***
					(0.15)	(0.16)	(0.31)	(0.25)
Number of observations	80	160	1000	1500	80	160	1000	1500
R-squared	0.714	0.479	0.042	0.022	0.546	0.113	0.051	0.002

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions includes a constant, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 14: Treatment effects on effort and outdegree

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
Payoff info	-1.35*	0.21	-0.04	0.74*	0.29*	0.05
	(0.76)	(0.65)	(0.37)	(0.45)	(0.17)	(0.07)
$N = 50$	6.53***	6.48***	0.30	1.48***	0.95**	0.17***
	(1.21)	(1.37)	(0.33)	(0.36)	(0.44)	(0.06)
Payoff info $\times$ $N = 50$	-8.90***	-5.72***	-0.39	-0.29	0.00	-0.10
	(1.83)	(1.93)	(0.44)	(0.57)	(0.54)	(0.08)
Average in Baseline50	15.70	11.33	2.84	1.18	1.28	1.04
Number of observations	120	120	2240	120	120	2240
R-squared	0.54	0.38	0.04	0.43	0.41	0.07

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 15: Treatment effects on effort and outdegree

	Mean effort			Mean outdegree		
	most connected	2nd most connected	others	most connected	2nd most connected	others
Payoff info	-0.55	0.20	0.06	-0.57	0.02	0.03
	(0.79)	(0.70)	(0.36)	(0.89)	(0.12)	(0.07)
$N = 100$	6.53***	10.26***	0.87***	0.75	0.86**	0.30***
	(1.33)	(1.48)	(0.32)	(1.94)	(0.34)	(0.06)
Payoff info $\times$ $N = 100$	-9.82***	-12.48***	-1.28***	2.30	-0.89**	-0.01
	(1.65)	(2.01)	(0.41)	(2.47)	(0.37)	(0.08)
Average in Baseline100	14.35	15.73	3.48	2.86	1.40	1.17
Number of observations	110	110	3260	110	110	3260
R-squared	0.53	0.68	0.07	0.54	0.32	0.04

Notes: Robust standard errors, clustered by individual subject, are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

Table 16: Treatment effects on payoffs

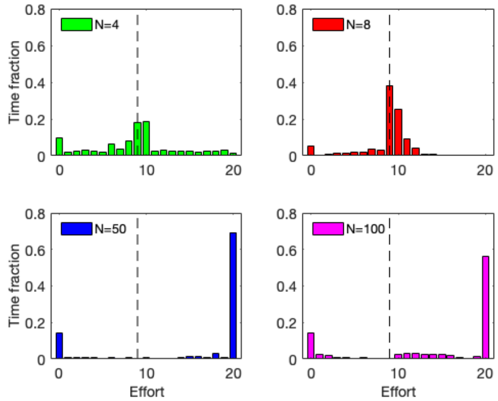
	Median payoff		
	most connected	2nd most connected	others
Payoff info	0.76	-18.73***	-6.07**
	(8.94)	(4.04)	(2.38)
$N = 50$	-57.53***	-48.79**	29.99***
	(11.82)	(19.15)	(2.46)
Payoff info $\times$ $N = 50$	142.27***	100.25***	-14.96***
	(18.28)	(29.02)	(2.26)
Median in Baseline50	48.50	51.00	118.00
Number of observations	120	120	2240
R-squared	0.21	0.14	0.11

Notes: Robust standard errors are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.

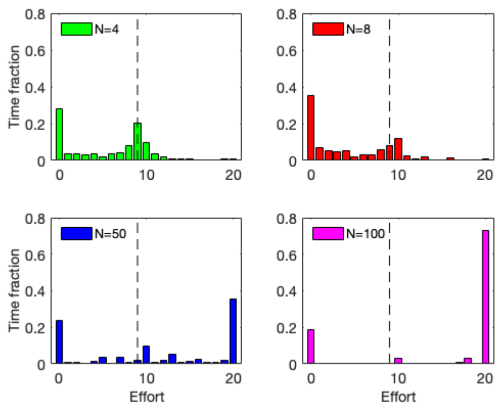
Table 17: Treatment effects on payoffs

	Median payoff		
	most connected	2nd most connected	others
Payoff info	-0.64	-15.63***	-11.36***
	(12.59)	(5.31)	(2.05)
$N = 100$	40.61**	-43.22	51.44***
	(17.34)	(27.99)	(1.85)
Payoff info $\times$ $N = 100$	92.09	160.98***	-20.70***
	(150.87)	(29.02)	(2.67)
Median in Baseline100	153.00	42.50	140.50
Number of observations	110	110	3260
R-squared	0.07	0.26	0.13

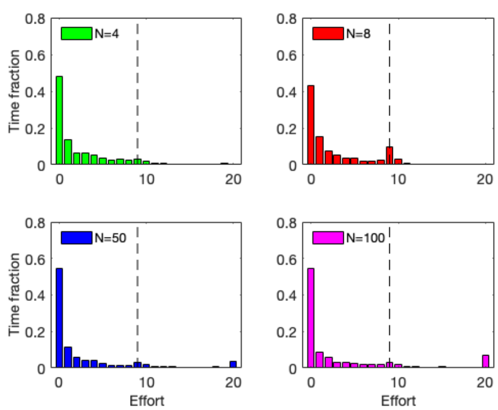
Notes: Robust standard errors are report in parenthesis. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. All regressions include a constant, round dummies, age, female, education, comprehension test score, experimental measures of risk aversion and altruism, and Big 5 personality.



(a) the 1st most connected

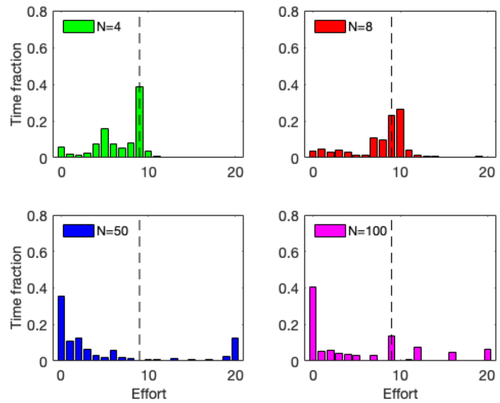


(b) the 2nd most connected

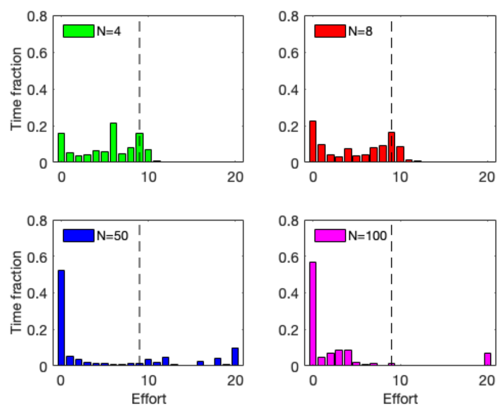


(c) the others

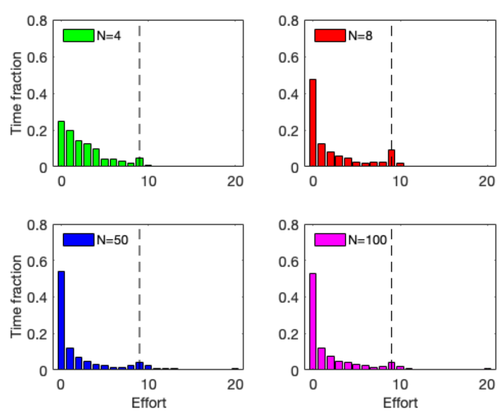
Figure 21: Distribution of efforts in the baseline treatment



(a) the 1st most connected

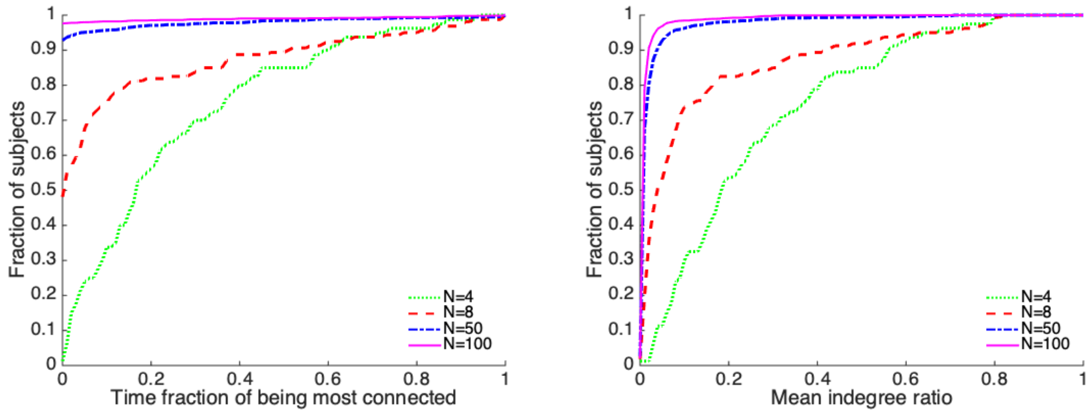


(b) the 2nd most connected



(c) the others

Figure 22: Distribution of efforts in the payoff information treatment



(a) Time fraction (b) Mean indegree ratio

Figure 23: Distribution of linking: information on others' payoff

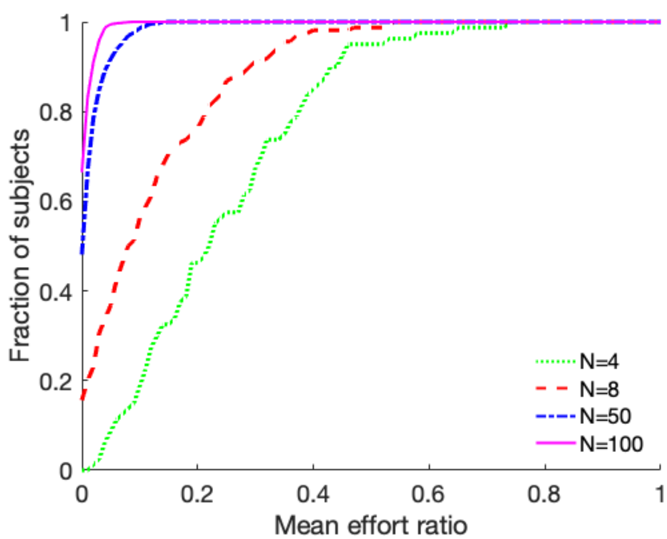


Figure 24: Distribution of Efforts in the payoff information treatments