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Individual Search and Social Networks

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Summary

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1 Introduction

Facebook, Twitter, and YouTube are very much part of our day to day life. Reviews of books on Amazon, individual score rating about buyers and sellers on E-bay, and ratings on Tripadvisor shape our decisions on what to buy, who to trade with, and where to stay and eat. The explosion in online social engagement is one of the most extraordinary developments of our time. As these social networks span an ever growing range of activities, it is important to understand the economic factors that shape their structure and functioning, and to estimate their welfare implications.[1]

Information exchange through social communication is one of the central aspects of online social engagement. Individuals obtain information through individual search and also from reviews and 'web-blogs' of others. Both these activities are costly. So, individuals compare the relative costs and benefits of these alternative sources of information. We view online social networks as a technological change that facilitates communication and thus reduces the relative costs of accessing information from others. This paper presents an empirical study of the economic implications of such a technological change.

We use the methodology of controlled laboratory experiments to study the fundamentals of the underlying trade-off between information acquisition through individual search and accessing information of others through communication. The laboratory is a suitable setting for our purposes as we can control the main variables directly: the costs and benefits of social communication and of individual search for information. Although we cannot approach the large scale information diffusion processes in online networks in the laboratory, we can study causal determinants of the processes at work. Moreover, we can estimate the information acquired and the utilities of individuals.

The theoretical framework is taken from a model of individual search and communication developed in Galeotti and Goyal (2010). Individuals choose a level of search (information acquisition) given by x_i and a level of social communication (number of directed communication links) with others, given by η_i. Search is costly: each unit of acquired information costs $c > 0$. Similarly, social communication is costly: each communication link costs $k > 0$. Information acquired by different individuals is substitutable. In particular, the marginal utility of own search is falling in the information acquired by friends (and connected others). Define $\hat{y}$ as the amount of information an isolated individual would optimally acquire, given his utility from information and the costs of search, c. Assume that $k < c\hat{y}$: this is necessary for individuals to form communication links.

[1]For a comprehensive recent survey of online networks, see Peitz and Waldfogel (2012).

Galeotti and Goyal (2010) show that every (strict) Nash equilibrium is characterized by information sharing. An individual's search level and the number of others who link to her are positively correlated. Every individual must access $\hat{y}$ information (own search plus information from others) and that total information acquisition by society is also $\hat{y}$, independently of the costs of linking.

We conduct a range of experiments with 4 subjects. In our baseline treatment we start with homogenous costs of information acquisition, c, and low costs for social communication, k. We then compute the level of $\hat{y}$. In the experiment, we find that all subjects indeed have access to $\hat{y}$ units of information. Total information acquired in society is much lower than $4 \times \hat{y}$: so there is extensive sharing of information. In line with theory, the information an individual acquires and the number of people who link with her are positively correlated.

We then turn to the effects of changing costs of social communication (linking).[2] As we raise costs of linking, the theory predicts that $\hat{y}$ remains unchanged. However, at a higher linking cost, a person must acquire more information for the link to be justified. As total information acquisition is constant, this implies that there will be fewer hubs and communication links. In the experiment, we find that subjects act very much in line with each of these predictions: the number of hubs and communication links fall as we raise costs of linking, while hubs raise their average information acquisition (search). Individuals access $\hat{y}$ units of information on average, at all cost levels.[3]

One important prediction of the theory is that total information acquired is invariant with respect to costs of social communication. In the experiment, we find that aggregate information acquisition is higher than predicted and increases with costs of linking. We develop an explanation for these two departures from the theory. In the equilibria the hub player is supposed to acquire significantly more information than the periphery players. Given the costs parameters, this implies that the hub earns a lower payoff than the peripheral players. These factors lead the hub player to shade information acquisition: in the baseline treatment linking with a hub remains attractive and so the network remains dense. However, peripheral players respond to this shading by acquiring more information. The hub maintains a higher

[2]The discussion starts with low cost and moves to higher costs of links; this is line with the order of presentation of the experimental findings, in Sections 2-4 below.

[3]We also considered a setting with heterogeneity in costs of acquiring information. We randomly determined one player in each group to have lower costs. The low-cost player i's stand-alone optimal investment is $\hat{y}_1 > \hat{y}$. The unique equilibrium network has the star architecture with the low-cost player as the hub, independently of the costs of linking. In the experiment we see indeed that the low-cost player is more likely to be the hub. The macroscopic patterns with regard to linking costs exhibit the same pattern as in the homogenous treatments: number of hubs and links fall as we raise costs of linking, while average investment by hubs rises. Individuals access $\hat{y}_1$ units of information on average, at all cost levels. Moreover, total information acquisition grows substantially as we increase the costs of linking.

than a best response investment level to this positive investment by peripheral players, for fear of losing the link. The overall effect is that aggregate information acquisition is in excess of equilibrium. As costs of linking grow, the demands on hubs become more onerous (to justify the higher cost of the link). If hubs are not forthcoming with these high information investments, non-hub players delete links giving rise to partially connected networks. Isolated players or dyads then make large investments which push up aggregate investments. These patterns are consistent with the data from the experiment.

The final major finding concerns the welfare implications of changes in costs of links. In the homogenous cost case (all players have the same costs for information acquisition), at high costs of linking, there is a unique equilibrium with a single hub. However, at lower costs of linking in addition to the single hub outcome, there also exist other equilibrium outcomes, with multiple hubs and more links. So the theoretical predictions on individual and aggregate welfare are *a priori* ambiguous. The data from the experiment yields two clear cut findings. Aggregate earnings are below the (least efficient) Nash equilibrium prediction in all cases. However, they are falling significantly in linking costs.[4]

To summarize, our experiment reveals that subjects form links to share information and that their linking is positively correlated with search intensity of those to whom they form links. Falling costs of linking, a prominent characteristic of online social networks, leads to more dispersed information acquisition and greater linking. Aggregate investment in information acquisition falls, but information available to individuals remains stable. The net effect of falling costs of links is a large increase in individual utility and aggregate welfare.

Our paper is a study of the effects of new information technologies on economic outcomes. While there is clear and widespread use of these technologies, evidence on productivity, distribution and welfare effects has been harder to come by. For discussions of this issue in the macro-economic context, see Solow (1987) and Brynjolfsson (1993). Attention has since moved to micro-level studies and authors have presented evidence for significant effects. Agarwal and Goldfarb (2008) present evidence on research productivity of mid-tier universities, Kim, Morseb, and Zingales (2009) report a fall in productivity premium of elite universities, while Varian (2010) reports fall in communication costs and predicts large productivity gains for workers. For a recent survey of these issues, see Brynjolfsson and Saunders (2010). They present a powerful argument for a more nuanced way of measuring value generated by online networks. Our paper contributes to this body of work by drawing out the quantitative effects

[4]While the macroscopic predictions are not ambiguous for treatments with heterogeneous costs (in which one player in the network has lower costs for information acquisition), we observe very similar patterns with regard to welfare.

of a specific economic trade-off – costs of search *versus* costs of communication – in shaping information acquisition, social structure and especially aggregate welfare.

In the literature on public goods experiments, an important general finding is that individuals contribute more than what theory predicts though they contribute less than the first best; for surveys, see Ledyard (1995), Croson (2010), and Holt and Laury (2012). Thus individual utility is generally higher than the Nash equilibrium level. The principal novelty in the present paper is that individual choices determine whether their actions and others' actions become public goods or remain 'private'. This is accomplished through the formation of links. The experiment reveals that this 'endogeneity' of public goods has important implications for behavior and welfare. In particular, falling costs of linking lead to more dispersed provision of the public good. The aggregate investment in 'public' goods falls, but due to greater linking, every individual has access to the same amount of it.

Our paper is also a contribution to the study of public goods in social networks. There is now a large theoretical literature on social networks, but an empirical assessment of their economic role remains a challenging problem. For a survey of the research, see Goyal (2007). In this paper we take an experimental approach to understanding the formation and the consequences of networks; for an early survey of network experiments, see Kosfeld (2004).[5] Seen against the background of the explosion of online social networks, the main findings of the experiment are about the economic effects of falling linking costs. These findings – especially those with regard to patterns in aggregate information acquisition and welfare – are substantively important and go beyond the theory.

Two recent papers, Rong and Houser (2012) and Leeuwen, Offerman and Schram (2013) also report experiments on the Galeotti and Goyal (2010) paper. Rong and Houser (2012) investigate network formation in best-shot public good games. Their interest is in the effects of link formation protocol and limits to investment as determining the emergence of star networks. Leeuwen, Offerman and Schram (2013) consider a repeated game and their interest is in effects of group size and social transfers in determining emergence of star (and superstar) networks. By contrast, our focus is on the effects of linking costs on investments in information and linking and on social welfare. Thus our paper and these two papers investigate complementary questions.

The rest of the paper is organized as follows: Section 2 describes the theoretical model. Section 3 presents the experimental design. Section 4 presents and discusses the experimental

[5]Contributions to network experiments include Charness, Corominas-Bosch and Frechette (2007), Cassar (2007), Falk and Kosfeld (2012), Callander and Plott (2005), Burger and Buskens (2009), Goeree et al. (2009) and Rosenkranz and Weitzel (2012).

findings. Section 5 concludes.

2 The network game

Suppose there is a set of agents $N = \{1, 2, ..., n\}$ with $n \geq 3$ and let i and j be members of this set. Let each player i choose $x_i \in X$ with $X \in [0, \overline{X}]$ (which denotes agent i's level of effort spent on the production of a local public good, in our case of acquiring information), and a set of links which is represented as a vector $g_i = (g_{i1}, ..., g_{ii-1}, g_{ii+1} ..., g_{in})$, where $g_{ij} \in \{0, 1\}$, for each $j \in N \backslash \{i\}$. If $g_{ij} = 1$, agent j has a link with player i and benefits directly from agent i's effort, and $g_{ij} = 0$ otherwise.[6] Suppose that $g_i \in G_i = \{0, 1\}^{n-1}$. The set of strategies of player i is denoted by $S_i = X \times G_i$.

Define $S = S_1 \times ... \times S_n$ as the set of strategies of all players. A strategy profile $s = (x, g) \in S$ specifies the personal information acquired by each player, $x = (x_1, x_2, ..., x_n)$, and the network of relations $g = (g_1, g_2, ..., g_n)$. The network of relations g is a directed graph; let G be the set of all possible directed graphs on n vertices. Define $N_i(g) = \{j \in N : g_{ij} = 1\}$ as the set of players with whom i has formed a link, and let $\eta_i(g) = |N_i(g)|$, the number of links formed by i. The closure of g is an undirected network denoted $\overline{g} = cl(g)$ where $\overline{g}_{ij} = max\{g_{ij}, g_{ji}\}$ for each i and j in N, reflecting the bilateral nature of information exchange between the two players. Define $N_i(\overline{g}) = \{j \in N : \overline{g}_{ij} = 1\}$ as the set of players directly connected to i. The payoff to player i under strategy profile $s = (x, g)$ is:

$$\Pi_i(s, g) = f(x_i + \sum_{j \in N_i(\overline{g})} x_j) - cx_i - \eta_i(g)k \tag{1}$$

Costs of information acquisition are represented by $c > 0$, while linking costs are represented by $k > 0$. The payoff function represents the tradeoff described in the introduction and the local public good character of information acquisition. The benefit $f(y)$ of a player depends on the aggregate information provided by her direct neighbors, which is not necessarily identical to the aggregate information available in the network.

For the experiment we assume that $f(y)$ is twice continuously differentiable, increasing, and strictly concave in y, and that $f(0) = 0, f'(0) > c$ and $f'(\overline{X}) = z < c$. Under these assumptions there exists a number $\widehat{y} \in (0, \overline{X})$, such that $\widehat{y} = \arg\max_{y \in X} f(y) - cy$.

For given c and k, define $I(s) = \{i \in N | x_i > 0\}$ as the set of players who acquire information personally. Galeotti and Goyal (2010) prove:

[6] The model is taken from Galeotti and Goyal (2010). This model combines the network formation model in Bala and Goyal (2000) and the public goods in networks, due to Bramoulle and Kranton (2007).

Proposition 1 *Suppose payoffs are given by (1) and $k < c\hat{y}$. In every strict equilibrium $s = (x, g)$: (1.) $\sum_{iN} x_i = \widehat{y}$, and (2.) the network has a core-periphery architecture, hubs acquire information personally and spokes acquire no information personally.*

They show that as the relative cost of linking k/c grows, the number of hubs decreases, each hub player acquires more information, and the total number of links decreases. In particular, if $k/c \in (\widehat{y}/2, \widehat{y})$, then there is only one hub, and the social communication structure takes the form of a periphery sponsored star.

Suppose that there exists a small heterogeneity in costs of information acquisition. Let $c_i = c$ for all $i \neq 1$ and $c_1 = c - \epsilon$, where $\epsilon > 0$. Define $\widehat{y}_1 = \arg\max_{y_1 \in X} f(y_1) - c_1 y$. Proposition 3 of Galeotti and Goyal (2010) establishes our next proposition:

Proposition 2 *Suppose that $k < f(\widehat{y}_1) - f(\widehat{y}) + c\hat{y}$. In every strict equilibrium $s^* = (g^*, x^*)$, (i) $\sum_{i \in N} x_i^* = \widehat{y}_1$ (ii) the network is a periphery-sponsored star with player 1 as hub, and (iii) either $x_1^* = \widehat{y}_1$ and $x_i^* = 0$, for all $i \neq 1$, OR $x_1^* = ((n-1)\widehat{y} - \widehat{y}_1)/(n-2)$, and $x_i = (\widehat{y}_1 - \widehat{y})(n-2)$, for all $i \neq 1$.*

Observe that a slight cost heterogeneity leads to the low-cost player being the unique hub player; moreover, as $\epsilon \to 0$, the hub chooses approximately $\hat{y}$ while all others choose 0, in the unique (strict) equilibrium.

3 The experimental design and hypotheses

In the experiment the subjects faced a decision problem as characterized above: groups of *N = 4* subjects choose a level of effort (information acquisition) and, simultaneously, to which other player they wanted to be connected. The payoff is given by:

$$\pi_i = (x_i + \sum_{j \in N(i;\bar{g})} x_j)(29 - (x_i + \sum_{j \in N(i;\bar{g})} x_j)) - c_i x_i - \eta_i(g)k.$$

This implies that (given the network) the optimal effort level x_i for a player i is:

$$x_i = (29 - c_i)/2 - \sum_{j \in N(i;\bar{g})} x_j.$$

Our design consists of two treatment variables: the costs k for forming a link, and the costs c_i for investing effort in acquiring information. In the experiment, investments were constrained to integers.

The baseline treatment

In the baseline treatment, we set $c = 5$ and $k = 10$. For these values $\widehat{y} = 12$, and the parameters satisfy $k < c\widehat{y}$. We refer to this as Treatment I.

Appendix I provides a proof that in every equilibrium the sum of total investments is equal to 12. We then apply Proposition 1 in Galeotti and Goyal (2010) to provide a characterization of equilibria. Table 1 presents the key features of equilibrium outcomes.

— Insert Table 1 here —

There are multiple equilibria possible but they share some key macroscopic properties: there is information sharing in all of them, every individual accesses 12 units of information, and aggregate information acquired in society is also 12. There is positive correlation between the information an individual acquires and the number of others who link with this person (her in-degree). Individual earnings vary greatly within an equilibrium and also across equilibria. Finally, we note that aggregate earnings also vary greatly across equilibria.

Our first hypothesis operationalizes Proposition 1 and considers the 'macroscopic' implications of strategic interaction on the distribution of information acquisition and linking in the baseline Treatment I.

H.1 *There is information sharing and positive correlation between the amount of information an individual acquires and her in-degree. Every individual has access to* 12 *units of information, total information acquired in society is also* 12.

Linking costs

A key aspect of the model is the comparison of costs of linking and the costs of information acquisition. To explore the role of this comparison we vary the costs of linking. We raise the costs from $k = 10$ to $k = 24$ and then to $k = 36$; we refer to these as Treatments II and III. Tables 2 and 3 provide a characterization of equilibrium outcomes.

— Insert Tables 2 and 3 here —

In Treatment II, with $k = 24$, equilibrium contains either 1 hub with 3 links or 2 hubs with 4 links. Investment by a hub must be at least 4.8 to justify linking by periphery players. In Treatment III with $k = 36$, equilibrium contains 1 hub and 3 links. Investment by the hub must exceed 7.2. Across these treatments, individuals access exactly 12 units of information and aggregate investment remains at 12. These observations yield our second hypothesis.

H.2 *Rising costs of linking leads to a fall in the number of hubs and links and an increase in investments by hubs. Individually accessed information and aggregate information acquired in society are independent of linking costs and equal to* 12 *units.*

Cost Heterogeneity

To further explore the economic mechanisms we consider the role of cost heterogeneity across individuals. Suppose $c_i = 5$ for all $i \neq 1$ and $c_1 = c - \epsilon$, where $\epsilon = 2$. We allow for the same three levels of linking costs as in the homogeneous treatments, i.e. $k = \{10, 24, 36\}$. It follows that the low-cost player's stand-alone optimal investment is $\widehat{y}_1 = 13$. Moreover, $k < f(\widehat{y}_1) - f(\widehat{y}) + c\widehat{y}$, which in combination with the discrete action space implies that the unique equilibrium network is a periphery-sponsored star and the low-cost player is the hub, investing $\widehat{y}_1$, irrespective of the costs of linking. The proof of this property is presented in Appendix I. We refer to these as Treatments IV-VI. Table 4 provides a characterization of equilibrium outcomes.

— Insert Table 4 here —

Our third hypothesis operationalizes Proposition 2 and refers to Treatments IV-VI.

H.3 *Heterogeneity with respect to costs of information acquisition leads to a unique equilibrium: the low-cost player is the hub. She invests* 13 *units in information acquisition; all other players invest* 0 *and form a link with the hub.*

3.1 Experimental procedures

The computerized experiment was designed using the software program z-tree (Fischbacher, 2007) and conducted in the Experimental Laboratory for Sociology and Economics (ELSE) at Utrecht University. In total, 8 experimental sessions of approximately one-and-a-half hours were scheduled and completed. Before the start of every experiment, general written instructions were given, which were kept identical across sessions (see Appendix II).

Using the ORSEE recruitment system (Greiner, 2004), over 1000 potential subjects were approached by e-mail to participate in the experiment. A total of 152 subjects (either 16 or 20 per session) participated. Each subject played 24 rounds of a local public goods game with linking decisions. At the beginning of each round, subjects were randomly allocated to a group together with three other participants. This resulted in $152/4 = 38$ observations at the group level per round. Subjects were indicated as circles on the screen and could identify themselves by color: each subject saw him- or herself as a blue circle while all neighbors were represented as black circles (see screen shots in Appendix II). Subjects were not identifiable between different rounds or at the end of the experiment.[7]

In each session we ran every treatment. The order of the treatments was balanced across sessions.[8] Every group played 24 rounds. Each of the six treatments I - VI described in the previous section was played for 4 rounds: 1 trial round and 3 payment rounds. As we did not use the data of the trial round in our analysis, this ultimately led to 114 (= 38 groups $\times$ 3 rounds) observations at the group level per treatment. Moreover, we obtained 456 (= 38 groups $\times$ 3 payed rounds $\times$ 4 players) observations at an individual level.

Every round had the same structure and lasted between 105 and 135 seconds each (on average 120.5 seconds). To prevent end round effects an unknown and random moment in this last time interval determined the end of the round.[9] Starting from a situation with no investments and no links, subjects indicated simultaneously on their computer terminals (by clicking on one of two buttons at the bottom of the screen) how much they wished to invest. By clicking on one of the circles on the screen representing another participant, subjects could link to this other participant. A one-headed arrow appeared to indicate the link and its direction. By clicking again on the other participant the arrow and, thus, the link was removed again. The participant who initiated this link had to pay some points for this link. If both participants had clicked for a specific link a two-headed arrow appeared and both participants needed to pay points for this link.

Full information about the investments and linking decisions of all other subjects was continuously provided. Also, resulting payoffs of all participants could continuously be observed on the screen. At the end of each round, subjects were informed about the number of points earned with the investments and links as were on the screen at the end of that round. In other words, subject earnings only depended on the situation at the (random) end of every round.

It is important to clarify some aspects of the experimental design.

Our *first* remark concerns the complexity of the game and the need for trial time: Experience with previous experiments on network formation suggests that individuals find the decision problem to be very complex and this inhibits behavior (Goeree et al., 2009; Falk and Kosfeld, 2012). Subjects appear to need time to understand the game and to coordinate their actions. We address this issue in our design by having a trial (non-payoff relevant) round, and in addition having a period of time until 90 seconds where actions do not have payoff impli-

[7]The aim of this allocation mechanism is to minimize the dependence across observations (Falk and Kosfeld, 2012).

[8]See Table 12 in Appendix II for the sequence of the treatments.

[9]On the screen subjects were informed about the start of the interval with random length (at 105 seconds).

cations. Moreover, to facilitate activity, we allowed subjects to choose links and information acquisition in continuous time.

The *second* set of remarks are about the relation between the theoretical model discussed in section 2, and the experimental design.

The first observation is that we may consider our experimental design as a sequence of simultaneous move games, with a stochastic end stage, and only the last stage behavior to be payoff relevant. In such an interpretation, it follows from standard arguments that any equilibrium of the stage game can be implemented in the stage game of our experiment.

The second observation is about the role of the first 90 seconds, that players know has no payoff relevance. Actions in this period may therefore be viewed as 'cheap talk'. This raises the question of whether this cheap talk can select between different equilibrium of the stage game. There is a large literature on this subject: a general message is that selection is cheap talk is more likely to be effective in equilibrium selection if equilibrium are Pareto ranked (see e.g., Farrell and Rabin (1996)). In our setting, equilibria are not Parteo ranked. So we believe that cheap talk is not an important consideration in our analysis.

The final observation is about the potential repeated game effects. The period from 90 seconds until the end of the game may be viewed as a type of 'repeated game', with an ending that is stochastic with a well defined finite end point (at 135 seconds). From the work of Benoit and Krishna (1985), we know that repetition may be used to select among different stage game equilibrium and indeed even go beyond stage game equilibrium – to Pareto improving profiles of actions. This is certainly a possibility in our experimental design. We come back to this issue after presenting our results in section 4, below.

At the end of the experiment, the points were converted to Euros at a rate of 200 points = Euro 1. The total was then rounded upwards to Euro 0.5. On average, the experiment lasted 80 minutes and subjects earned Euro 14.40. At the end of the experiment subjects were asked to fill in a short questionnaire.

4 Experimental findings

4.1 Description of sample and variables

Table 5 describes the sample across all sessions and treatments.[10] An average subject contributed 4.4 units and had 1.04 links as in-/out-degrees. On average, a period lasted 120.5

[10]Approximately 65% of the 152 subjects participating in the experiment were female and 62% were Dutch. On average, a subject knew 0.7 other people in the lab by first name ('friends'), and was 21.3 years old.

seconds during which a subject took 24.7 linking decisions and 52 investment decisions. Thus the experiment was characterized by high level of activity in both investment and linking decisions.

— Insert Table 5 here —

Table 6 provides a summary of investments and linking per treatment, and reports profits at the individual and at the group level. In the following section we will discuss these variables and the differences between treatments, and report the relevant statistical tests. Treatments V and VI are robustness checks for Treatment IV, because Hypothesis 3 applies to all three treatments with heterogeneous players. In the following section we therefore focus on the results for Treatments I-IV and report the analyses for Treatments V and VI in Appendix II.

— Insert Table 6 here —

4.2 Testing the Hypotheses

Hypothesis 1 predicts that, in the baseline Treatment I, *there is information sharing and positive correlation between the amount of information an individual acquires and her in-degree. Every individual has access to* 12 *units of information, total information acquired in society is also* 12*.*

We start with the statistical analysis of the relation between an individual's information acquisition and her in-degree, i.e. the number of directed, incoming links from other individuals. Figure 1 presents a box plot on this relation, i.e. the average node investment (for $x_i < 19$, corresponding to 99% of all observations) per node in-degree (x-axis). Non-parametric tests of pairwise correlation show that investment is indeed significantly higher for players with a higher in-degree. The Pearson correlation coefficient between in-degree and investment at a 1% level of statistical significance (99% CI) is 0.4196 for the homogeneous Treatments I-III.

The positive correlation between in-degree and investment is also confirmed in an OLS regression, with investment as the dependent variable, and in-degree and all levels of linking costs k as independent variables.[11]

— Insert Figure 1 here —

To get more insight into information sharing we next analyze the network structure. A direct examination of linking patterns reveals that the network is connected in over 90% of

[11] This is reported in Table 14, in Appendix II, where Model 1, in the first column of Table 14, presents the data from the baseline Treatment I (k=10, c=5)).

the cases, see Table 7. Table 6 shows that the mean (median) number of directed ties is 4.842 (5) in the baseline Treatment I. Table 5 shows that there is significant linking activity (in all treatments).[12]

— Insert Table 7 here —

We next turn to the statistical analysis of the aggregate information. In Table 6 we observe a mean (median) total investment per group of 15.175 (14) units. A Wilcoxon rank-sum (Mann-Whitney) test for the equality of medians and a Kolmogorov-Smirnov test for the equality of distribution functions confirm that aggregate investment is statistically significantly higher than 12 at a 99% level of confidence.

Turning to individual investment, Table 6 shows that the median player accesses exactly 12 units of investment, while the average access is 12.693 units. Although the difference of the average access from 12 is statistically significant (two-tailed t-test, $p < 0.01$) this deviation is less than 1 unit from the predicted value, which was the minimum increment in the experiment.

While total information acquired in society is larger than predicted, it still is much lower than 48 units, the level that would prevail if every individual would choose its optimal level independently. As each individual, on average, has access to approximately 12 units of information, this means that individuals *must* be sharing their investments. Taken together, these observations confirm Hypothesis 1 and offer strong support for information sharing in the laboratory.

We now turn to the central question regarding the impact of changing linking costs. Hypothesis 2 says that *rising costs of linking lead to a fall in the number of hubs and links and an increase in investments by hubs. Individually accessed information and aggregate information acquired in society are independent of linking costs and equal to* 12 *units.*

Define a 'Hub (invest)' as someone who invests $x_i > k/c$. For $k = 10, 24, 36$ and $c = 5$, these critical investment levels are $2, 4.8$ and 7.2, respectively. In Table 8, the column Hub (invest) shows the number of players per group who qualify as a hub, according to this definition. If $k = 10$ there are on average 2.6 hubs, if $k = 24$, there are on average 1.8 hubs, and if $k = 36$ there are on average 0.9 hubs per group. A Kolmogorov-Smirnov test for the equality of distribution functions comparing the number of Hubs (invest) with the remaining two levels of k, shows that these differences are significant at the 1% level. The number of hubs is thus declining when linking costs increase.

To test whether the investment by hubs increases with rising linking costs, we cannot

[12] Although equilibrium outcomes arise very rarely in the laboratory, 25.4% of all groups are in a network structure as described by equilibrium (for evidence on this refer to Table 13 in Appendix II).

use the above definition of a hub that is based on a player's investment due to problems of endogeneity. Instead we use an alternative definition, considering a player's incoming links (in-degree). In line with the equilibrium predictions for the treatments, define a 'Hub (in-degree)' as someone who has an in-degree larger than or equal to 2 if $k = 10, 24$, and equal to 3 if $k = 36$.[13] Table 8 shows that mean (median) investment into information acquisition by Hubs (in-degree) is 5.1 (5) at $k = 10$, 6.6 (7) at $k = 24$, and 7.4 (7) at $k = 36$. Table 8 also reports the statistical tests (Wilcoxon and Kolmogorov-Smirnov): investment levels both for $k = 24$ and for $k = 36$ are significantly higher than for $k = 10$ at the 1% level, while the investment levels for $k = 24$ and $k = 36$ do not differ statistically.[14]

— Insert Table 8 here —

Next consider the number of links. Table 6 on group descriptives reports the median and mean number of directed ties per group. A Wilcoxon rank-sum (Mann-Whitney) test as well as a Kolmogorov-Smirnov test confirm that higher levels of linking costs $k = 24$ ($k = 36$) are associated with lower levels of linking (number of directed ties) relative to $k = 10$ (and statistically significant with $p < 0.01$). Both tests also show that the number of directed ties per group for $k = 24$ is statistically different from that for $k = 36$ at the 5% level.

Table 6 also reveals that the median individual accesses 12 units of information, in all the cost treatments, while the average individual access is slightly above 12 units. As theoretically predicted, we find that the individually accessed investment does not, on average, change in the level of linking costs k. The same applies to the median.[15]

Aggregate information acquired in society is growing with cost of linking: it is, on average, 15.175 at $k = 10$, rises to 17.588 at $k = 24$ and then rises further to 19.465 at $k = 36$.[16]

[13]In Table 8 the column Hub (in-degree) shows the average number of players per group that qualify as a hub according to this definition. If $k = 10$ there are on average 1.6 hubs, if $k = 24$ there are on average 1.1 hubs, and if $k = 36$ there are on average 0.4 hubs per group. A Kolmogorov-Smirnov test for the equality of distribution functions comparing the number of Hubs (in-degree) with the remaining two levels of k, shows that also these differences are significant at the 1% level.

[14]Table 14 in Appendix II shows a positive correlation between in-degree and investment in general. Model 2 shows the estimations for the data from the heterogeneous Treatment IV with k=10, Model 3 for all data from the homogeneous Treatments I-III pooled, and Model 4 for all data of the full sample (Treatments I-VI) pooled. In the latter two models dummies for the treatments with linking costs $k = 10$ and $k = 36$ are added and the results show that with higher linking costs individual investment is higher (for both levels of linking costs in the pooled Model 4, for $k = 36$ in the homogeneous treatments). The dummy for $k = 36$ is significant at a level of 11.8% when compared to $k = 24$.

[15]T-tests show p-values of 0.187 and 0.631 for a comparison of averages across levels of $k = 10$ and $k = 24$, and of $k = 24$ and $k = 36$, respectively. The corresponding z-values of Wilcoxon rank-sum tests for the equality of medians are $p = 0.328$ and $p = 0.861$, respectively.

[16]This rise of aggregate information is statistically significant at a 95% level of confidence in t-tests, Wilcoxon rank-sum tests as well as a Kolmogorov-Smirnov tests across levels of k. With the same tests we also confirm

This is a clear departure from the theoretical prediction. We provide an explanation for this deviation below, after discussing the hypotheses. Thus, except for aggregate information, our observations largely confirm Hypothesis 2.

Next we turn to the effect of heterogeneity in the costs of information acquisition. Hypothesis 3 says that *heterogeneity with respect to costs of information acquisition leads to a unique equilibrium: the low-cost player is the single hub. This player invests* 13 *in information acquisition. Every player forms a link with this low cost player and has access to* 13 *units of information.*

First we test whether the low-cost player is the hub player. Table 9 presents probit estimations for Treatment IV with a dummy for hubs, as defined in the previous section, as the dependent variable. Further, the low-cost player is dummied and included as explanatory variable.[17] The results of both models confirm that the likelihood that a player is a hub is significantly higher for low-cost players than for high-cost players.

— Insert Table 9 here —

We further examine the effect of cost heterogeneity on the number of hubs. Table 8 shows that the average number of players per group that qualify as a Hub (in-degree) in the heterogeneous Treatment IV is 0.693 and significantly lower (with $p < 0.01$) than the corresponding average in the homogeneous baseline treatment (1.596). Moreover, univariate tests confirm that investment by these hub players is significantly higher in the heterogeneous treatment, 6.519, than in the homogeneous treatment, 5.093 (with $p < 0.01$). These results confirm the first part of Hypothesis 3. However, Table 6 shows that in the heterogeneous treatment with $k = 10$ the network has on average 5 links. In addition, Table 8 shows that there are on average 2.5 players who qualify as hubs in terms of investment. This average is statistically significantly larger than 1 at a 99% level of confidence ($p < 0.01$), which clearly violates the theory.

We then turn to the issue of information: the data of Treatment IV reveal that the median subject accesses 13 units of information. We also find that the observed average is statistically not different from the theoretically predicted value of 13 (two-tailed t-test, $p = 0.229$). On the other hand, aggregate information acquisition is 15.386, which is statistically significantly higher than 13 the theoretical prediction (with $p < 0.01$). Thus, while some of our observations confirm Hypothesis 3, support for the effects of heterogeneity is rather weak.

statistically that aggregate investment is higher than 12 at a 99% level of confidence.

[17] All control variables of the econometric specification in Table 14 are included in Table 9 as well, with the exception of a dummy for c, as we focus on the heterogeneous sample only.

For a robustness check we also consider the heterogeneous treatments.[18] Equivalent analyses reveal that the patterns are very similar to what we observe in the homogenous costs treatments: Table 6 reports the effects of changing linking costs in the heterogeneous cost treatments. In line with theory, we observe that individuals, in the median, access 13 units of investment regardless of the level of linking costs.[19] Moreover, the aggregate information acquisition increases with linking costs, from 15.386 all the way to 19.509 as we raise linking costs.

4.3 Findings on aggregate investment and welfare

We now turn to an explanation of the information acquisition patterns. Our explanation builds on the observation that hub players are expected to make significantly higher investments than the peripheral players. Table 1 shows that this difference is especially stark in the equilibrium where peripheral players make zero investment. Differences in information acquisition translate in large payoff differences: for instance, in the single hub outcome, the hub earns 144 while the periphery players earn 194.

We conjecture that, faced with this unfavorable situation, the potential hub shades his information acquisition downward. With low costs of linking, the other players retain their links but respond by making positive investments. If the hub has multiple links with non-hubs who are making investments, then the original choice of the hub is in excess of the best response. Let us relate this explanation to the data from the experiment.

Table 7 shows that in the baseline treatment the network is connected in over 92.11% of the cases. Table 10 shows that the hub does indeed over-invest relative to the best response given his neighbors' choices, while the non-hubs choose actions roughly in line with their best response.

— Table 10 here —

When costs of linking are large, a shading of investment by a hub player may trigger a deletion in links by periphery players. This in turn may lead to isolated nodes or dyads. Isolated nodes or dyads will make large investments as they optimally want access to 12 units of information. This explanation is consistent with the data. Table 7 shows that the fraction

[18] See Table 15 in Appendix II for the relation between in-degree and investment in Treatment V and VI.

[19] Wilcoxon rank-sum tests for the equality of medians show that the accessed levels of investment for $k = 24$ and $k = 36$ do not differ significantly ($z = 0.455$) and only at $z = 0.093$ for $k = 10$ and $k = 24$. T-tests for a comparison of the averages show a similar pattern with a p-value of 0.438 for $k = 24$ and $k = 36$, and $p = 0.002$ for $k = 10$ versus $k = 24$.

of connected network is over 92% when $k = 10$ or $k = 24$ but it falls sharply to 71% when $k = 36$. Finally, in Table 10, we observe that investment by non-hub players is increasing sharply in the costs of linking: it goes up from 2.93 for $k = 10$ all the way to 4.579 for $k = 36$.

These patterns of information acquisition have important implications for individual and aggregate earnings. To get a sense of the magnitude of the effects, it is instructive to start with the theory. Tables 1-3 provide the relevant information. In the baseline treatment, a variety of equilibria arise: in the single hub case (Star) the hub earns much less than the peripheral players (144 versus 194). In the 4 hubs case (4-Star) all players earn roughly similar payoffs. The aggregate earnings are falling in the number of hubs due to the higher total costs of links in multiple hub outcomes; they range from 726 all the way down to 696. By contrast, in the case of high linking cost, $k = 36$, the equilibrium has one hub. Table 3 reports that the hub is predicted to earn lower payoffs than the peripheral players (144 versus 168) and that aggregate earnings are lower than in the worst equilibrium of the baseline treatment (648 versus 696).

Table 11 reports data from the experiment on individual and aggregate earnings. They reveal that hubs generally earn more than peripheral players. This is a consequence of the strategic shading by the hubs highlighted above. Indeed, we find that in most treatments the hubs earn more than the theoretically predicted payoffs, while peripheral players earn less than the predicted payoffs.

Table 6 shows that aggregate earnings are below the (worst) Nash equilibrium prediction in all treatments. Moreover, aggregate earnings are falling significantly in linking costs, all the way from 658 under $k = 10$ to 612 under $k = 36$. The median declines from 680 to 611.[20]

— Table 11 here —

We now briefly discuss the experimental findings in relation to equilibrium of the repeated game. The general argument is that if there are multiple equilibria in the stage game, then players may be able to use the choice of equilibrium in a subsequent stage as an incentive to induce welfare improving play in the current stage. Our experimental findings suggest outcomes that rank worse than the worst Nash equilibrium of the stage game. This leads us to believe that repeated game equilibria are probably not a good way to account for the behavior observed.

An explanation for observed behavior may lie in the direction of non-standard preferences: players may enjoy being a 'hub' and/or may place weight on fairness. This may motivate

[20] This fall of aggregate earnings is statistically significant at a 99% level of confidence in Wilcoxon rank-sum tests as well as a Kolmogorov-Smirnov tests, across all levels of k. Similar patterns and significance levels are observed in the treatment with heterogeneous costs.

them to place themselves in hub positions and also to shade investments until payoffs are less unequal than equilibrium payoffs. Developing this line of reasoning would take us too far afield, given our focus on costs of links and the relation with developments on the internet. So we do not develop this line of argument further in this paper.

5 Conclusion

The past decade witnessed an explosion of online social networks. This paper presents an enquiry into their structure and their welfare effects. A central feature of social networks is information exchange. Online social networks may be viewed as a technological change that lowers the cost of information exchange. The lower cost affects the relative attractiveness of individual search vis-a-vis communication with others to access their information. It therefore has implications for how much information individuals gather themselves and how much they link to others to share their information. This paper reports the findings of an experiment that assesses these effects.

In our experiment we indeed see substantial information sharing. Our experiment moreover reveals that falling costs of information exchange lead to more dispersed information acquisition in society and this is accompanied by greater sharing among subjects. Most strikingly, we find that aggregate investment in information acquisition falls with falling costs of information exchange in all treatments, while at the same time information available to individuals remains stable, due to greater linking among subjects. The net effect of falling linking costs is a significant increase in individual utility and aggregate welfare.

Of course, we need to be careful to not overinterpret the effects of our small-scale experiment to large-scale information diffusion phenomena in online networks. At the same time, the fact that we can already observe the greater information sharing even in the very small networks in the laboratory is certainly an indication that this phenomenon can expose itself in an enlarged form in online networks. Two subsequent steps in this research line can be the following. First, to decrease the gap between online applications and small-scale experiments, we might develop similar experiments in a larger context, e.g., using larger subject pools such as available through Amazons Mechanical Turk. Second, to decrease the gap between the formal theoretical model by Galeotti and Goyal (2010) and the experimental set-up, we might want to develop a more dynamic model of network formation that possibly also includes non-standard preferences such as fairness concerns.

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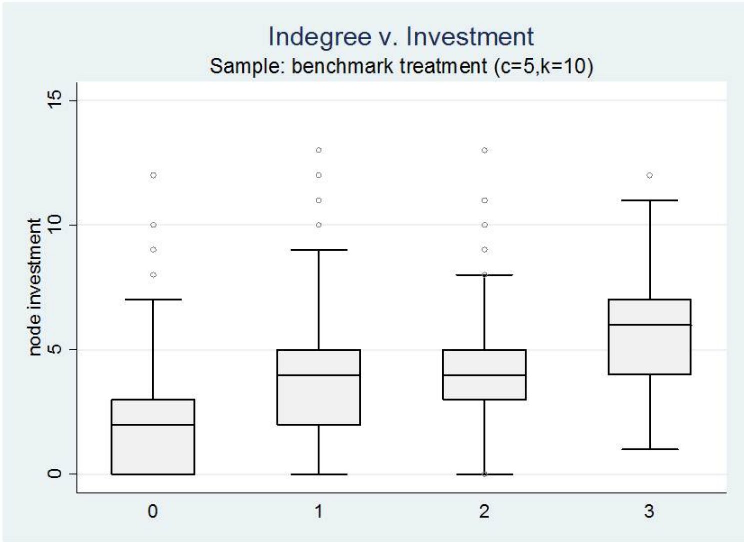


Figure 1: Box plot investment versus in-degree

Structure	Investments				Out-degree				Payoff				$\sum$ Payoff
Star	periph	periph	hub	periph	periph	periph	hub	periph	periph	periph	hub	periph	
	0	0	12	0	1	1	0	1	194	194	144	194	726
2-Star	periph	periph	hub	hub	periph	periph	hub	hub	periph	periph	hub	hub	
	0	0	$2 \leq x_i \leq 10$, $\sum x_i = 12$		2	2	1	0	184	184	144-184	154-194	706
3-Star	periph	hub	hub	hub	periph	hub	hub	hub	periph	periph	hub	hub	
	0	$2 \leq x_i \leq 8$, $\sum x_i = 12$			3	1	1	1	174	154-184	154-184	154-184	696
4-star	hub	hub	hub	hub	hub	hub	hub	hub	hub	hub	hub	hub	
	$2 \leq x_i \leq 6$, $\sum x_i = 12$				1	1	2	2	174-184	174-184	164-174	164-174	696

Table 1: Equilibrium under Treatment I (N=4, c=5, k=10)

Network	Investments				Out-degree				Payoff				$\sum$ payoff
Star	periph	periph	hub	periph	periph	periph	hub	periph	periph	periph	hub	periph	
	0	0	12	0	1	1	0	1	180	180	144	180	684
2-Star	periph	periph	hub	hub	periph	periph	hub	hub	periph	periph	hub	hub	
	0	0	$2 \leq x_i \leq 10, \sum x_i = 12$		2	2	1	0	156	156	130-170	154-194	636

Table 2: Equilibrium under Treatment II (N=4, c=5, k=24)

Network	Investments				Out-degree				Payoff				$\sum$ Payoff
Star	periph	periph	hub	periph	periph	periph	hub	periph	periph	periph	hub	periph	
	0	0	12	0	1	1	0	1	168	168	144	168	648

Table 3: Equilibrium under Treatment III (N=4, c=5, k=36)

	Network	Investments				Out-degree				Payoff				$\sum$Payoff
Treat: IV	Star	periph	periph	hub 1	periph	periph	periph	hub 1	periph	periph	periph	hub 1	periph	
		0	0	13	0	1	1	0	1	198	198	169	198	763
Treat: V	Star	periph	periph	hub 1	periph	periph	periph	hub 1	periph	periph	periph	hub 1	periph	
		0	0	13	0	1	1	0	1	184	184	169	184	721
Treat: VI	Star	periph	periph	hub 1	periph	periph	periph	hub 1	periph	periph	periph	hub 1	periph	
		0	0	13	0	1	1	0	1	172	172	169	172	685

Table 4: Equilibrium under Treatments IV - VI (N=4, $c_1 = 3$, $c_{i \neq 1} = 5, k = 10, 24, 36$)

	N*	Mean	S.D.	Min	Max
Age	152	21.368	2.454	17	31
Friends in the lab	152	0.711	1.183	0	6
Male	152	35.50%	0.48	0	1
Foreign nationality	152	38.20%	0.487	0	1
Investment (final decision)	2736	4.401	3.364	0	30
In-degree (final decision)	2736	1.03	1.09	0	3
Outdegree (final decision)	2736	1.03	0.841	0	3
Linking decisions (per node, round)	38485	24.746	16.387	1	91
Investment decisions (per node, round)	96166	52.015	32.434	1	241

* Number of subjects (N=152); number of individual decisions at end of round
(N = 152 subjects multiplied by 18 non-trial rounds).

Table 5: Descriptive statistics of sample

		Homogeneous, $c = 5$			Heterogeneous, $c_i = 3$		
Treatment		I	II	III	IV	V	VI
		k=10	k=24	k=36	k=10	k=24	k=36
Number of directed	median	5	4	3	5	4	3
ties per group	mean	4.842	3.833	3.684	4.965	3.746	3.658
	SD	(1.252)	(3.611)	(1.826)	(1.545)	(0.870)	(1.356)
Total investment	median	14	17	19	14	17.5	19
per group	mean	15.175	17.588	19.465	15.386	18.491	19.509
	SD	(4.502)	(4.560)	(6.444)	(4.586)	(4.876)	(6.886)
Total profit	median	680	636	611	698	645	621.5
per group	mean	658.588	622.526	611.912	669.491	640.956	628.5
	SD	(54.843)	(41.616)	(56.702)	(58.871)	(37.813)	(61.14)
	N	114	114	114	114	114	114
Individually	median	12	12	12	13	13	13
accessed investment	mean	12.693	12.993	12.879	12.833	13.564	13.355
	SD	(2.942)	(3.611)	(3.557)	(2.957)	(3.958)	(4.141)
Indiviual	median	169	158	156.5	172.5	160	160
profit	mean	164.647	155.632	152.978	167.373	160.239	157.125
	SD	20.209	21.481	23.915	(20.449)	(20.809)	(23.981)
	N	456	456	456	456	456	456

Table 6: Descriptive statistics at the group level

Network structures	Treatment I c=5, k=10	Treatment II c=5, k=24	Treatment III c=5, k=36	Treatment IV $c_i = 3$, k=10
Connected	105 (92.11%)	109 (95.61%)	81 (71.05%)	104 (91.23%)
1 Isolate	4 (3.51%)	4 (3.51%)	18 (15.79%)	6 (5.26%)
2 Isolates	0	0	5 (4.39%)	0
Dyads	5 (4.39%)	1 (0.88%)	10 (8.77%)	4 (3.51%)
Total	114	114	114	114

Table reports number of observations and % of total (in parenthesis).

Table 7: Components in networks

		Hub (invest)		Hub (in-degree)		Investment of Hub (in-degree)	
	N	n	avg n/grp (sd)[1]	n	avg n/grp (sd)[1]	median[2]	mean (sd)[3]
Baseline c=5, k=10	456	295	2.588*** (0.815)	182	1.596*** (0.646)	5	5.093 (2.285)
Treatment II c=5, k=24	456	205	1.798*** (0.871)	124	1.088 *** (0.556)	7***	6.645*** (2.516)
Treatment III c=5, k=36	456	102	0.895*** (0.863)	47	0.412*** (0.527)	7***	7.362*** (2.847)
Treatment IV c=3, k=10	456 [114][4]	290 [96]	2.544 (0.891)	79 [42]	0.693+++ (0.58)	6+++	6.519+++ (2.717)

*,**,*** and +,++,+++ denote $< .1, < .05, < 0.01$ levels of statistical significance. *,**,*** indicate significance levels of values for Treatments I-III compared with each of the remaining two levels of k. +,++,+++ indicate difference between Treatments I and IV.

1 Kolmogorov-Smirnov test for equality of distribution functions.

2 Wilcoxon rank-sum (Mann-Whitney) test for equality of medians. Medians of k=24 and k=36 do not differ statistically.

3 Kolmogorov-Smirnov test for equality of distribution functions. Means and distributions of k=24 and k=36 do not differ statistically.

4 Number of heterogeneous players qualifying as hubs.

Table 8: Number of hubs and investment by hubs

	Hub (invest)	Hub (in-degree)
low-cost Player	0.850***	0.931***
	[4.864]	[5.434]
Period	-0.003	0.018
	[-0.170]	[1.270]
Session dummies	yes	yes
Period dummies	yes	yes
Constant	0.417	-1.438***
	[1.440]	[-4.421]
No. observations	456	456
No. clusters	114	114
Log Likelihood	-277,071	-186,121
Pseudo R2	0.073	0.115
χ^2	38,319	55,741
Prob > χ^2	0.001	0.000

Table reports marginal effects; z-values in parenthesis; heteroskedasticity-consistent estimator of variance; standard errors corrected for intra-network correlation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Probit estimation on the likelihood that the low-cost player is a hub (Treatment IV)

		Treatment I c=5, k=10	Treatment II c=5, k=24	Treatment III c=5, k=36	Treatment IV $c_i = 3$, k=10
Hubs:	investment	5.093***	6.645***	7.361***	6.518**
	best response	3.983	4.250	4.765	5.860
	p-value	0.000	0.000	0.000	0.0687
Non-hubs:	investment	2.930	3.557	4.579*	3.286***
	best response	2.974	3.731	4.288	3.888
	p-value	0.7748	0.2226	0.0512	0.000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ for a Wilcoxon sign-rank test comparing investment to best response.

Table 10: Best-response for hubs (in-degree) and non-hubs

Costs	Hub (in-degree)	N	Profit[1] (mean)	99% CI low	99% CI high	Theory low	Theory high	Theory v CI
c=5, k=10	no	274	158.781	155.311	162.251	154	194	154< CI< 194
	yes	182	173.478	171.146	175.810	144	184	144 < CI < 184
	all	456	164.647	162.206	167.088	174	182	CI < 174
c=5, k=24	no	332	150.515	147.432	153.598	154	194	CI < 154
	yes	124	169.331	166.307	172.355	130	170	130 < CI 170
	all	456	155.632	153.037	158.227	159	171	CI < 159
c=5, k=36	no	409	151.377	148.289	154.465	168	168	CI < 168
	yes	47	166.915	161.159	172.671	144	144	144 < CI
	all	456	152.978	150.088	155.868	162	162	CI < 162
$c_i = 3$, k=10	no	377	165.390	162.617	168.164	198	198	CI < 198
	yes	79	176.835	172.423	181.247	169	169	169 < CI
	all	456	167.373	164.901	169.845	190.75	190.75	CI < 190.75

1 All hub profits are greater than non-hub profits at a confidence level (CI) of 99% (t-statistic, 2-tailed).

Table 11: Profits Hubs (in-degree) and Non-Hubs

Appendix I

Proposition 3 *In Treatments I-III, aggregate investments in equilibrium are equal to 12.*

Proof: The proof exploits the assumption that investments take integer values and that n=4. First we prove that in equilibrium the network is connected. Suppose it is not connected then we need to consider networks of one, two, three (and four) isolated players and networks with disconnected pairs. Observe that no network with single isolated player is an equilibrium: this is because the isolated player will optimally choose 12. But then from Galeotti and Goyal (2010) we know that there must be only one hub, which contradicts the hypothesis that the player is isolated. So we need to consider the case of two disconnected pairs only. When k=10 or 24, in each pair there is at least one player who chooses 6 or more. But then the larger investing player in one pair has an incentive to form a link with the larger investing players in the other pair. When k=36, it follows that in each pair the higher investing player is choosing 8 or more. But then the higher investing player in one pair has a strict incentive to form a link with the higher investing player in the other pair.

So consider connected networks. If only one player invests then it follows from optimality that this player must be investing 12. If only two players are investing then it follows from arguments in Galeotti and Goyal (2010) that neither is investing 12. So they must be connected to each other. This implies from optimality of individual actions that each of them must access exactly 12. Consider next the case that 3 players are investing. Again all of them must be investing strictly less than 12. As everyone accesses 12, each of them must access at least one other player. If a positive investing player accesses all three then the sum total investments must equal 12. So in the three investors case we have proved that sum total of investments must equal 12.

Finally, consider the case that all four players make positive investments. We first consider the case that a player with x is a leaf. Observe that in this case there is a player with y such that $x + y = 12$, However, as the network is connected y must have one other link with someone with investment z. So there is a player who access $x + y + z$, where all investments are positive. From optimality of individual investments it follows that $x + y + z = 12$, but this is a contradiction. So no player is a leaf. Similarly, we can show that a network in which a player has three links must imply that this player accesses all investments, which must then be equal to 12. So the only possibility left is that every player has two links. This means that the network is a ring. This means that all players must make equal investments and sum of three investments must equal 12. In other words, every player invests 4. This is impossible if k=24 or k=36. If k=10, then each player is strictly better off cutting down own investment and linking with a new player. This completes the proof. **QED**

Proposition 4 *In Treatments IV-VI, in equilibrium all high-cost players choose* 0 *investments.*

Proof: The proof of connectedness is as in the previous result. So from now on we restrict attention to connected networks.

We go through the different cases with 1,2, 3 and 4 contributors. Suppose there is 1 contributor. This contributor cannot be the High cost player as he will choose 12; but then the Low cost player will raise his investment to a positive amount so that total investment accessed is 13.

Next consider the case of two contributors. If both are High cost and contributing then neither can be contributing 12. But then it follows from optimality of individual behavior that the sum of investments must add up to 12. But then the Low cost player will have a strict incentive to increase investment to 1. So consider the case where one investor is High and the other is Low. Again it follows that the sum must be 13 and both players must access each other. But then High cost player is accessing too much investment.

Consider next the case of 3 contributors. We need to separately consider the case of three H players and 2 H players and 1 L player. Straightforward arguments which exploit the fact that L must access at least 13 and an active H must access exactly 12, now show that this is not sustainable in equilibrium.

Finally, consider the case of 4 contributors. Here we follow the line of argument in the previous result. We start by showing that a player cannot be a spoke in an equilibrium network. We then consider networks in which no player is a spoke. Here we take up networks in which some player has 3 links. If this is an H player then it contradicts the requirement that an H player must access exactly 12, while there is an L player who is accessing exactly 13. Similarly, if the L player has 3 links then we need to consider a range of networks with 3, 4, 5 and 6 links and in each case we can use integer investments, and the requirement that the L player must access exactly 13, while the H player accesses exactly 12, to show that this cannot be sustained in equilibrium. This leaves only the case in which every player has exactly 2 links. In the ring network, it can be checked that we run afoul of integer constraints. So 4 contributors cannot be sustained in equilibrium. We are left with only one option: one contributor who is of low-cost type. **QED**

Appendix II

Session	Treatments					
1	I (k=10, c=5)	II (k=24, c=5)	III (k=36, c=5)	IV (k=10, c_1=3)	V (k=24, c_1=3)	VI (k=36, c_1=3)
2	III (k=36, c=5)	II (k=24, c=5)	I (k=10, c=5)	VI (k=36, c_1=3)	V (k=24, c_1=3)	IV (k=10, c_1=3)
3	IV (k=10, c_1=3)	V (k=24, c_1=3)	VI (k=36, c_1=3)	I (k=10, c=5)	II (k=24, c=5)	III (k=36, c=5)
4	VI (k=36, c_1=3)	V (k=24, c_1=3)	IV (k=10, c_1=3)	III (k=36, c=5)	II (k=24, c=5)	I (k=10, c=5)
5	I (k=10, c=5)	II (k=24, c=5)	III (k=36, c=5)	IV (k=10, c_1=3)	V (k=24, c_1=3)	VI (k=36, c_1=3)
6	III (k=36, c=5)	II (k=24, c=5)	I (k=10, c=5)	VI (k=36, c_1=3)	V (k=24, c_1=3)	IV (k=10, c_1=3)
7	IV (k=10, c_1=3)	V (k=24, c_1=3)	VI (k=36, c_1=3)	I (k=10, c=5)	II (k=24, c=5)	III (k=36, c=5)
8	VI (k=36, c_1=3)	V (k=24, c_1=3)	IV (k=10, c_1=3)	III (k=36, c=5)	II (k=24, c=5)	I (k=10, c=5)

Table 12: Sequence of treatments

	Treatment I c=5, k=10	Treatment II c=5, k=24	Treatment III c=5, k=36	Treatment IV $c_i = 3$, k=10
Data				
Equilibria	1 (0.8%)	4 (3.4%)	2 (1.7%)	2 (1.7%)
Equilibrium structures	29 (25.4%)	34 (29.7%)	17 (14.9%)	5 (4.4%)
Chance				
Equilibria	< 0.01 ($< 0.001\%$)	< 0.01 ($< 0.001\%$)	< 0.01 ($< 0.001\%$)	< 0.01 ($< 0.001\%$)
Equilibrium structures	5.79 (5%)	3.56 (3.1%)	1.78 (1.5%)	0.44 (0.4%)
Total	114	114	114	114

Table reports number of observations and % of total (in parenthesis).

Table 13: Frequencies and percentages of equilibria and equilibrium structures

	Model 1 Baseline Treatment I	Model 2 Treatment IV $c_i = 3$, k=10	Model 3 Homogeneous Treatments I-III	Model 4 Full Sample
in-degree	1.367***	1.574***	1.316***	1.413***
	[13.501]	[12.183]	[18.549]	[25.094]
k_10			-0.868**	1.422***
			[-2.493]	[4.021]
k_36			0.581	1.486***
			[1.565]	[8.704]
c_5				-0.095
				[-0.753]
Round	-0.088	-1.99	0.017	-0.079
	[-0.510]	[-0.735]	[0.100]	[-0.376]
Session dummies	yes	yes	yes	yes
Period dummies	yes	yes	yes	yes
Constant	1.911***	1.770	2.962***	2.399***
	[2.805]	[1.927]	[6.241]	[4.511]
No. observations	456	456	1368	2736
No. clusters	114	114	342	684
R^2(adj.)	15.261	13.090	16.953	26.872
F	0.340	0.328	0.214	0.221
Prob $> F$	0.000	0.000	0.000	0.000

Table reports t-values in parenthesis; heteroskedasticity-consistent estimator of variance; standard errors corrected for intra-network correlation; period and session dummies incl.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: OLS regressions with individual investment as dependent variable, Treatments I - III, IV

	Model 5 Treatment V $c_i = 3$, k=24	Model 6 Treatment VI $c_i = 3$, k=36
in-degree	1.567***	2.025***
	[13.694]	[10.236]
Round	0.156	-0.824
	[0.757]	[-1.942]
Session dummies	yes	yes
Period dummies	yes	yes
Constant	3.914***	6.162***
	[7.426]	[4.638]
No. observations	456	456
No. clusters	114	114
R^2(adj.)	15,261	13,090
F	0.340	0.328
Prob > F	0.000	0.000

Table reports t-values in parenthesis; heteroskedasticity-consistent estimator of variance; standard errors corrected for intra-network correlation.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: OLS regression with individual investment as dependent variable, Treatments V and VI

- Instructions -

Please read the following instructions carefully. These instructions are equal 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 approach you in order to answer your question.

You can earn money by means of 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 earn during the experiment will be exchanged at an exchange rate of:

200 points = 1 Euro

The money you earn will be paid out in cash at the end of the experiment without other participants being able to see how much you earned. Further instructions on this will follow in due time. During the experiment you are not allowed to communicate with other participants. Turn off your mobile phone and put it in your bag. Also, you may only use the functions on the screen that are necessary to carry out the experiment. Thank you very much.

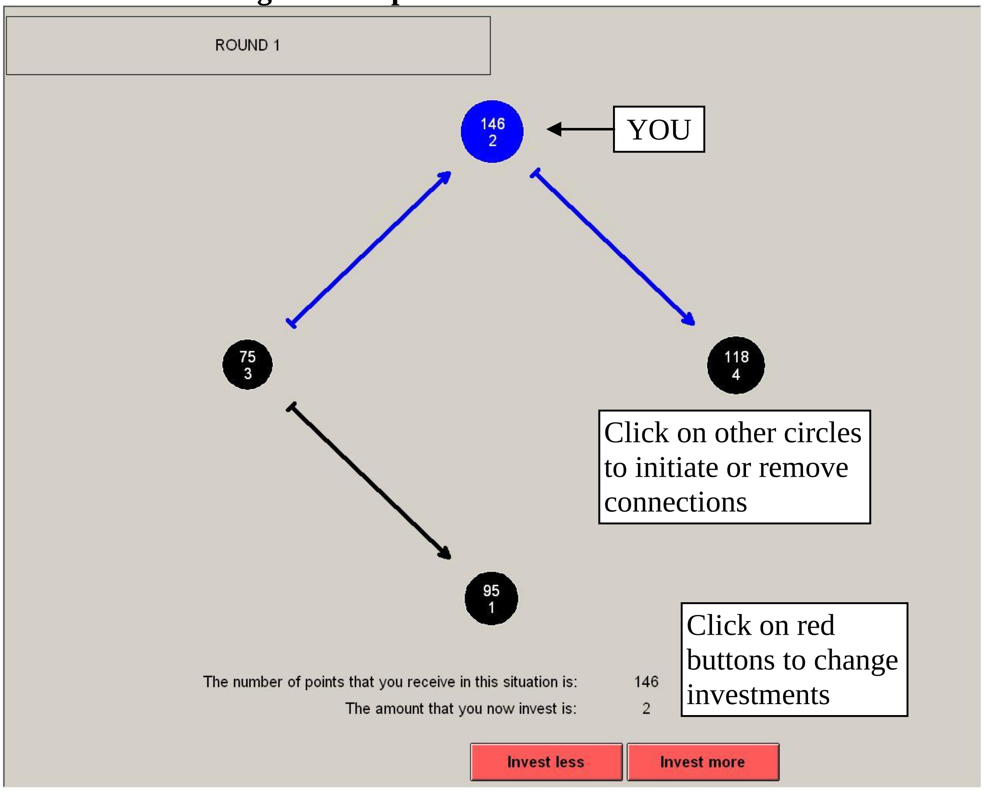
- Overview of the experiment -

The experiment consists of *six scenarios*. Each scenario consists again of *one trial round* and *three paid rounds* (altogether 24 rounds of which 18 are relevant for your earnings).

In *all scenarios* you will be *grouped* with three other randomly selected participants. At the beginning of *each of the 24 rounds*, the groups and the positions within the groups will be randomly changed. The participants that you are grouped with in one round are very likely different participants from those you will be grouped with in the next round. It will not be revealed with whom you were grouped at any moment during or after the experiment.

The participants in your group will be shown as circles on the screen (see Figure 1). You are displayed as a **blue** circle, while the other participants are displayed as **black** circles. You will be able to connect to one or more other participants in your group during each round. By clicking on one of the other participants, you become connected to this other participant. An arrow appears to indicate the connection. By clicking again on the participant the arrow and, thus, the connection is removed again. You are also connected to another participant if this other participant clicks once on you. The participant on whose side a one-sided arrow starts has initiated this connection and has to pay some points for this connection. If both participants have clicked for a specific connection a two-headed arrow appears and both participants need to pay points for this connection. All participants that are connected to you by any kind of arrow will be called *your neighbors*. Hence, in Figure 1 the participants with “75” and with “118” in their circles are your neighbors.

Figure 1: Explanation of screen elements



You can earn **points** in a round by investing, but investing also costs points. The points you receive in the end depend on your own investment and the investments of your neighbors. By clicking on one of the two buttons at the bottom of the screen you increase or decrease your investment. At the end of the round, you receive the amount of points that is shown on the screen at that moment in time. In other words, your final earnings only depend on the situation at the end of every round.

Each round lasts *between 105 and 135 seconds*. The end will be at an unknown and random moment in this time interval. Therefore, different rounds will not last equally long.

The points you will *receive* can be seen as the *top number* in your blue circle. The points others will receive are indicated as the top number in the black circles of others. Next to this, the *size of the circles* changes with the points that you and the other participants will receive: a larger circle means that the particular participant receives more points. The *bottom number* in the circles indicates the amount *invested* by that participant.

<u>Remarks:</u>

- It can occur that there is a time-lag between your click and the changes of the numbers on the screen. One click is enough to change a connection or to change your investment by one unit. A subsequent click will not be effective before the previous click is effectuated.
- **Therefore wait until a connection is changed or your investment is adapted before making further changes!**

- Your earnings -

Now we explain in detail how the number of points that you earn depends on the investments and the connections. Read this carefully. Do not worry if you find it difficult to grasp immediately. We also present an example with calculations below. Next to this, there is a trial round for each scenario to gain experience with how connections and investments affect your earnings.

In all scenarios, the points you receive at the end of each round depend in a similar way on two factors:

1. **Every connection that you initiated yourself costs a given number of points (this will be either 10, 24 or 36).**
2. **Every unit that you invest yourself will cost you 5 points most of the time; in some scenarios, there is one participant in your group (maybe yourself) for whom every unit investment costs only 3 points. This participant will be displayed with an additional square around the circle (see Figure 3).**
3. **You earn points for each unit that you invest yourself and for each unit that your neighbors invest (the earnings related to a neighbor's investments do not depend on whether an arrow points toward yourself, toward the neighbor, or in both directions).**

If you sum up all units of investment of yourself and your neighbors, the following table gives you the points that you earn from these investments:

Your investment plus your neighbors' investments	0	1	2	3	4	5	6	7	8	9	10
Points	0	28	54	78	100	120	138	154	168	180	190

Your investment plus your neighbors' investments	11	12	13	14	15	16	17	18	19	20	21
Points	198	204	208	210	211	212	213	214	215	216	217

The higher the total investments, the lower are the points earned from an additional unit of investment. Beyond an investment of 21, you earn one extra point for every additional unit invested by you or one of your neighbors.

Note: if your and your neighbors' investments add up to 12 or more, earnings increase by less than 5 points for each additional unit of investment.

- Example shown in Figure 2 -

Suppose

1. initiating connections costs 24 points in this scenario;
2. you initiated one connection with one participant and one other participant initiated a connection with you;
3. you invested 2 units;
4. one of your neighbors invested 3 units and the other neighbor invested 4 units.

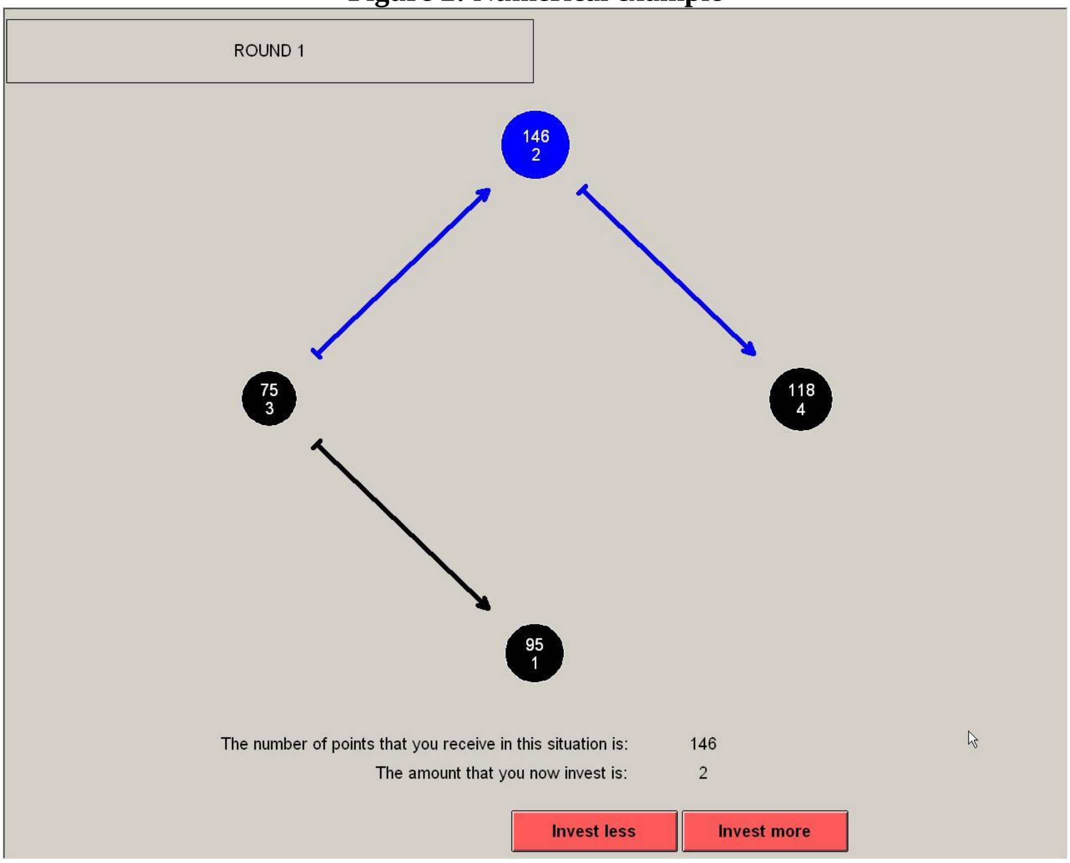
Then you have to pay 24 points for the connection you initiated and 2 times 5 = 10 points for your own investments. Therefore, your total costs are 34 points.

The investments that you profit from are your own plus your neighbors' investments: 2 + 3 + 4 = 9 (see bottom numbers in the circles from you and your neighbors on the right and on the left). In the table you can see that your earnings from this are 180 points.

In total, you would receive 180 − 34 = 146 points if this would be the situation at the end of the round. Figure 2 shows this example as it would appear on the screen. The investment of the fourth participant in your group (at the bottom of the screen) does not affect your earnings. In the trial round before each scenario, you will have time to get used to how the points you receive change with investments.

The participant on the left has initiated two connections, invests in 3 units himself and profits from 3 + 2 + 1 = 6 units in total. Therefore, this participant receives in this situation 138 (see table) $- 2 \times 24 - 3 \times 5 = 75$ points.

Figure 2: Numerical example



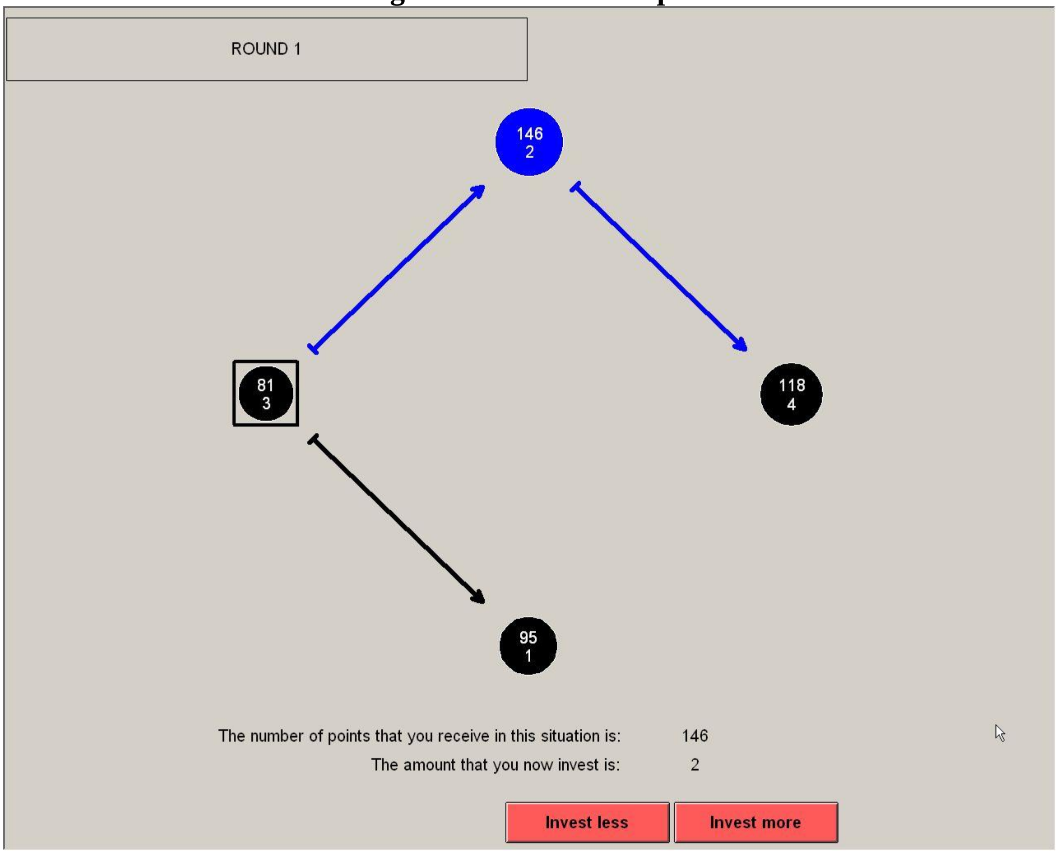
- Scenarios -

All rounds are basically the same. The things that change between scenarios are:

1. The costs for a connection will be 10, 24, or 36 points.
2. There might be one participant who pays only 3 points per unit of investment. This participant is marked with an additional square. In Figure 3, this is the participant on the left. This participant earns 6 points more than in Figure 2 because he pays $3 \times 2 = 6$ points less for his three units of investments, which brings his total earnings to $138 - 2 \times 24 - 3 \times 3 = 81$.

When a new scenario starts, you will get a message on the screen that describes the new scenario. Please read these messages carefully. As indicated before each scenario starts with a trial round. At the top of the screen you can also see when you are in a trial round. Paying rounds are indicated by "ROUND" while trial rounds are indicated by "TRIAL ROUND".

Figure 3: Second example



- Questionnaire -

After the 24 rounds you will be asked to fill in a questionnaire. Please take your time to fill in this questionnaire accurately. In the mean time your earnings will be counted. Please remain seated until the payment has taken place.

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